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Journal of Information System Exploration and Research

https://shmpublisher.com/index.php/joiser

p-ISSN 2964-1160 | e-ISSN 2963-6361

Analysis and Visualization of Purchasing Pattern in Retail Product Transaction using Apriori Algorithm

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DOI: https://doi.org/10.52465/joiser.v4i1.650
Received 22 January 2026; Accepted 08 February 2026; Available online 08 February 2026

Article Info

Keywords:
Data mining;
Apriori algorithm;
Retail transaction analysis;
Market basket analysis;
Power BI

Abstract

The rapid growth of the retail industry generates large volumes of transaction data that can be analyzed to support data-driven business decision making. This study aims to analyze and visualize purchasing patterns in retail product transactions by applying data mining techniques using the Apriori algorithm and business intelligence visualization through Microsoft Power BI. The dataset consists of 1 million retail transactions collected from an open retail transaction repository. The research stages include data collection, transaction data preprocessing, implementation of the Apriori algorithm with a minimum support threshold of 0.002 and a minimum confidence of 0.5, and visualization of the analysis results through interactive dashboards using Power BI and a Python-based application developed with the Streamlit framework. The results indicate that the Apriori algorithm successfully identifies frequent product associations and generates 12 association rules that meet the criteria of strong association rules. Power BI visualizations provide comprehensive insights into transaction trends based on customer categories, store types, payment methods, seasons, and transaction regions. These findings are expected to assist retail companies in formulating marketing strategies, developing product recommendations, and optimizing inventory management in a more effective and data-driven manner. This study contributes by integrating large-scale association rule mining with interactive business intelligence visualization for retail decision support.

1. Introduction

In today's world, retail is one of the fastest-growing industries and generates revenue at a rapid rate [1]. Retail transactions are not merely numerical records but represent strategic elements that can

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provide insights and knowledge through clear and in-depth visualizations, including total transaction values, payment methods, store types, customer categories, seasonal transaction patterns, and the availability of promotions for purchased products [2]. However, a major challenge frequently faced is how raw data can be processed into meaningful and comprehensible information that accurately reflects existing conditions to support transaction pattern analysis in retail companies.

Microsoft Power BI, as one of the leading business intelligence (BI) tools [3] [4] offers a solution for visualizing retail transaction data in the form of interactive dashboards. This tool also enables effective data integration and transformation from raw numerical data into informative and sustainable insights, allowing transaction pattern analysis to be performed more efficiently and quickly. Moreover, Power BI serves not only as a data summary tool but also as a means to facilitate business decision making [5]. In addition, many companies are still unaware of the purchasing patterns within individual transactions, such as when customers purchase product X followed by products Y, Z, and so on. This occurs because customers typically purchase multiple products within a single transaction, while transaction data are often used merely as archives rather than being analyzed according to their potential value [6][7].

Retailers or companies can utilize transaction data to identify and understand customer purchasing patterns[8]. For retail transaction data analysis, Market Basket Analysis using the Apriori algorithm is applied. The results provide information on product combinations that are frequently purchased together, thereby assisting retail companies in managing transactions more effectively [9] . The implementation of the Apriori method applies minimum support and minimum confidence thresholds to analyze purchasing patterns for each product. Previous research by M. Khusnun Najib and Evy Maya Stefany [3], focused on Power BI visualizations limited to sales trends, product category contributions, revenue distribution, and customer preferences, while research conducted by Hilda Fitriana Dewi, Hanny Hikmayanti Handayani, and Jamaludin Indra [1], utilized the Apriori method to identify consumer purchasing patterns and frequently purchased items.

Based on these issues, this study formulates several research objectives, including the visualization of retail transaction data through interactive dashboards to enhance company understanding of frequently used payment methods, dominant customer categories, and store types with the highest transaction volumes [10][11]. However, previous studies rarely integrate large-scale association rule mining with multi-dimensional business intelligence dashboards using real-world transaction data exceeding one million records. In addition to dashboard visualization using Power BI, customer purchasing pattern analysis is conducted using association rule mining with the Apriori algorithm to identify subsequent product purchases following an initial purchase, presented through a web-based visualization. The dataset used in this study consists of 1 million retail transactions from the period 2020–2024 obtained from the Kaggle platform. The objective of using Microsoft Power BI is to help companies better understand retail transaction data through interactive visualizations and to identify customer purchasing patterns by applying association methods with the Apriori algorithm in a web-based visualization developed using the Python programming language.

