Data Mining Application for Analyzing Pattern of Customer Purchase Using Apriori Algorithm

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Abstract - The study aims to implement Data Mining with Apriori Algorithm and Association Methods (shop cart analysis) to analyze the sales pattern of Kaffa Beauty Shop stores as a case study. Sales information obtained from stores is used to find out the repeated buying habits of cosmetic products. This analysis provides store owners with valuable information to make more useful decisions about product inventory management, marketing strategies, and other aspects of their business. The Apriori Algorithm implementation follows steps including data preprocessing, subsetting, frequent dataset search, and strong association rules (strong Association Rules). The results of the analysis show that there are important purchasing patterns among some cosmetic products that can be the basis of a more effective sales strategy. The study helps understand how data mining and Apriori Algorithms can be applied in business contexts such as Kaffa Beauty Shop stores. Therefore, the results of this analysis are expected to contribute greatly to improving business efficiency and optimizing marketing strategies for store owners and stakeholders. The research is also expected to show the enormous potential of data analysis to support optimal business decision making.

Keywords - Data Mining, Apriori, Association Methods (shopping cart analysis), Frequent Itemset, Sales Strategy

1. INTRODUCTION

In today's digitally-driven and highly competitive market, the cosmetics industry faces significant challenges in maintaining competitiveness and sustaining growth. To address these challenges, it's crucial for companies like Kaffa Cosmetic Store to implement effective strategies aimed at improving product quality and leveraging data-driven insights to enhance their offerings and customer experience. The Insight Center survey's findings highlight the immense popularity of beauty and cosmetic products, indicating a strong demand in both online and offline markets [1], [2], [3]. This underscores the importance for companies to capitalize on this trend by understanding consumer behavior and preferences through the analysis of sales data. With the advent of digitization, businesses have access to vast amounts of sales data from their customers [4]. This data, encompassing information about purchased products and transaction details, presents a valuable opportunity for companies to gain insights into consumer preferences and purchasing patterns [5], [6], [7].

One effective approach to manage and analyze this sales data is through the application of data mining techniques, particularly the Apriori algorithm for Market Basket Analysis [8], [9],

[10]. By applying this method to the sales transactions of Kaffa Cosmetic Store, the company can uncover associations between products frequently purchased together, enabling them to identify trends and make informed decisions regarding promotions [11], inventory management [12], and sales strategies [13], [14]. Understanding customer buying behavior is paramount for Kaffa Cosmetic Store to remain competitive in the market. By utilizing data mining techniques, the company can gain valuable insights that empower them to tailor their offerings to meet customer preferences more effectively, ultimately driving sales and improving overall business performance. Despite experiencing stable sales on a monthly basis, Kaffa Beauty Shop faces challenges during periods of heightened competition, such as during promotional events by competitors. To address this, the company must adopt accurate and effective strategies for analyzing customer purchasing patterns and responding proactively to market dynamics. In conclusion, leveraging data mining techniques like the Apriori algorithm allows companies like Kaffa Cosmetic Store to gain valuable insights into customer behavior and preferences [15], [16], [17]. By applying these insights strategically, companies can enhance product quality, optimize inventory management, and develop targeted sales strategies, ultimately improving competitiveness and driving sustainable growth in the cosmetics market. Using Apriori Algorithm to analyze sales data has the advantage of being able to process large amounts of data with optimal performance. Apriori algorithm consists of two main processes: merging and pruning. The merger process can process data on a large scale by combining existing items until further merging cannot be done. Instead, the cleaning process focuses on cleaning the combined items based on the minimum support threshold specified by the user. This is done to ensure optimal algorithm performance. Using a better understanding of customer buying patterns can help develop more effective marketing strategies and improve customer satisfaction.
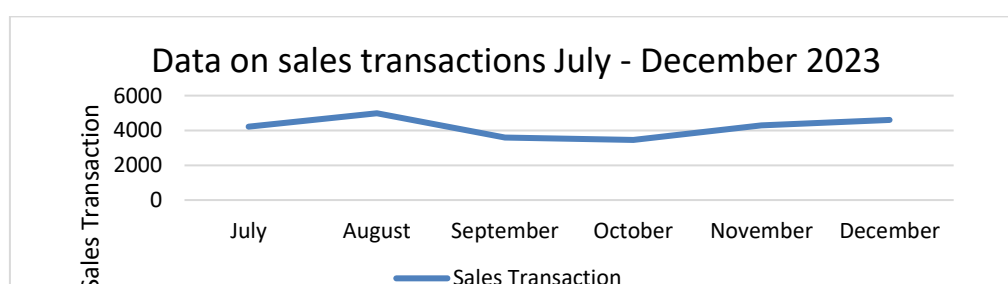

