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# Implementation of the FP-Growth Algorithm for Bundling Strategy and Store Layout Redesign at Toko Kasih Ibu

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**ABSTRACT**

Grocery stores like Toko Kasih Ibu face increasing challenges in staying competitive against modern markets offering better convenience, product variety, and services. A notable sales decline in 2024 highlights the need for improved marketing and store layout strategies. This study analyzes purchasing patterns using the FP-Growth algorithm within a Market Basket Analysis (MBA) framework to design product bundling and optimal layout recommendations. Using the CRISP-DM approach, 468,507 transaction records from 2022–2024 were processed, followed by data preparation and transformation. The FP-Growth model was applied with a minimum support of 2% and confidence of 50%, resulting in 11 strong association rules—such as bundling Fom Burger Per 10, Pilus SP 500 RTG BAL, and Indomie Goreng PC. Additionally, category-level analysis using the Activity Relationship Chart (ARC) with the AEIOUX scale suggested reorganizing the store into four sectors to improve customer convenience and encourage combined purchases. The findings demonstrate that applying the FP-Growth algorithm with appropriate parameters offers valuable insights for effective bundling and layout strategies, supporting promotional efforts and sales goals.

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## 1. Introduction

The retail industry in Indonesia includes various forms of economic businesses, one of which is the traditional convenience store known as a toko kelontong. These stores sell a variety of daily necessities such as staple foods, snacks, and household goods [1]. They are widely spread in both rural and urban areas, serving as essential providers for the community. However, with the rise of modern markets that are more structured and mostly located in urban areas, traditional stores are facing major challenges in maintaining their competitiveness. Modern markets offer convenience, product variety, and better services, which are the main attractions for consumers, especially from the middle to upper class [2].

These challenges also affect Toko Kasih Ibu, a traditional store located at Jl. Kalimantan No. 127, Sukomulyo, Manyar, Gresik. In order to remain relevant in an increasingly competitive market, the store must adapt and seek new strategies. As the subject of this research, Toko Kasih Ibu has adopted the use of computers to support sales and inventory management through a Microsoft Visual FoxPro-based application. However, this use of technology alone is not sufficient to stay competitive amid the rapid growth of modern retail. The store also faces strong competition from nearby modern retailers, such as Alfamart, which affects customer loyalty and puts pressure on the store's marketing strategies.

This competition is clearly reflected in the sales turnover trends of Toko Kasih Ibu from 2022 to 2024. Although sales performance remained relatively stable in 2022 and 2023, there was a significant decline beginning in 2024 that continued until the end of the year. This condition indicates that the store is facing serious challenges in maintaining its sales. Therefore, a more effective business strategy is needed, including the use of technology for data analysis and better planning. One potential solution is to utilize historical transaction data, as this data contains valuable information that can be used to increase product sales [3]. By performing in-depth analysis on transaction history, Toko Kasih Ibu can discover specific patterns such as frequently purchased item combinations or purchasing trends during certain periods [4][5].

The application of data mining as a technique for discovering hidden patterns and generating new knowledge from large datasets [6] is highly relevant in this context. Data mining helps extract insights about consumer behavior and market trends, enabling businesses to make more informed and effective decisions to improve performance and competitiveness [7]. One suitable data mining technique for analyzing purchasing patterns is Market Basket Analysis (MBA), which aims to find associations between products that are frequently purchased together in a single transaction [8].

In Market Basket Analysis, the FP-Growth algorithm is considered more efficient than Apriori in identifying frequent itemsets. FP-Growth uses a data structure called an FP-Tree to represent frequent itemsets without the need for repeated database scanning. Previous studies [9] have shown that FP-Growth can produce more association rules with similar processing time compared to Apriori, making it a more suitable algorithm for the Toko Kasih Ibu case, which requires high efficiency in identifying purchase patterns.

Since its establishment in 2007, Toko Kasih Ibu has not applied any product bundling strategies. All products are still sold individually, even though bundling products that are frequently bought together can potentially increase sales. This strategy not only attracts consumers with more appealing prices but also encourages them to purchase in larger quantities [10]. By applying Market Basket Analysis using the FP-Growth algorithm, the store can design product bundles that better suit customer needs and preferences [11], which can ultimately improve customer loyalty and increase visit frequency.