2. Method

This study adopts a quantitative approach using data mining and business intelligence methods to analyze and visualize purchasing patterns in retail product transactions. The research stages are systematically designed, starting from data collection to the visualization of analysis results, in order to support business decision making.

2.1. Data Source and Data Collection

The data used in this study consist of a retail transaction dataset obtained from the Kaggle website. The dataset comprises 1 million transaction records from the period 2020–2024, including attributes such as purchased products, customer categories, payment methods, store types, seasons, transaction cities, and transaction values. This dataset was selected because it has representative characteristics for analyzing purchasing patterns in the retail industry.

2.2. Preprocessing Data

The preprocessing stage is conducted to ensure data quality and readiness prior to analysis [12]. This process includes cleaning the data by handling missing values, removing duplicate records, and transforming transaction data into a one-hot encoding format to meet the requirements of the Apriori algorithm [13]. This stage aims to improve the accuracy of purchasing pattern analysis results.

2.3. Association Method

The method used to identify product purchasing patterns in each transaction is the association method. Association methods, or association rule mining techniques, are data mining techniques used to discover associative rules among combinations of items [14]. This technique is applied to identify patterns or trends by detecting sets of attributes that frequently occur together, commonly referred to as affinity analysis or market basket analysis. In this study, the association method is implemented using the Apriori algorithm to obtain recommendations and analyze purchasing patterns in retail transactions conducted by customers [15]. The Apriori algorithm is used to identify frequent itemsets in Boolean association rules [16]. First, frequent itemsets (sets of items that satisfy the minimum support threshold) are generated from the transaction database. Second, itemsets with low frequencies are eliminated based on a predefined minimum support level. Subsequently, association rules are constructed from itemsets that meet the minimum confidence threshold in the database [17].
The support value of an item is calculated using the Formula (1).

$$\text{Support(A)}= \frac{\text{Number of transactions containing A and B}}{\text{Total number of transactionsi}} \tag{1}$$

The support value of two items is calculated as Formula (2).

$$\text{Support(A,B)} = \frac{\text{Number of transactions containing A and B}}{\text{Total number of transactions}} \tag{2}$$

A frequent itemset indicates an itemset whose frequency of occurrence exceeds the predetermined minimum threshold (ϕ). For example, if ϕ = 2, then all itemsets with a frequency of at least two occurrences are considered frequent [18]. The confidence value of the rule A → B is calculated using the Formula (3).

$$\text{Confidence P(B|A)}= \frac{\text{Number of transactions containing A and B}}{\text{Number of transactions containing A}} \tag{3}$$

From the process of forming association rules, confidence values for each itemset are obtained [19], and a minimum confidence threshold is then determined to generate association rules.

2.4. Association Method Flow Using the Apriori Algorithm

The flow of the association method using the Apriori algorithm represents the procedure employed in this study to identify and analyze the most frequently purchased retail products by customers based on retail transaction data[20], as illustrated in Figure 1