Figure 1. Graphics Data on sales transactions July - December 2023

2. RESEARCH METHOD

2.1. Experiment Stages

Based on Figure 2, the research outlined has been describe as follow:
1. Data collection is the first step. Early data is collected through observation, interviews, documentation, and library studies.
2. Next do data analysis. This analysis process involves identifying problems, searching solutions, and selection of algorithms to manage data.
3. Conducting data classification process. This classification process uses algorithms used to determine how data is interconnected, taking into account the minimum support and minimum convenience values.
4. Lastly, perform data processing, where the python language program is used as a trial to the validant of the data that has been processed.
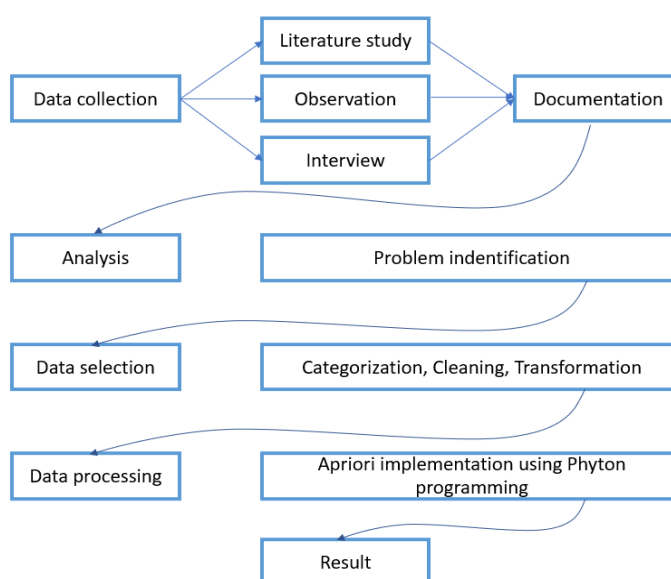
Figure 1. Experiment Stages

2.2. Proposed Method

In this study, researchers adopted data analysis methods using Apriori Algorithm in association domain analysis and market basket analysis. Apriori algorithm is applied to the sales transaction data of Kaffa Beauty Shop. This transaction data is processed to identify purchasing patterns and relationships between products purchased by customers. Apriori algorithm is used to better understand customer shopping behavior and develop association rules that help shop owners make smarter decisions regarding product inventory management and marketing strategies. System Design includes the use of Python language programming as a tool to implement Apriori algorithms and analyze transaction data. There is also a flowchart of the a priori algorithm as in the Figure 2. Apriori algorithm is used to better understand customer shopping behavior and develop association rules that help shop owners make smarter decisions regarding product inventory management and marketing strategies. System Design includes the use of Python language programming as a tool to implement Apriori algorithms and analyze transaction data. There is also a flowchart of the a priori algorithm as in the Figure 2. The Apriori algorithm flowchart consists of several key steps, ranging from initialization with the formation of candidate itemsets, new candidate itemsets generation, candidate itemset filtering, support counting, to the determination of association rules. This algorithm helps in finding important patterns in transaction data, such as associations between items that are often bought together, so that businesses can create more effective marketing strategies and increase sales.
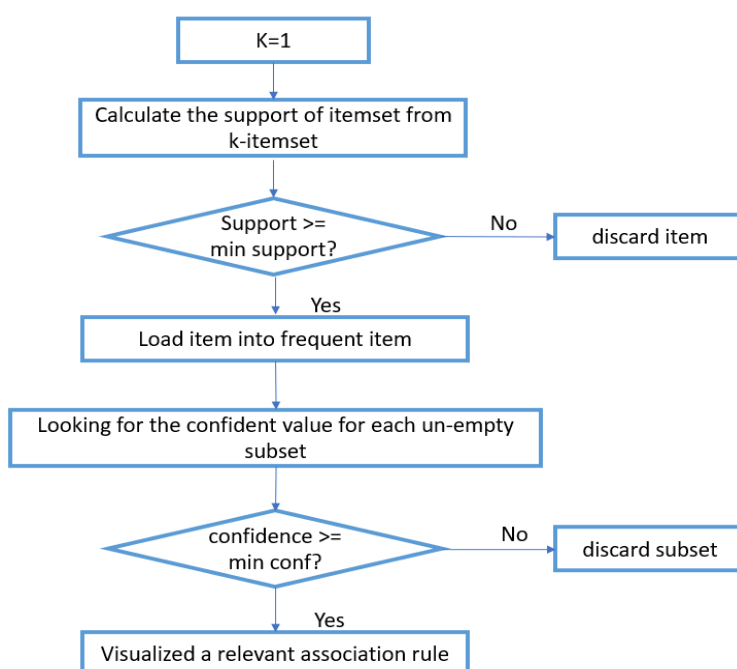
Figure 2. The Common Apriori Flowchart

2.3. Data source

The data source of this research is data collected through direct observation at the Kaffa Beauty Shop store. This includes the types of cosmetic products available, the number of products purchased by customers of each type of product, and all details of the transaction occurring, including the time of transaction, purchased products, prices and payment methods. In addition, the description of the store layout, the location of the cashier, and the layout of the surrounding products, here are the layout plans at the Kaffa Beauty Shop store as in Figure 3. At this stage collects sales data from Kaffa Beauty Shop from July to December. This dataset contains information about sales transactions, such as products that customers bought during that half-year period. The underlying data is analyzed using Apriori algorithm to identify the correlation between the product and the buying pattern. This allows the system to conduct relevant analysis and identify consumer spending behavior. Here is the item code from the drawing of 12 store plan kaffa beauty shop as in Table 1.