In addition to bundling, the product layout at Toko Kasih Ibu is also not well organized, making it difficult for customers to find what they need and potentially lowering customer satisfaction. Direct observations show that the disorganized product placement creates challenges for both customers and cashiers in finding items, which leads to longer shopping times and slows down the service process. Product arrangement or item display plays an important role in optimizing sales and improving the overall shopping experience [12]. A well-organized store interior not only influences purchasing decisions but also helps create a more comfortable and enjoyable shopping experience [12].

Therefore, reorganizing the store layout at Toko Kasih Ibu is necessary, and in this study, it will be supported by a visualization of relationships between product categories using an Activity Relationship Chart (ARC), which is constructed based on association rules generated by the FP-Growth algorithm.

This study adopts the CRISP-DM (Cross Industry Standard Process for Data Mining) framework as the main methodology. The process includes business understanding, data understanding, data preparation, modeling using FP-Growth, evaluation of association rules, and deployment in the form of bundling strategy recommendations and a revised product layout based on the analysis results. By implementing a bundling strategy and improving product layout using Market Basket Analysis, Toko Kasih Ibu is expected to enhance its marketing effectiveness and competitiveness in the face of modern retail. These improvements also have the potential to increase customer loyalty by offering a more convenient and appealing shopping experience. By gaining deeper insights into customer purchasing behavior, the store can develop more relevant and data-driven marketing strategies. In the long term, this optimization is expected to support more sustainable business growth and strengthen Toko Kasih Ibu's position in the local retail market. Therefore, the application of Market Basket Analysis using the FP-Growth algorithm is a strategic step toward more modern and data-driven store management.

## 2. Research Method

This research follows a structured process flow based on the CRISP-DM framework, which is visualized in the form of a flowchart in Figure 1. This method enables a systematic and sequential execution of literature review, business understanding, data exploration and preparation, FP-Growth modeling, evaluation, and implementation of the analysis results.

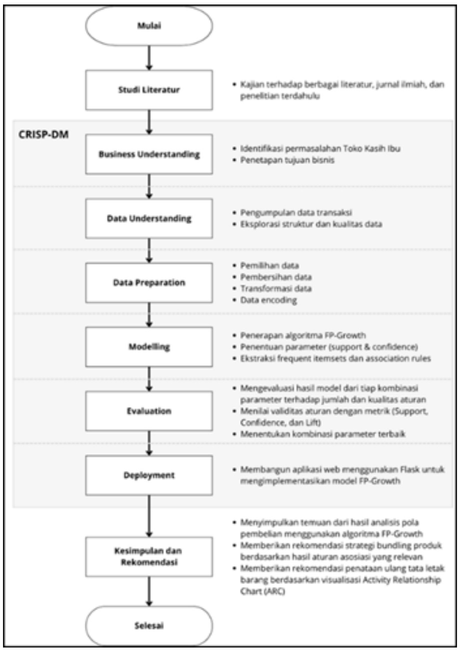


Figure 1. Research Flowchart

## 2.1. Literature Review

The literature review stage was conducted to build a strong theoretical foundation for the research. The references studied include books, scientific journals, articles, and previous relevant studies. First, the basic concept of data mining is discussed as a process of extracting information from large data collections, which according to Han et al. (2012) [13], has five main functions: classification, clustering, association, regression, and prediction. This study focuses on the association function, particularly through the Market Basket Analysis (MBA) technique, which aims to discover relationships between products frequently purchased together [13][14]. To identify these patterns, this research uses the FP-Growth algorithm, selected for its efficiency compared to the Apriori algorithm. FP-Growth uses an FP-Tree data structure that allows for the discovery of frequent itemsets without the need to generate candidate itemsets first [15][16]. The effectiveness of this algorithm has been proven in various prior studies, both in implementing product bundling strategies [17] and in designing product layouts in retail stores [18].

In the process of discovering association rules, this study also refers to the Association Rules Mining method, using metrics such as support, confidence, and lift to assess the strength and relevance of the discovered patterns [19][20][21]. The entire research process follows the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework, which consists of six stages: business understanding, data understanding, data preparation, modeling, evaluation, and deployment [22]. As part of implementing the analysis results, this study also adopts Flask technology, a lightweight and flexible web framework based on Python. Flask is used to build an application interface that interactively displays the results of the FP-Growth analysis [23].