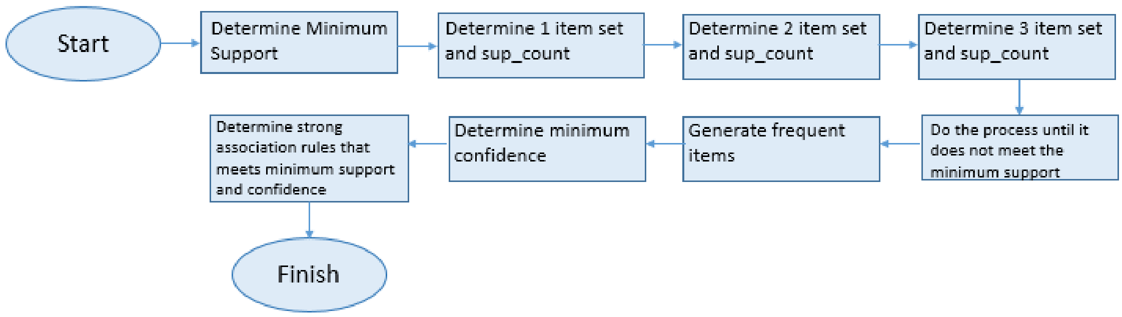

Figure 1. Association Method Flow With Apriori Algorithm

3. Results and Discussion

3.1. Implementation of the Association Method Using the Apriori Algorithm

The implementation of the association method in this study is carried out using the Apriori algorithm to identify purchasing patterns of products in retail transactions. The Apriori algorithm is employed due to its capability to discover relationships among items based on the frequency of their co-occurrence within transactions [21]. The implementation process begins by determining the minimum support and minimum confidence values as the main parameters for generating association rules. In this study, the minimum support is set to 0.002, while the minimum confidence is set to 0.5 (50%). The results of applying the Apriori algorithm, which produce 12 transaction rules, are as follows:

a. Rule 1: ['Air Freshener', 'Laundry Detergent'] → ['Shaving Cream'], support count = 2, and prior occurrence of ['Shaving Cream'] support count = 4
b. Rule 2: ['Shaving Cream', 'Laundry Detergent'] → ['Air Freshener'], support count = 2, and prior occurrence of ['Air Freshener'] support count = 3
c. Rule 3: ['Banana', 'Canned Soup'] → ['Chips'], support count = 2, and prior occurrence of ['Chips'] support count = 3
d. Rule 4: ['Canned Soup', 'Chips'] → ['Banana'], support count = 2, and prior occurrence of ['Banana'] support count = 4
e. Rule 5: ['Beef', 'Cheese'] → ['Insect Repellent'], support count = 2, and prior occurrence of ['Insect Repellent'] support count = 4
f. Rule 6: ['Bread', 'Chicken'] → ['Mustard'], support count = 2, and prior occurrence of ['Mustard'] support count = 3
g. Rule 7: ['Bread', 'Mustard'] → ['Chicken'], support count = 2, and prior occurrence of ['Chicken'] support count = 3
h. Rule 8: ['Orange', 'Pasta'] → ['Extension Cords'], support count = 2, and prior occurrence of ['Extension Cords'] support count = 3
i. Rule 9: ['Tea', 'Ketchup'] → ['Honey'], support count = 2, and prior occurrence of ['Honey'] support count = 3
j. Rule 10: ['Shower Gel', 'Plant Fertilizer'] → ['Tuna'], support count = 2, and prior occurrence of ['Tuna'] support count = 3
k. Rule 11: ['Shower Gel', 'Tuna'] → ['Plant Fertilizer'], support count = 2, and prior occurrence of ['Plant Fertilizer'] support count = 3
l. Rule 12: ['Plant Fertilizer', 'Tuna'] → ['Shower Gel'], support count = 2, and prior occurrence of ['Shower Gel'] support count = 4

3.2. Application of Apriori Algorithm Calculation Matching

The table illustrating the application of calculation matching for the Apriori algorithm is presented in Table 1.