Table 1. The store plan of Kaffa beauty

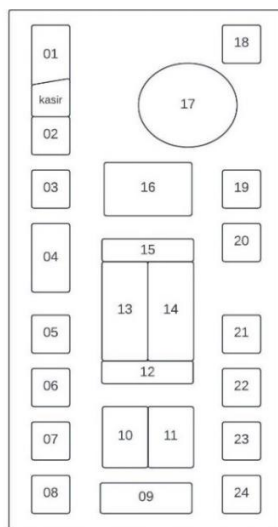| No	Category	No	Category
1	Bella Square	13	Parfum
2	Ms. Glow	14	Viva
3	Pashmina	15	Originate
4	Masker	16	Lipstick zone
5	Body scrub	17	Meja scarlet
6	Body lotion	18	Hyi amino
7	Garnier	19	Make up
8	Semir	20	You
9	Aksesoris	21	Skincare
10	Beauty tools	22	Azzarine
11	Skincare	23	Emina
12	Parfum	24	Wardah

Figure 3. Store plans for Kafa Beauty Shop

2.4. Preprocessing Data

Preprocessing data is a stage in data analysis that aims to ensure the quality of data used in models or analysis [18], [19]. One of the main steps in this process is to identify rows or columns that contain lost values and choose to replace them with appropriate values, such as average, median, or mode. Furthermore, data cleaning is done thoroughly to ensure the quality of data used. Figure 5 shows daily sales reports during the period of July 1, 2023 to July 31, 2023. Daily sales transactions are displayed on this table. The dataset also includes additional information such as recession numbers, dates, and any discounts or coupons used. In addition, this report shows the type of product, quantity, and sales for a certain period of time, and provides detailed details for each transaction, including name, code, number of units sold, price per unit, and subtotal.

Figure 4. A Realtime Kaffa Beauty dataset

date	item
01/07/2023	IMPLORA EYE PENCIL BLACK 001
01/07/2023	KAPAS SELECTION 35GR
01/07/2023	KAPAS SELECTION 35GR
01/07/2023	KAPAS SELECTION 50GR
01/07/2023	AC JARUM PENTUL BSR SK
01/07/2023	KC BELLA SQ NECI
01/07/2023	KC BELLA SQ NECI
01/07/2023	AC JEDAY KCL SK
01/07/2023	MAR NAIL POL 089 NUDE
01/07/2023	IMPLORA NAIL POL CLEAR
01/07/2023	AC CAIRAN SOFLENS ICE 60ML

Figure 5. Preprocessing result of dataset

2.5. Data transformation

The transformation of data into CSV format (Comma-Separated Values) is the next step after the preprocessing stage of data as it allows the use of various analytical tools and platforms to facilitate the use of data that previously may be in various formats or structures [20]. The process of transformation of data into CSV includes dividing data into rows and columns with comma marks between each column, here are data transformation that has been done in Figure 6. The program is created using Python programming language and runs at the Data Mining Process stage through the Streamlit web platform. In its early stages, Apriori algorithms are used to analyze associations on daily sales datasets. The association rules allow programs to identify

items that are often purchased together. The analysis results are also presented in table form and graphics to facilitate understanding.

Figure 6. Preprocessing files that have been converted into csv format

Users can enter datasets and control the strict rules created through the web interface. Users can set parameters such as support value and trust. With its simple and interactive interface, Streamlit allows users to perform and manage data mining processes without having to have complex programming skills. The following is a comparison of the total total data on a month and the total amount of transaction data after reprocessing as in Table 2. The above data compares the total number of initial transactions in a given month with the total number of transactions after the reprocessing process, where only data with support value above 0.3000 is entered. in the table above, where the preprocessing process here is determined, researchers will perform calculations on each month, after conducting the analysis of July dataset followed by processing data using the Streamlit website, after the program can be run, the following results of the Association Rules testing that has been made on the July transaction dataset as follows in Table 3.

Table 21. TitleComparison of data after preprocessing

Month	Early data (total transactions)	Data after reprocessing (total transactions)
July	4221	585
August	4985	758
September	3599	541
October	3453	613
November	4290	509
December	4606	698

Table 3. Comparison of data after preprocessing

No	Item	Transaction	Support
1	Kc Bella Sq Neci	57	3.56
2	Implora Eye Pencil Black 001	29	1.81
3	Kapas Selection 35gr	25	1.56
4	Msg Facial Wash Ke	25	1.56
...	...	...	...
16	Ac Jeday Sedang Sk	16	1

At level 1 (L1) the above analysis is done to find elements whose support amount exceeds the specified threshold. The results of this analysis are listing individual significant factors that use the formula, then produce results as in Figure 9, as for the example of the calculation as in (1). The next process is level 2 (L2), in this phase an analysis of two sets of items that occur simultaneously. The following formula is used to calculate support and trust for association rules as in (2). Once accurate calculations are generated, the following are the result of the merger of two itemsets that have been formed as in Table 4.

$$Support(A) = \frac{57}{16} \times 100\% = 3.5625 \tag{1}$$

$$Support(A,B) \frac{\text{Implora Eye Pencil Black 001} \cup \text{Kc Bella Sq Neci}}{16} \times 100\% = 0,94 \tag{2}$$