## 2.2. CRISP-DM

This study adopts the CRISP-DM (Cross-Industry Standard Process for Data Mining) approach as the main framework to guide the entire analytical process. The approach consists of six interrelated phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment [24].

a. Business Understanding, Toko Kasih Ibu is facing competition and declining sales. A data-driven strategy is needed using the FP-Growth algorithm to identify customer purchasing patterns that support bundling and product arrangement strategies.
b. Data Understanding, Transaction data from 2022 to 2024 is used, consisting of 468,507 rows. The dataset includes important attributes such as product code, product name, invoice number, sales date, selling price, and item quantity. These attributes are analyzed to understand the structure and context of customer transactions.

c. Data Preparation, The data is selected, cleaned, and transformed by adding new attributes such as TOTAL_TRANSAKSI and KATEGORI_PRODUK, which are classified into 27 categories. Categorical data is converted using One-Hot Encoding to prepare it for analysis.
d. Modeling, In this stage, the FP-Growth algorithm is used to find frequent itemsets and generate association rules based on minimum support and confidence parameters. The process begins with the construction of an F-List by calculating item frequencies, sorting them by frequency, and filtering using minimum support. An FP-Tree is then built to efficiently store purchase patterns, followed by the generation of conditional pattern bases and conditional FP-Trees for each itemset. From this structure, frequent itemsets are identified and used to form association rules in the form of implications, such as "if A is purchased, then B is also likely to be purchased." Rule evaluation is conducted based on support, confidence, and lift values. The model is built for two approaches: product-level and category-level, which serve as the basis for bundling recommendations and strategic store layout planning.
e. Evaluation, The resulting rules are evaluated using support, confidence, and lift metrics. The evaluation results are used to determine potential product pairs for bundling and product placements based on strong associations.
f. Deployment, The model is implemented in a Flask-based web application that provides features such as data upload, association rule visualization, and practical narrative-based recommendations. This application helps store managers apply data-driven strategies more easily.

### *2.3. Conclusion and Recommendations*

The analysis using the FP-Growth algorithm successfully identified customer purchasing patterns at both product and category levels. Frequently purchased products are recommended for bundling to increase sales and reduce slow-moving stock. At the category level, associations were visualized using the Activity Relationship Chart (ARC), which is a method used to support facility layout planning by considering the closeness relationship between activities or product categories [25]. In retail contexts, ARC uses symbols such as A, E, I, O, U, and X to indicate the urgency of proximity between categories, based on data such as purchasing patterns and activity relationships [26]. These ARC-based associations provide a systematic foundation for designing store layouts that improve customer convenience and enable cross-selling strategies. The main recommendations of this study include the implementation of a bundling strategy and a redesigned store layout, both of which are expected to support more optimal data-driven business decision-making.

## 3. Result and Discussion

In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily [2, 5]. The discussion can be made in several sub-chapters.

### *3.1. Business Understanding*

Observations and transaction data analysis at Toko Kasih Ibu reveal challenges in competitiveness, particularly due to pressure from modern minimarkets and suboptimal product placement that does not yet support marketing strategies such as bundling. The declining sales trend in 2024 indicates that transaction data has not been optimally utilized in business decision-making. Therefore, Market Basket Analysis (MBA) using the FP-Growth algorithm was conducted to identify associations between products that are frequently purchased together. These findings are used to design bundling strategies and more strategic product arrangements to improve sales effectiveness and customer loyalty.

### *3.2. Data Understanding*

The data analyzed were sourced from the cashier system of Toko Kasih Ibu during the period 2022 to 2024, consisting of 468,507 rows of transactions. Important attributes used include product code (KD_STOCK), product name (NM_ST), invoice number (NO_FAKTUR), transaction date (TG_JUAL), selling price (HR_JUAL), quantity sold (JL_JUAL), and additional information such as cost of goods sold and profit. The attributes NM_ST and NO_FAKTUR played a central role in building associations between products in a single transaction. Meanwhile, the other attributes provided economic and temporal context useful for interpreting the results. A thorough understanding of this data structure is a crucial foundation for pattern analysis using the FP-Growth algorithm.