Tabel 1 Application of Apriori Algorithm Calculation Validation

No	*Rule*	*Support*	*confidence*
1	['Air Freshener', 'Laundry Detergent'] ---> ['Shaving Cream']	0,4 %	2/4x100% = 50.0%
2	['Shaving Cream', 'Laundry Detergent'] ---> ['Air Freshener']	0,4%	2/3x100% = 66,67%
3	['Banana', 'Canned Soup'] --> ['Chips']	0.4%	2/3x100% = 66,67%
4	['Canned Soup', 'Chips']---> ['Banana']	0.4%	2/4x100% = 50.0%
5	['Beef', 'Cheese'] --->['Insect Repellent']	0.4%	2/4x100% = 50.0%
6	['Bread', 'Chicken'] ---> ['Mustard']	0.4%	2/3x100% = 66,67%
7	['Bread', 'Mustard'] ---> ['Chicken']	0.4%	2/3x100% = 66,67%
8	['Orange', 'Pasta'] ---> ['Extension Cords']	0.4%	2/3x100% = 66,67%
9	['Tea', 'Ketchup'] ---> ['Honey']	0.4%	2/3x100% = 66,67%
10	['Shower Gel', 'Plant Fertilizer'] ---> ['Tuna']	0.4%	2/3x100% = 66,67%
11	['Shower Gel', 'Tuna'] ---> ['Plant Fertilizer']	0.4%	2/3x100% = 66,67%
12	['Plant Fertilizer', 'Tuna'] ---> ['Shower Gel']	0.4%	2/4x100% = 50.0%

Table 1 presents the association rules or consumer product purchasing patterns obtained by setting a minimum support of 0.002 and a confidence value of 0.5 (50%). A relatively small minimum support value was applied because higher minimum support thresholds did not produce any rules; therefore, a lower threshold was required to reveal purchasing patterns in the transaction data.

a. Rule 1 has a support value of 0.4%, indicating that the combination of these three items appears in 0.4% of the total transactions, with a confidence value of 50%, meaning that this rule qualifies as a strong association rule as it meets the predefined confidence threshold. This pattern indicates that when consumers purchase *Air Freshener* and *Laundry Detergent*, they tend to also purchase *Shaving Cream*.

b. Rule 2 has a support value of 0.4% and a confidence value of 66.67%, indicating a strong association rule. This pattern shows that consumers who purchase *Shaving Cream* and *Laundry Detergent* tend to also purchase *Air Freshener*.
c. Rule 3 has a support value of 0.4% and a confidence value of 66.67%, indicating that consumers who purchase *Banana* and *Canned Soup* tend to also purchase *Chips*].
d. Rule 4 has a support value of 0.4% and a confidence value of 50%, indicating that consumers who purchase *Canned Soup* and *Chips* tend to also purchase *Banana*.
e. Rule 5 has a support value of 0.4% and a confidence value of 50%, indicating that consumers who purchase *Beef* and *Cheese* tend to also purchase *Insect Repellent*.
f. Rule 6 has a support value of 0.4% and a confidence value of 66.67%, indicating that consumers who purchase *Bread* and *Chicken* tend to also purchase *Mustard*.
g. Rule 7 has a support value of 0.4% and a confidence value of 66.67%, indicating that consumers who purchase *Bread* and *Mustard* tend to also purchase *Chicken*.
h. Rule 8 has a support value of 0.4% and a confidence value of 66.67%, indicating that consumers who purchase *Orange* and *Pasta* tend to also purchase *Extension Cords*.
i. Rule 9 has a support value of 0.4% and a confidence value of 66.67%, indicating that consumers who purchase *Tea* and *Ketchup* tend to also purchase *Honey*.
j. Rule 10 has a support value of 0.4% and a confidence value of 66.67%, indicating that consumers who purchase *Shower Gel* and *Plant Fertilizer* tend to also purchase *Tuna*.
k. Rule 11 has a support value of 0.4% and a confidence value of 66.67%, indicating that consumers who purchase *Shower Gel* and *Tuna* tend to also purchase *Plant Fertilizer*.
l. Rule 12 has a support value of 0.4% and a confidence value of 50%, indicating that consumers who purchase *Plant Fertilizer* and *Tuna* tend to also purchase *Shower Gel*.