Table 4. 2 itemset on July transaction

No	Item	Transaction	Support
1	Implora Eye Pencil Black 001, Kc Bella Sq Neci	15	0.94
2	Kapas Selection 35gr, Kc Bella Sq Neci	12	0.75
3	Kc Bella Sq Neci, Msg Facial Wash Ke	14	0.87
4	Kapas Selection 50gr, Kc Bella Sq Neci	15	0.94
…	…	…	…
61	Implora Nail Pol Clear, Kapas Selection Spc Tipis 60gr	7	0.44

Once a combination of two sets is obtained, the next level is level 3 (L3). In this phase, an analysis of three combinations of items that mostly occur simultaneously. The following formula is used to calculate support and trust for association rules as in (3).

$$Support(A,B) \frac{\text{Implora Eye Pencil } \cup \text{ Kc Bella Sq Neci } \cup \text{ Msg Facial Wash Ke}}{16} = 0,44 \quad (3)$$

Formula (3) allows to systematically analyze the pattern of Level 1 to Level 3 products to understand the relationship between the transaction record elements, the following are the result of a combination of three itemsets that have been known to the transaction value and support as in Table 5. After identifying the product combination at level 3, the next step is to calculate the value of the confident to evaluate how strong the relationship between the two products is in a transaction. This helps to understand how often products A are purchased along with product B, allowing calculations to recommend products that are more relevant based on strong relationships between the two, here are the confident calculations using this formula (4). From the formula (4), the association rules are generated as in Table 6.

Table 5. 3 itemset on July transaction

No	Item	Transaction	Support
1	Implora Eye Pencil Black 001, Kc Bella Sq Neci, Msg Facial Wash Ke	7	0.44
2	Implora Eye Pencil Black 001, Kapas Selection 50gr, Kc Bella Sq Neci	10	0.62
3	Ac Jeday Kcl Sk, Implora Eye Pencil Black 001, Kc Bella Sq Neci	8	0.5
4	Brsv Kutek 64 Maroon, Implora Eye Pencil Black 001, Kc Bella Sq Neci	7	0.44
…	…	…	…
12	Implora Nail Pol Clear, Kapas Selection Spc Tipis 60gr, Msg Facial Wash Ke	7	0.44

$$Confidence(A \rightarrow B) = P(B|A) \quad (4)$$
$$P(B|A) = \frac{\sum transactions\ containing\ A\ and\ B}{\sum transactions\ containing\ A} \times 100\%$$

Based on the analysis and calculations above, researchers selected association rules with a trust level greater than 0.9 and support greater than 8 to provide product sample suggestions to store owners. This is because the rules with a high level of trust (above 0.9) indicate a strong relationship between products, and the rules with support levels above 8 indicate that product combinations are very common in customer transactions. In this way, the sample suggestions of the resulting products will be more reliable and relevant to customers. Table 7 describes the results of conjoin analysis performed using data mining methods or market basket analysis. In July, there are four association rules that meet minimum support and minimum confidence criteria. The first and second rules indicate that the purchase of certain combinations such as the 60ml Ice Soflens Liquid Ac and Brsv Kutek 64 Maroon or the 100% BSR Sk Touch Needle and Cotton Selection 50gr will always be followed by the purchase of Kc Bella Sq Neci with 100% certainty. Meanwhile, the third rule shows that purchasing Cotton Selection

50gr and Msg Facial Wash Ke has a confident of 0.9000 or 90% to follow by the purchase of Kc Bella Sq Neci. Last, the fourth rule confirms that the purchase of the Implora Eye Pencil Black 001 and Cotton Selection 50gr will always be followed by the purchase of Kc Bella Sq Neci with 100% certainty. Thus, this analysis provides valuable insight for retailers to understand customer buying patterns and improve related product marketing strategies, likewise until August – December.

Table 6. Association rules of results L3

No	Itemset	Subset	Confidence	Status
1	Implora Eye Pencil Black 001, Kapas Selection 50gr, Kc Bella Sq Neci	Kapas Selection 50gr, Kc Bella Sq Neci	0.6667	Not Accepted
2	Implora Eye Pencil Black 001, Kapas Selection 50gr, Kc Bella Sq Neci	Implora Eye Pencil Black 001, Kc Bella Sq Neci	0.6667	Not Accepted
3	Implora Eye Pencil Black 001, Kapas Selection 50gr, Kc Bella Sq Neci	Implora Eye Pencil Black 001, Kapas Selection 50gr	1.0000	Accepted
4	Implora Eye Pencil Black 001, Kapas Selection 50gr, Kc Bella Sq Neci	Kapas Selection 50gr	0.4348	Not Accepted
…	…	…	…	…
71	Ac Cairan Soflens Ice 60ml, Ac Jarum Pentul Bsr Sk, Implora Eye Pencil Black 001	Ac Cairan Soflens Ice 60ml	0.5000	Not Accepted

Table 7. July transaction

No	Min Support	Min Confident	Itemset	Confident
1	8	0,90	Jika membeli Ac Cairan Soflens Ice 60ml dan Brsv Kutek 64 Maroon maka juga membeli Kc Bella Sq Neci	1.0000
2	8	0,90	Jika membeli Ac Jarum Pentul Bsr Sk dan Kapas Selection 50gr maka juga membeli Kc Bella Sq Neci	1.0000
3	8	0,90	Jika membeli Kapas Selection 50gr dan Msg Facial Wash Ke maka juga membeli Kc Bella Sq Neci	0.9000
4	8	0,90	Jika membeli Implora Eye Pencil Black 001 dan Kapas Selection 50gr maka juga membeli Kc Bella Sq Neci	1.0000