### 3.3. Data Preparation

In this stage, data was prepared to be suitable for analysis using the FP-Growth algorithm. The Data Preparation phase consisted of several main steps:

1. Data Selection, Selected relevant transactions from 2022 to 2024 and important attributes such as product name, product code, invoice number, date, selling price, and quantity sold, resulting in 414,832 rows of data from the initial 468,507.
2. Data Cleaning, Removed duplicates, invalid transactions, and missing values, and corrected product code formats. Manual verification of product names was also performed, resulting in a clean dataset of 406,719 rows.
3. Data Transformation, Added product category and total transaction columns, grouping 4,970 products into 27 categories to facilitate category-level association analysis.
4. Encoding, Applied one-hot encoding to product names and product categories, producing two separate datasets representing transactions by product and by category, ready for FP-Growth analysis.

### 3.4. Modeling

This stage aimed to discover relationships between products and product categories that are frequently purchased together using the FP-Growth algorithm. The algorithm was chosen for its efficiency in discovering frequent itemsets without explicitly generating candidate itemsets. The analysis was carried out on two levels, namely the product level and the category level. A sensitivity test on minimum support values (1 to 5 percent) was conducted to evaluate the quantity and quality of frequent itemsets and association rules. The minimum confidence threshold was set at 50 percent to ensure strong item relationships within transactions.

#### 3.4.1. FP-Growth on Products

a. Frequent List (F-List), Products were filtered based on their frequency of occurrence in transactions. Products with support ≥ 2 percent were selected as the analysis basis. For example, "Gula Lokal" (local sugar) was the top product with 7,044 occurrences.
b. FP-Tree Construction, Conditional pattern bases were formed from transactions containing the highest-frequency product. The FP-Tree was visualized using igraph and Plotly, illustrating relationships between products in a transaction. For example: Gula Lokal → Aoka Aneka Dll → GD Frez Mofrio RTG /12 (Figure 2).

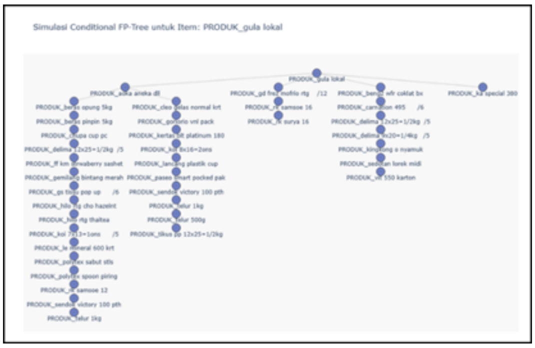


Figure 2. FP-Tree Result (PRODUCT_gula lokal)

c. Frequent Itemsets Extraction
Frequently co-purchased product combinations were identified and are shown in Table 1. The number of itemsets decreases as the support threshold increases.

Table 1. Number of Frequent Itemsets by Support Threshold (Product Level)

| Minimum Support | Number of Frequent Itemsets |
|---|---|

| | |
|---|---|
| 1% | 174 |
| 2% | 43 |
| 3% | 25 |
| 4% | 9 |
| 5% | 8 |

d. Association Rules Generation

Association rules were generated from itemset combinations that met the minimum confidence threshold of 50 percent and lift ≥ 1. These rules describe purchasing patterns, such as "if product A is bought, product B is also likely to be bought." Table 2 provides sample rules generated with a support of 2 percent and confidence of at least 50 percent.

Table 2. Sample Product Association Rules (support 2%, confidence ≥ 50%)

| Antecedents | Consequents | Support | Confidence | Lift |
|---|---|---|---|---|
| ('PRODUK_fom burger per 10') | ('KATEGORI_Makanan Instan', 'KATEGORI_Houseware') | 0,0282 | 0,668246445 | 33,41232227 |
| ('KATEGORI_Makanan Instan', 'KATEGORI_Condiment') | ('KATEGORI_Snack', 'KATEGORI_Houseware') | 0,0379 | 0,567365269 | 27,01739378 |
| ('KATEGORI_Houseware', 'KATEGORI_Breakfast') | ('KATEGORI_Drink') | 0,0242 | 0,663013699 | 1,268440212 |

Table 3 shows the number of association rules generated for each minimum support value, with a fixed minimum confidence of 50 percent. As support increases, the number of rules decreases.

Table 3. Number of Product Association Rules by Support Threshold

| Minimum Support | Minimum Confidence | Number of Rules |
|---|---|---|
| 1% | | 51 |
| 2% | | 11 |
| 3% | 50% | 2 |
| 4% | | 0 |
| 5% | | 0 |

### *3.4.2. FP-Growth on Product Categories*

a. Frequent List (F-List), Categories were filtered with support ≥ 2 percent. "Drink" ranked highest (50,445 occurrences), followed by "Breakfast" and "Condiment".

b. FP-Tree Construction, Conditional pattern bases were created from transactions containing the highest-frequency categories. The FP-Tree was visualized with igraph and Plotly, showing relationships between categories such as: Drink → Breakfast → Egg (Figure 3).