3.3. Program Implementation Results

This section presents the output of the program implementation developed using Visual Studio Code by applying the association method with the Apriori algorithm. The program is used to analyze product purchasing patterns based on the specified minimum support and minimum confidence values, as shown in Figure 2

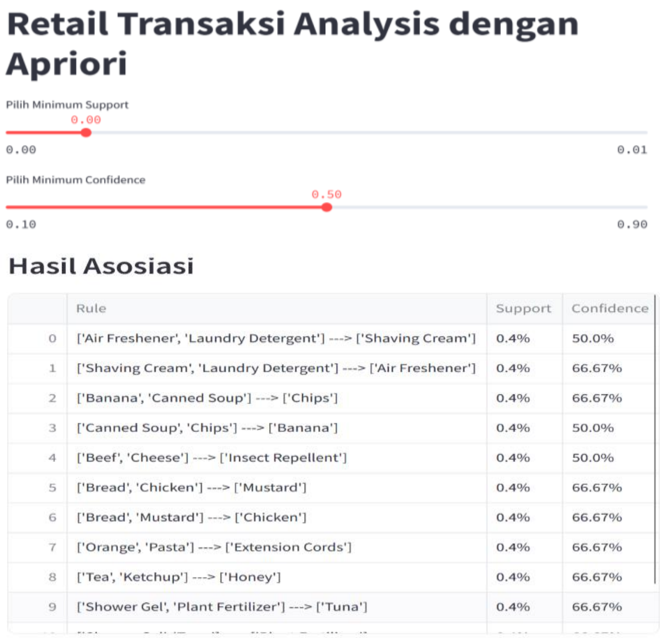

Figure 2. Web Application Interface of the Apriori Algorithm

Figure 2 shows the interface of the web application generated from the Python program code that implements the association method using the Apriori algorithm. The results indicate that by selecting a minimum support value of 0.002 and a minimum confidence of 0.5 (50%), the association results are consistent with the previous manual calculations, producing 12 rules with identical support and confidence values. This implementation enables retail companies to analyze customer purchasing behavior more effectively and to gain a deeper understanding of each transaction carried out by customers.

3.4. Power BI Visualization

This study produces various forms of retail transaction data visualizations that provide interactive and insightful information regarding business performance[22]. Through Power BI, retail transaction data are processed and presented in the form of graphical and diagrammatic visualizations. The implementation of Power BI reveals several analytical findings in retail transactions, such as the availability of promotions for products leading to increased purchase volumes across different store types and customer categories [23]. In addition, seasonal factors also influence retail transactions, with the autumn (fall) season recording the highest number of transactions conducted by customers. Furthermore, cash is identified as the most frequently used payment method [24] . The dashboard page that displays all graphs and diagrams generated using Microsoft Power BI is shown in Figure 2.

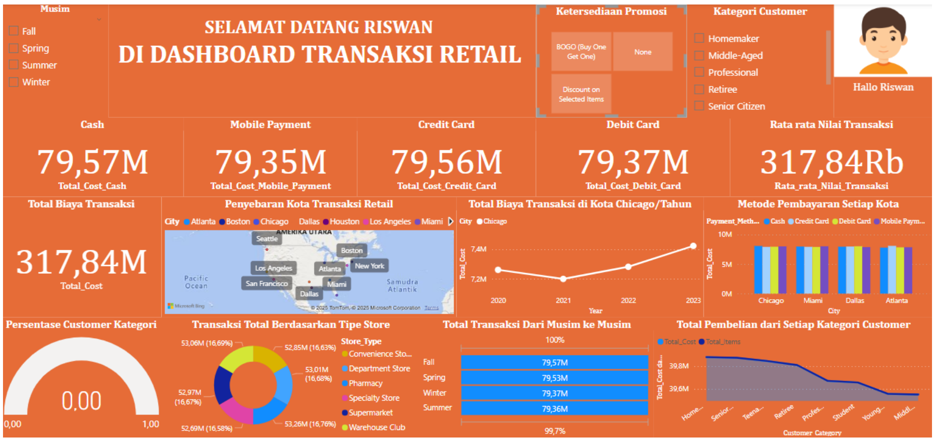

Figure 3. Dashboard Page

Another diagram or chart presents the Total Purchase Transactions by Customer Category, as shown in Figure 4