3. RESULTS AND DISCUSSION

Data mining phase with Python often uses a variety of popular libraries and modules such as Pandas, NumPy, and Scikit-learn. Data processing is done with Panda for data processing array, while NumPy supports numerical array operations. Scikit-learn machine learning algorithm is used for analysis and prediction. In addition, streamlit websites are used as an interactive development environment for running and managing data mining processes using Python programming languages, the following stages:

1. Dataset option is the first step. Users can select the dataset you want to use from the pre-prepared dataset option, this option can include a number of relevant datasets for analysis. Once the data set is selected, the next step is to determine the analysis parameters. Users can set support and trust values through the input provided. These values allow users to control how strictly the association rules will be generated by the algorithm. 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. The discussion can be made in several sub-chapters.

Figure 7. GUI Shop Display Kaffa Beauty Shop AR Algorithm Apriori program

2. Once the parameters are determined, the user can start the analysis process by clicking the "Start" button. Once the user selects the dataset, the program displays the dataset display in CSV format in GUI. This can be done as a separate panel or table that displays data in an easy to read the format. Users can clearly see the structure and value of the data set to be used for link analysis.

Figure 8. Dataset view that the user has selected

3. The next display is preprocessing which features a merging iteration of products that have a concurrent pattern, this iteration process involves searching for a collection of items that often occur in the data set. Each iteration is labeled Cn (Candidate Itemset) and Ln (Frequent Itemset) for the nth iteration. Candidate itemset is a set of items that often appear, while frequent itemset is a set of items that meet the specified minimum support limitations.

Figure 9. Iteration table display

Figure 10. Iteration table display product combination data display from the last iteration

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In Figure 9 is iteration 1, of each dataset has different iterations, with the maximum iteration infinity, while in the example above iteration stops in the third iteration or L3, If iteration stops in the L3 iteration, then the program will display the frequent itemset result obtained in the iteration. This is the end result of associate analysis that can provide insight into the set of items that often appear in data sets as in Figure 10. The next view is the associate analysis results on the L3 loop used to find Association Rules (AR). This process involves the application of the minimum user-defined support and the minimum confidence value. As a result, association rules can provide insight into the relationships between elements in a data set, allowing users to identify patterns that can support better decision-making in a variety of different contexts, such as marketing or commercial strategies.

4. The "Discovering Ars from L3" table is an association analysis that shows the association rules found in the last iteration (L3). Each line of the table represents the table "Discovering Ars from L3" which is the result of an association analysis showing the association rules found in the last iteration (L3). Each line in the table represents the association rules associated with a certain number of items or products, called "itemsets". The first rule example includes a series of entries including the IMPLORA EYE BLACK 001, the SELECTION 50GR COMPLAY, and the KC BELLA SQ NECI. The "subset" column shows a subgroup of items used to calculate trust levels, while the "Confidence" column shows how correct the rules in the data are, measured in percentages. "Accepted" indicates whether the rules are accepted based on the specified minimum belief value. These tables provide insight into the relationship between elements in the data set, allowing a deeper understanding of consumer purchasing habits or preferences that can support proper business decision making.

Discovering ARs From L3

	itemset	subset	confidence	accepted
0	IMPLORA EYE PENCIL BLACK 001,KAPAS SELECTION 50GR,KC BELLA SQ NECI	KAPAS SELECTION 50GR,KC BELLA SQ NECI	0.6667	accepted
1	IMPLORA EYE PENCIL BLACK 001,KAPAS SELECTION 50GR,KC BELLA SQ NECI	IMPLORA EYE PENCIL BLACK 001,KC BELLA SQ NECI	0.6667	accepted
2	IMPLORA EYE PENCIL BLACK 001,KAPAS SELECTION 50GR,KC BELLA SQ NECI	IMPLORA EYE PENCIL BLACK 001,KAPAS SELECTION 50GR	1.0000	accepted
3	IMPLORA EYE PENCIL BLACK 001,KAPAS SELECTION 50GR,KC BELLA SQ NECI	KC BELLA SQ NECI	0.1754	not accepted

Figure 11. Results of Association Rules

This section addresses the concurrent buying patterns identified when analyzing data using the Mining Rule Association algorithm with the Apriori method. The simultaneous purchase model is a combination of products that are often purchased simultaneously by customers. This analysis helps understand the relationship between various products and can provide strategic insight to businesses. Below is a summary of the identifiable concurrent purchase patterns. In Table 8, there is a record of purchasing products simultaneously on the store or platform. Each line represents a set of items, including multiple products purchased simultaneously by customers in one transaction. For example, in the first transaction, there was a purchase with "Implora Eye Pencil Black 001" and "Cotton Selection 50gr". This data has the potential to provide insight into alignment patterns in product purchases and can be analyzed using algorithmic methods such as Apriori. Product layout suggestions can be made based on the identified purchase pattern. Products that are often purchased together are placed close to the storefront to make it easier to find by customers. For example, if products A and B are often purchased together, then A and B should be placed adjacent to the shelf/ethalase or the same area in the store.