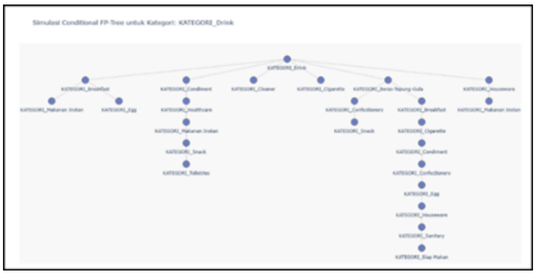


Figure 3. FP-Tree Result (CATEGORY_Drink)

c. Frequent Itemsets Extraction

Frequently co-purchased category combinations were identified and are shown in Table 4. The number of itemsets decreased as support increased.

Table 4. Number of Frequent Itemsets by Support Threshold (Category Level)

| Minimum Support | Number of Frequent Itemsets |
|---|---|
| 1% | 357 |
| 2% | 166 |

| | |
|---|---|
| 3% | 102 |
| 4% | 70 |
| 5% | 50 |

d. Association Rules Generation
Association rules were generated from itemset combinations that met the minimum confidence threshold of 50 percent and lift ≥ 1. These rules reflect purchasing behavior between categories. Sample rules are shown in Table 5.

Table 5. Sample Product Association Rules (support 2%, confidence ≥ 50%)

| Antecedents | Consequents | Support | Confidence | Lift |
|---|---|---|---|---|
| ('KATEGORI_Egg') | ('PRODUK_pilus sp 500 rtg bal', 'PRODUK_indomie goreng pc') | 0,0221 | 0,701587302 | 19,11682021 |
| ('PRODUK_indomie soto spcl pc') | ('PRODUK_indomie goreng pc') | 0,023 | 0,732484076 | 10,60034843 |
| ('PRODUK_gd capucino rtng /') | ('PRODUK_gd frez mofrio rtg /12') | 0,0246 | 0,503067485 | 7,207270554 |

Table 6 shows the number of category association rules generated at each support level, with a fixed minimum confidence of 50 percent. As support increases, the number of rules decreases.

Table 6. Number of Product Association Rules by Support Threshold

| Minimum Support | Minimum Confidence | Number of Rules |
|---|---|---|
| 1% | | 613 |
| 2% | | 265 |
| 3% | 50% | 109 |
| 4% | | 47 |
| 5% | | 24 |

## 3.5. *Evaluation*

Evaluation was conducted to assess the effectiveness of the minimum support and minimum confidence parameters in generating relevant association rules for bundling strategies and product placement.

a. Evaluation of FP-Growth on Products, From testing across support values of 1 to 5 percent with confidence set at 50 percent, the combination of 2 percent support and 50 percent confidence was found to be the most optimal. This configuration produced a sufficient number of relevant rules, avoiding redundancy (as found with 1 percent support) and limitations (as occurred with support values above 3 percent). It provided a balance between quality and quantity of rules, making it a suitable basis for product bundling strategies.
b. Evaluation of FP-Growth on Product Categories, For product categories, a support threshold of 2 percent also yielded the best results. Although support at 1 percent produced a large number of rules (613), many were redundant or less applicable. On the other hand, support values of 3 percent or higher resulted in too few rules, risking the loss of important patterns. Moreover, the highest lift value was observed at 1 percent support (up to 85), but it dropped significantly at 5 percent support (around 4), indicating that lower support thresholds may reveal strong but rare associations. Considering the number of rules, pattern variety, and strength of associations (lift), the combination of 2 percent support and 50 percent confidence was selected as the optimal configuration for category-level analysis. This combination offers meaningful insights while maintaining practical relevance in the business context.

## 3.6. *Deployment*

The FP-Growth model was deployed through an interactive website built using Flask to help the management of Toko Kasih Ibu easily access the Market Basket Analysis (MBA) results in a user-friendly manner without technical difficulties.

a. Home Page, The homepage provides an interface to upload transaction files (.xlsx/.csv) that will be used as the dataset for analysis. Figure 4 shows the appearance of the Home Page in the browser.