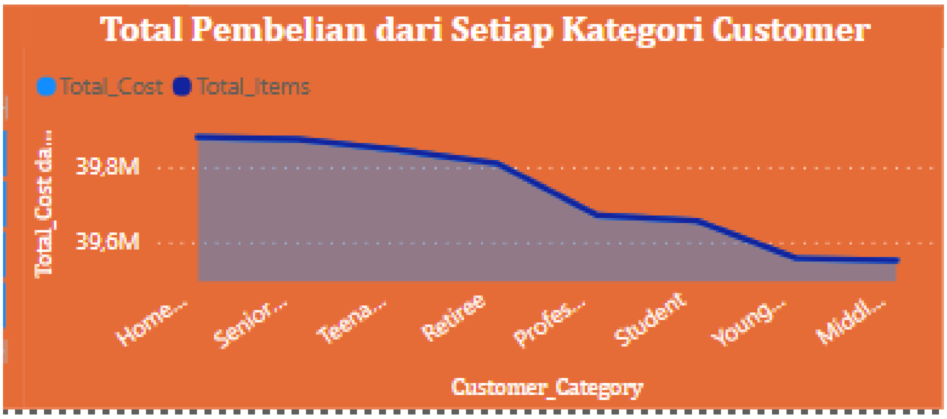

Figure 4. Total Purchase Transactions by Customer Category

Figure 5 illustrates the total purchase transactions based on customer categories, displaying the total cost and the number of items purchased [25]. The *homemaker* customer category shows the highest transaction volume, while the *middle-aged* category records the lowest. This indicates that customers in the homemaker category contribute the most to item purchases. Based on this insight, retail companies can analyze that demand from this customer category is the highest and adjust product availability accordingly. Another visualization shows the total purchase transactions across seasons, as presented in Figure 5.

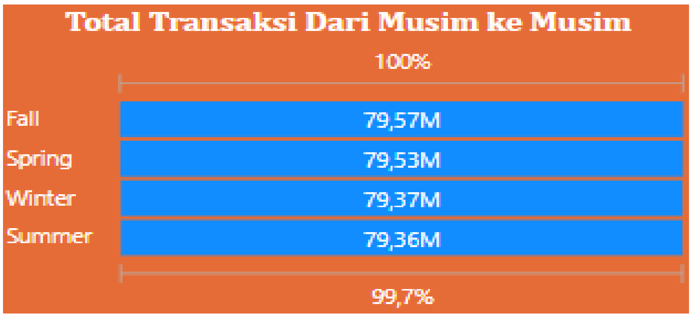

Figure 5. Total Purchase Transactions Across Seasons

Figure 6 indicates that the fall season records the highest number of transactions compared to other seasons, although the differences are not significant. The fall season also has the highest total transaction cost, amounting to 79.47 million, followed by spring, winter, and summer. This information enables companies to analyze customer purchasing patterns based on seasonal factors.

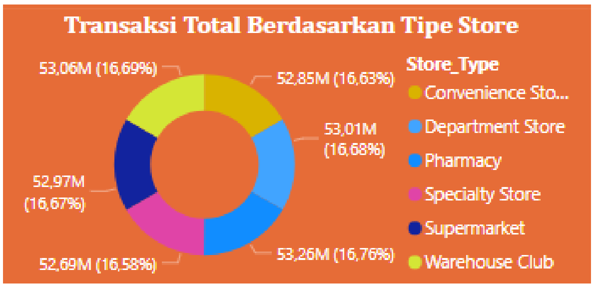

Figure 6. Total Transactions by Store Type

Figure 7 displays a donut chart showing that the percentage differences among store types are relatively small. However, the *pharmacy* store type records the highest transaction volume, accounting for 16.76% of the total cost and items purchased. This allows retail companies to analyze transaction patterns based on store types. Another chart presents the percentage of customer categories, as shown in Figure 7.

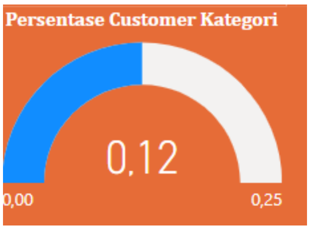

Figure 7. Customer Category Percentage

Figure 8 shows the transaction percentages based on customer categories. When a specific category is selected on the dashboard, the transaction percentage corresponding to that category is displayed. This enables companies to analyze transaction patterns according to customer categories. Another chart illustrates the payment methods used in transactions across cities, as shown in Figure 8.