1. Cotton Selection 50gr (ethalase accessoris), Msg Facial Wash To (ethalase Ms. Glow) and Implora Eye Pencil Black 001 (lipstick etalage), should be placed near the same area in the store as the three are often purchased together.
2. Brsv Kutek Nude (lipstick etalase), Implora Eye Pencil Dork Brown 007 (lipstick etalase) and Hs Lp Boba 02 Brown (lipstick etalase) are often purchased with a combination of other products and have been placed in the same area by the store owner.
3. Some product combinations, such as Ac Jeday Medium Declips (ethalase accessoris), and 'c Bella Sq Laser Cut M (ethalase Bella Square), have similar simultaneous buying patterns and must be placed close together so that customers can easily find them.

By setting up products based on identified purchasing patterns, Kaffa Beauty Shop can improve customer shopping experience and improve product sales efficiency. Through this study, it is expected to identify meaningful association patterns and related relationships between products, thus contributing to understanding consumer behavior and marketing strategies in the related business environment. As described on the updated business plan.
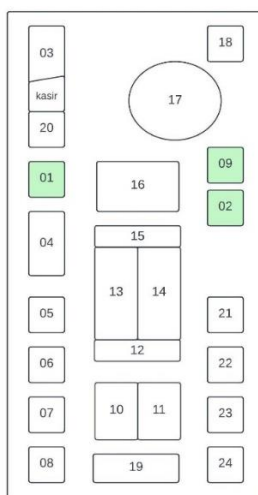

Figure 12. The plan after the change is made

Among the proposed changes in the plan, there are some rearrangements of the product layout at Kaffa Beauty Shop. Here are the explanations, reasons, and solutions of any such changes:
1. Transfer from Ethalase 1 (Bella Square) to Ethalase 3 (Pashmina). The transfer of the 1 (Bella Square) storefront to the 3 (Pashmina) storefront is done taking into account the combination of products that have similar relationships or target markets. This is part of the effort to improve the efficiency of the product display in the store. The solution taken is to migrate Bella Square products to 3 storefront and ensure the product layout is consistent with relevant categories or themes.
2. Transfer from Ethalase 9 (Accesoris) to Ethalase 19 (make up). Changes to the 9 storefront that previously featured accessories, are now brought to the 19 storefront that was previously used as a makeup rack. The purpose of this displacement may be related to the need to increase visibility or sale of accessory products by placing them in a more aesthetically oriented space. At the same time, the makeup storefront (Rack 19), which was previously located at the front row location, was moved to the area near the display of the Beauty Tool and the appearance of Skin Care.
3. Transfer from Ethalase 2 (Ms. glow) to Ethalase 20 (You). The previous 2 shelf displayed Ms. Glow has been moved to Rack 20, where branded products are previously on display. This conversion can be done to group products with similar brands or to optimize the positioning

of a particular brand. The selected solution is to transfer Ms products. Switch to 20 storefront and pay attention to product alignment with other brands and meet customer preferences.

Therefore, the rearrangement of the display of the product at Kaffa Beauty Shop aims to improve sales efficiency, improve product affordability, and improve customer shopping experience. With these changes, it is expected that stores can better meet consumer needs and strengthen relationships between similar products or brands. Thus, this adjustment not only impacts the improvement of operational efficiency but also strengthens the image of the store as a shopping destination that meets the needs of customers.

Table 8. Purchase pattern results

| No | Itemset | | No | Itemset | |
	Products purchased	If purchased simultaneously		Products purchased	If purchased simultaneously
1	Kapas Selection 50gr, Msg Facial Wash Ke	Kc Bella Sq Neci	12	Kc Bella Sq Laser Cut M, Kc Bella Sq Neci	Uv Shield Ess Sunscreen Spf30, Xiu Eyebrow Pencil Black
2	Implora Eye Pencil Black 001, Kapas Selection	Kc Bella Sq Neci	13	Ac Bando Matte Motif Sk, Kc Bella Sq Neci	Mkz Shampo Royal Jl 10ml, Viva Air Mawar
3	Brsv Kutek Nudes, Implora Eye Pencil Drk, Kc Bella Sq Neci	Msg Facial Wash Kp, Msg White Day Cream, Wardah Uv	14	Ac Karet Spiral Warna Sk, Brsv Kutek 101 Maroon, Brsv Kutek Nudes	Implora Eye Pencil Black 001, Kc Bella Sq Neci
4	Brsv Kutek Nudes, Hs Lp Boba, Implora Eye Pencil Drk	Kc Bella Sq Neci, Msg White Day Cream Kp, Wardah Uv Shield	15	Ac Jeday Sedang Declips, Kc Bella Sq Laser Cut M	Kc Bella Sq Neci, Salsa Kutek Set A
5	Ac Jarum Pentul Bsr Sk, Brsv Kutek Nudes, Hs Lp Boba 02 Brown	Implora Eye Pencil Drk Brown 007, Kc Bella Sq Neci, Msg	16	Ac Jeday Sedang Declips, Kc Bella Sq Laser Cut M	Kc Bella Sq Neci, Msg Facial Wash Ke
6	Ac Jeday Matte Bsr Sk, Implora Eye Pencil	Kc Bella Sq Neci, Xiu Eyebrow Pencil Black	17	Ac Jeday Sedang Declips, Kc Bella Sq Laser Cut M	Kc Bella Sq Neci, Syb Naturgo Greentea Acne Pom 10gr
7	Ac Jeday Matte Bsr Sk, Kb Geamoore Basic Club Authentic 50ml	Kc Bella Sq Neci, Xiu Eyebrow Pencil Black	18	Ac Jeday Sedang Declips, Brsv Kutek Nudes	Kc Bella Sq Laser Cut M, Kc Bella Sq Neci
8	Ac Jeday Matte Bsr Sk, Kb Geamoore Basic Club Authentic 50ml	Kc Bella Sq Neci, Msg Facial Wash Ke	19	Ac Jeday Sedang Declips, Implora Eye Pencil Black 001,	Kc Bella Sq Laser Cut M, Kc Bella Sq Neci
9	Ac Jeday Matte Bsr Sk, Implora Eye Pencil	Kb Geamoore Basic Club Authentic 50ml, Kc Bella Sq Neci	20	Ac Jarum Pentul Bsr Sk, Ac Jeday Kilau 8s Mj	Ac Jeday Matte Bsr 8s Pm, Kc Bella Sq Neci
10	Implora Eye Pencil Brown, Kc Bella Sq Neci	Kc Rok Plisket, Xiu Eyebrow Pencil Black	21	Ac Jeday Sedang Declips, Ac Kuncir Dnt Polos Kecil, Kc Bella Sq	Kc Jilbab Motif Osaka, Wardah Uv Shield Ess Sunscreen Spf30
11	Implora Eye Pencil Brown, Kc Bella Sq Neci	Kc Rok Plisket, Wardah Uv Shield Ess	22	Ac Jarum Pentul Bsr Sk, Ac Jeday Sedang Declips, Ac Kuncir Dnt	Kc Bella Sq Neci, Kc Jilbab Motif Osaka