Figure 4. Home Page Interface

b. Association Page, This page displays transaction data and allows filtering by date range. Users can adjust the analysis period and run the FP-Growth model as needed. Figure 5 shows the appearance of the Association Page.

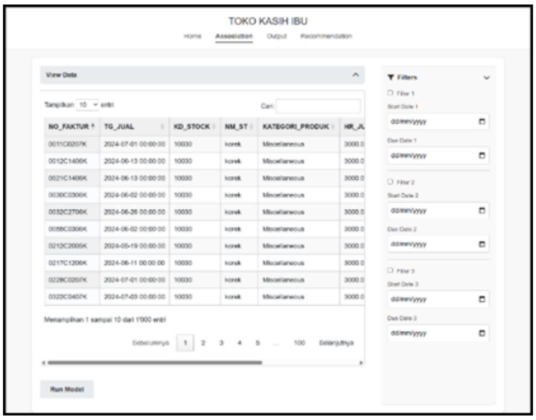


Figure 5. Association Page Interface

c. Output Page, This page displays the generated association rules in tabular form, complete with support, confidence, and lift values. The display is designed for users with technical knowledge but remains informative for evaluating rules. Figure 6 shows the Output Page.

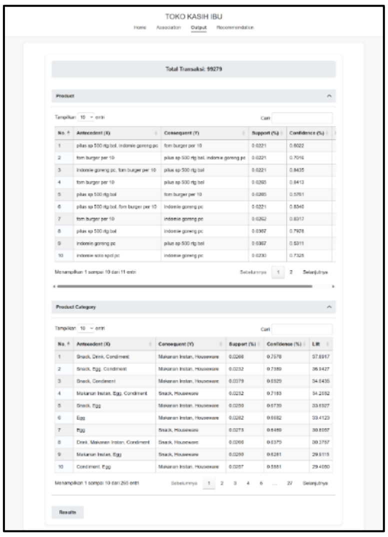


Figure 6. Output Page Interface

d. Recommendation Page, This page presents a narrative interpretation of the association rules. Rules with high confidence and lift values are converted into practical recommendation statements, such as “If customers buy Snack and Condiment categories, they also tend to buy Instant Food.” This page helps non-technical users understand insights and formulate bundling or product placement strategies. Figure 7 shows the Recommendation Page interface.

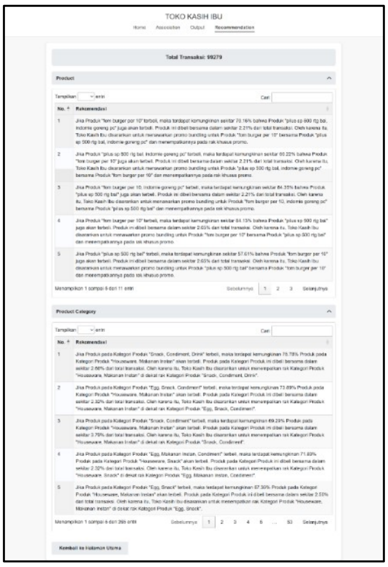


Figure 7. Recommendation Page Interface

## *3.7. Interpretation of Results*

a. Product Purchase Pattern Analysis, A total of 11 strong product association rules were identified with a minimum support of 2 percent and minimum confidence of 50 percent. These rules revealed strong purchase relationships between items:
    1. Fom Burger Per 10 ⇔ (Pilus SP 500 RTG BAL, Indomie Goreng PC): This is the strongest association (confidence 70.16 percent and lift 19.12), showing these products are frequently bought together.
    2. Fom Burger Per 10 ⇔ Pilus SP 500 RTG BAL: Another strong association (confidence 84.13 percent and lift 18.29).
    3. Pilus SP 500 RTG BAL ⇔ Indomie Goreng PC: Also strong (confidence 79.78 percent and lift 11.55).
    4. Indomie Soto Spcl PC ⇔ Indomie Goreng PC: Reflects consumer preference for instant noodle variants (confidence 73.25 percent and lift 10.60).
    5. GD Capucino RTNG ⇔ GD Frez Mofrio RTG /12: Indicates beverage variant association (confidence 50.31 percent and lift 7.21).
b. Category Purchase Pattern Analysis, Category-level analysis produced 263 association rules with a minimum support of 2 percent and confidence of 50 percent. These rules were grouped using the Activity Relationship Chart (ARC) based on confidence values (AIEOUX scale), as visualized in Figure 8.