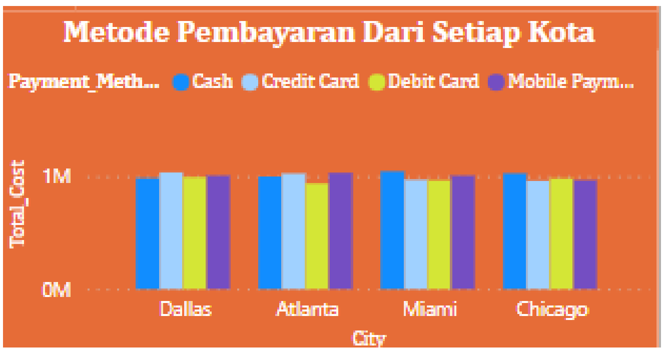

Figure 8. Payment Methods Used In Transactions Across Cities

Figure 9 compares the payment methods used in transactions across different cities. In Dallas and Atlanta, mobile payment is the most frequently used method, while in Miami and Chicago, cash is the most commonly used payment method. Another visualization shows the total annual transaction cost in Chicago, as presented in Figure 9.

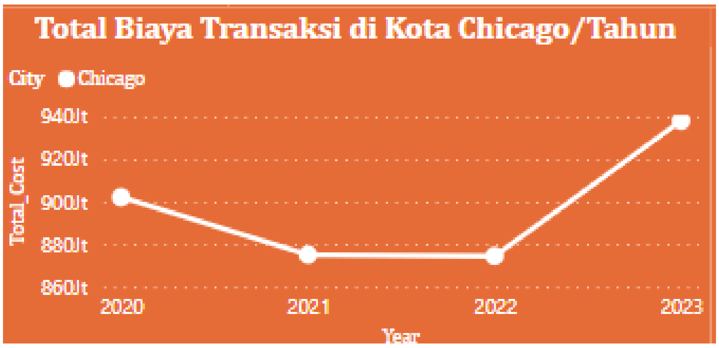

Figure 9. Total Transaction Cost in Chicago per Year

Figure 10 illustrates that the total transaction cost of customers in Chicago fluctuated annually from 2020 to 2023, with the highest value occurring in 2023. This increase may be attributed to product promotions or rising demand for certain products in the city compared to previous years. These trends may vary depending on promotional availability, seasonal changes, and customer categories, allowing companies to analyze purchasing patterns in Chicago over time. Another visualization presents the geographical distribution of retail transaction cities, as shown in Figure 10.

Figure 10. Distribution of Retail Transaction Cities

Figure 10 shows that retail transactions are distributed across several cities, including Seattle, Los Angeles, San Francisco, New York, Atlanta, Miami, Dallas, and others. This indicates a wide geographical spread of retail operations, with transaction patterns varying across cities

4. Conclusion

Based on the results of the study, it can be concluded that the application of the Apriori algorithm in retail transaction analysis is effective in identifying customer purchasing patterns through the formation of association rules among frequently purchased products. By applying a minimum support value of 0.002 and a minimum confidence value of 0.5, this study successfully generates several strong association rules that provide meaningful insights into consumer purchasing behavior. The integration of business intelligence visualization further enhances the interpretability of retail transaction data by presenting interactive dashboards that illustrate transaction trends across customer categories, store types, payment methods, seasons, regions, and time periods, thereby supporting data-driven business decision making. However, this study is subject to certain limitations, including the use of a secondary dataset that restricts control over contextual business factors and the application of a relatively low support threshold, which may limit the generalizability of the identified patterns. Future research may address these limitations by applying more efficient association rule mining algorithms such as FP-

Growth, integrating real-time business intelligence systems for continuous pattern monitoring, and combining association rule mining with customer clustering techniques to obtain deeper and more personalized insights into customer purchasing behavior.

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