4. CONCLUSION

Based on the results and discussions on the above research, it can be concluded that the results of the association rule analysis in July to December have data amounts of 25,154 data transactions by applying the a priori algorithm method, obtained by 23 purchasing patterns simultaneously. The number of sales transactions fluctuates month by month. Analysis of these trends can provide insight into factors that affect such changes, such as shopping seasons or special promotions. The increase in the number of transactions in August due to the Kaffa Beauty Shop providing a store anniversary voucher that coincides with August 17, in addition in December it may be related to factors such as Christmas holidays or year-end special offers. After the processing stage, qualified data with support value >0.3000 will be selected where the previous July 4221 transaction data to 585 data, so on until December data. The association

rules can provide valuable information to optimize marketing strategies. By optimizing the product layout based on the identified purchasing pattern, stores can help customers find what they are looking for while improving sales efficiency and customer shopping experience. Thus, the results of this study can contribute to decision making related to store inventory management and the formulation of more effective marketing strategies at Kaffa Beauty Shop. Further understanding of customer buying patterns can help improve customer experience and optimize sales.

REFERENCES

[1] S. N. Khasanah, L. Juniarti, S. J. Kuryanti, and E. Yulianto, "Implementation of The Apriori Algorithm for Spare Parts Data Sales," *Jurnal Mantik*, vol. 4, no. 3, 2020, [Online]. Available: https://iocscience.org/ejournal/index.php/mantik

[2] E. H. Hermaliani, L. Kurniawati, T. Haryanti, N. Mutiah, A. Kurniawan, and B. S. Renhoran, "Data Mining Technique to Determine the Pattern of Fruits Sales & Supplies Using Apriori Algorithm," in *Journal of Physics: Conference Series*, IOP Publishing Ltd, Nov. 2020. doi: 10.1088/1742-6596/1641/1/012070.

[3] A. Sani, Samuel, P. Nur Nawaningtyas, B. Waseso, G. Gunadi, and T. Haryanto, "Data Mining on Sales Transaction Data Using the Association Method with Apriori Algorithm," in *2022 10th International Conference on Cyber and IT Service Management, CITSM 2022*, Institute of Electrical and Electronics Engineers Inc., 2022. doi: 10.1109/CITSM56380.2022.9935890.

[4] M. Hossain, A. H. M. S. Sattar, and M. K. Paul, "Market basket analysis using apriori and FP growth algorithm," in *2019 22nd International Conference on Computer and Information Technology, ICCIT 2019*, Institute of Electrical and Electronics Engineers Inc., Dec. 2019. doi: 10.1109/ICCIT48885.2019.9038197.

[5] Islamiyah, P. L. Ginting, N. Dengen, and M. Taruk, "Comparison of Priori and FP-Growth Algorithms in Determining Association Rules," in *ICEEIE 2019 - International Conference on Electrical, Electronics and Information Engineering: Emerging Innovative Technology for Sustainable Future*, Institute of Electrical and Electronics Engineers Inc., Oct. 2019, pp. 320–323. doi: 10.1109/ICEEIE47180.2019.8981438.

[6] A. A. Aldino, E. D. Pratiwi, Setiawansyah, S. Sintaro, and A. D. Putra, "Comparison of Market Basket Analysis to Determine Consumer Purchasing Patterns Using Fp-Growth and Apriori Algorithm," in *2021 International Conference on Computer Science, Information Technology, and Electrical Engineering, ICOMITEE 2021*, Institute of Electrical and Electronics Engineers Inc., 2021, pp. 29–34. doi: 10.1109/ICOMITEE53461.2021.9650317.