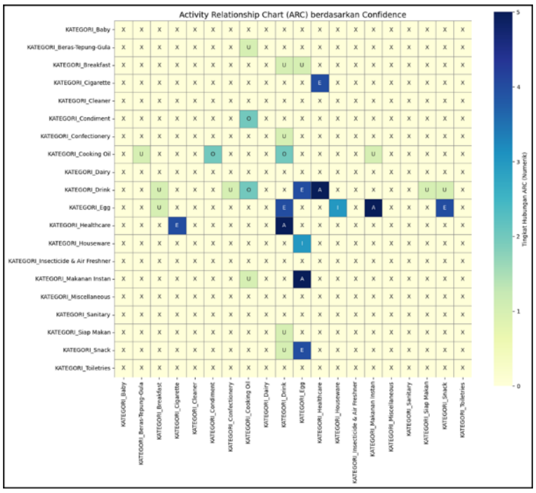


Figure 8. Activity Relationship Chart (ARC) Based on Confidence Value

Based on Figure 8, ARC classifies the relationships into six proximity levels according to confidence value:

1. Level A (Absolute, Confidence ≥ 0.91), Categories must be placed close together. Example: Egg with Instant Food, Healthcare with Drink.
2. Level E (Very Important, Confidence ≥ 0.81), Categories should ideally be placed nearby. Example: Healthcare with Cigarette, Egg with Snack, Egg with Drink.
3. Level I (Important, Confidence ≥ 0.71), Proximity is recommended. Example: Egg with Houseware.
4. Level O (Optional, Confidence ≥ 0.61), Proximity is optional and not critical. Example: Condiment with Cooking Oil, Cooking Oil with Drink.
5. Level U (Unimportant, Confidence ≥ 0.50), Proximity has little impact. Example: Rice-Flour-Sugar with Cooking Oil, Breakfast with Drink.
6. Level X (Not Recommended, Confidence < 0.50), No strong purchase pattern. Placement is flexible.

### *3.8. Recommendations*

a. Product Bundling Strategy Recommendations, Based on the association rules, the following product bundles are recommended:
    1. Hemat Wholesale Bundle: Fom Burger Per 10, Pilus SP 500 RTG BAL, and Indomie Goreng PC. Targeted at small retailers or shop owners to benefit from strong associations among these products.
    2. Indomie Variant Bundle: Indomie Goreng PC and Indomie Soto Spcl PC. Leverages consumer preference for flavor variety.
    3. GoodDay Variant Bundle: GD Capucino RTNG and GD Frez Mofrio RTG. Attracts buyers looking for drink variations.

b. Product Layout Redesign Recommendations, The current layout of Toko Kasih Ibu is unstructured and inefficient, as shown in Figure 9.

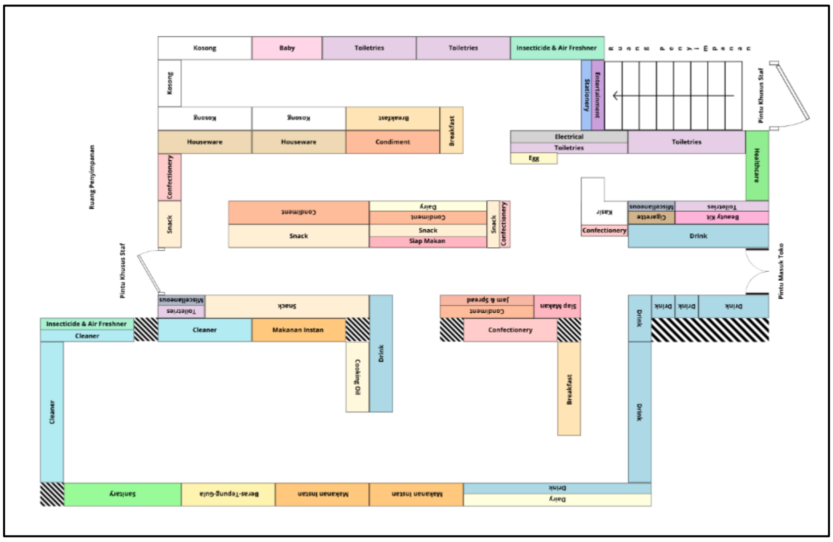

Figure 9. Existing Store Layout at Toko Kasih Ibu

Based on category analysis and ARC, the proposed layout redesign includes:

1. Proximity Placement Based on ARC Levels, Categories with strong relationships (A, E, I) should be placed close together, such as Egg with Instant Food, Healthcare with Drink, Cigarette with Healthcare, Egg with Snack, and Egg with Houseware. Categories with lower proximity levels (O, U, X) can be placed more flexibly.
2. Store Sector Division, The store should be divided into four main sectors: Food and Beverage, Neutral, Chemical and Cleaning, and Cashier Sector. The Food and Beverage sector must be separated from the Chemical sector to avoid contamination. The Neutral sector acts as a buffer, and the cashier should remain near the exit for efficiency.
3. Space Optimization, Shelving placement should maximize visibility, accessibility, and minimize narrow spaces.

The proposed layout redesign is visualized in Figure 10.

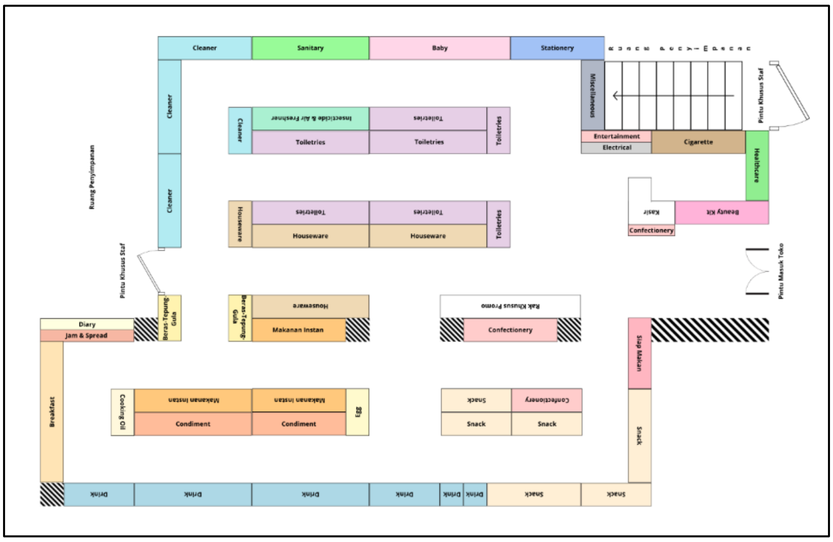

Figure 10. Proposed Store Layout at Toko Kasih Ibu

## 4. Conclusion

This study successfully applied the FP-Growth algorithm to analyze transaction data from Toko Kasih Ibu over the period 2022 to 2024, with the main objective of identifying product purchase association patterns that can be utilized for bundling strategies and product arrangement on display shelves. By using a minimum support of 2 percent and a minimum confidence of 50 percent, a set of association rules was generated to represent both product-level and category-level purchasing patterns frequently observed among customers.

At the product level, strong purchase patterns were identified, particularly between items such as Fom Burger Per 10, Pilus SP 500 RTG BAL, and Indomie Goreng PC. These rules showed confidence values above 70 percent and lift values exceeding 10, indicating a very strong buying relationship. These products are highly suitable for bundling, not only to increase transaction value but also to offer convenience to customers, especially small retailers who tend to buy in bulk. In addition, consistent purchasing patterns were found among product variants, such as various flavors of Indomie and GoodDay beverages, opening up opportunities for variant-based bundling strategies to attract customers with specific flavor preferences. The bundled products are recommended to be placed on special promotional display racks near the cashier to encourage impulse purchases.

At the product category level, the results of the association analysis were classified using the Activity Relationship Chart (ARC) based on confidence values. Categories with the highest closeness levels, such as Egg and Instant Food, and Healthcare and Drink, are recommended to be placed near each other on shelves to enhance shopping convenience and increase the likelihood of combined purchases. Meanwhile, categories with lower closeness levels can be arranged more flexibly, depending on the store’s scale and available space. This classification forms the basis for the proposed redesign of the store layout at Toko Kasih Ibu, with a focus on organization, space efficiency, and improving customer comfort while shopping.

Overall, the application of the FP-Growth algorithm in this study has provided valuable data-driven strategic insights for store management. These findings serve as a strong foundation for decision-making aimed at improving operational efficiency, enhancing customer satisfaction, and strengthening the competitiveness of Toko Kasih Ibu in the face of an increasingly modern and competitive retail market landscape.

## Acknowledgement

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