[7] A. D. Laksito and Kusrini, "Apriori algorithm optimization using temporary table," in *2019 International Conference on Information and Communications Technology, ICOIACT 2019*, Institute of Electrical and Electronics Engineers Inc., Jul. 2019, pp. 560–565. doi: 10.1109/ICOIACT46704.2019.8938475.

[8] H. J. Kim, J. H. Shin, Y. H. Song, and J. W. Chang, "Privacy-preserving association rule mining algorithm for encrypted data in cloud computing," in *IEEE International Conference on Cloud Computing, CLOUD*, IEEE Computer Society, Jul. 2019, pp. 487–489. doi: 10.1109/CLOUD.2019.00086.

[9] M. S. Krishnan, A. S. Nair, and J. Sebastian, "Comparative Analysis of Apriori and ECLAT Algorithm for Frequent Itemset Data Mining," in *Smart Innovation, Systems and Technologies*, Springer Science and Business Media Deutschland GmbH, 2022, pp. 489–497. doi: 10.1007/978-981-16-3675-2_37.

[10] S. Marselina, J. Haerul Jaman, and D. Ely Kurniawan, "Sales Analysis Using Apriori Algorithm in Data Mining Application on Food and Beverage (F&B) Transactions," 2023. [Online]. Available: http://jurnal.polibatam.ac.id/index.php/JAIC

[11] A. D. Laksito and Kusrini, "Apriori algorithm optimization using temporary table," in *2019 International Conference on Information and Communications Technology, ICOIACT 2019*, Institute of Electrical and Electronics Engineers Inc., Jul. 2019, pp. 560–565. doi: 10.1109/ICOIACT46704.2019.8938475.

[12] A. Sani, Samuel, P. Nur Nawaningtyas, B. Waseso, G. Gunadi, and T. Haryanto, "Data Mining on Sales Transaction Data Using the Association Method with Apriori Algorithm," in *2022 10th International Conference on Cyber and IT Service Management, CITSM 2022*, Institute of Electrical and Electronics Engineers Inc., 2022. doi: 10.1109/CITSM56380.2022.9935890.

[13] M. Hossain, A. H. M. S. Sattar, and M. K. Paul, "Market basket analysis using apriori and FP growth algorithm," in *2019 22nd International Conference on Computer and Information Technology, ICCIT 2019*, Institute of Electrical and Electronics Engineers Inc., Dec. 2019. doi: 10.1109/ICCIT48885.2019.9038197.

[14] H. J. Kim, J. H. Shin, Y. H. Song, and J. W. Chang, "Privacy-preserving association rule mining algorithm for encrypted data in cloud computing," in *IEEE International Conference on Cloud Computing, CLOUD*, IEEE Computer Society, Jul. 2019, pp. 487–489. doi: 10.1109/CLOUD.2019.00086.

[15] Islamiyah, P. L. Ginting, N. Dengen, and M. Taruk, "Comparison of Priori and FP-Growth Algorithms in Determining Association Rules," in *ICEEIE 2019 - International Conference on Electrical, Electronics and Information Engineering: Emerging Innovative Technology for Sustainable Future*, Institute of Electrical and Electronics Engineers Inc., Oct. 2019, pp. 320–323. doi: 10.1109/ICEEIE47180.2019.8981438.

[16] M. S. Krishnan, A. S. Nair, and J. Sebastian, "Comparative Analysis of Apriori and ECLAT Algorithm for Frequent Itemset Data Mining," in *Smart Innovation, Systems and Technologies*, Springer Science and Business Media Deutschland GmbH, 2022, pp. 489–497. doi: 10.1007/978-981-16-3675-2_37.

[17] A. A. Aldino, E. D. Pratiwi, Setiawansyah, S. Sintaro, and A. D. Putra, "Comparison of Market Basket Analysis to Determine Consumer Purchasing Patterns Using Fp-Growth and Apriori Algorithm," in *2021 International Conference on Computer Science, Information Technology, and Electrical Engineering, ICOMITEE 2021*, Institute of Electrical and Electronics Engineers Inc., 2021, pp. 29–34. doi: 10.1109/ICOMITEE53461.2021.9650317.

[18] S. N. Khasanah, L. Juniarti, S. J. Kuryanti, and E. Yulianto, "Implementation of The Apriori Algorithm for Spare Parts Data Sales," *Jurnal Mantik*, vol. 4, no. 3, 2020, [Online]. Available: https://iocscience.org/ejournal/index.php/mantik

[19] E. H. Hermaliani, L. Kurniawati, T. Haryanti, N. Mutiah, A. Kurniawan, and B. S. Renhoran, "Data Mining Technique to Determine the Pattern of Fruits Sales & Supplies Using Apriori Algorithm," *J Phys Conf Ser*, vol. 1641, no. 1, p. 012070, Nov. 2020, doi: 10.1088/1742-6596/1641/1/012070.

[20] S. Marselina, J. Haerul Jaman, and D. Ely Kurniawan, "Sales Analysis Using Apriori Algorithm in Data Mining Application on Food and Beverage (F&B) Transactions," 2023. [Online]. Available: http://jurnal.polibatam.ac.id/index.php/JAIC