Journal of Elektronik Sistem InformasI (JESII)
Volume 3 No 1 June 2025
DOI : 10.31848/jesii.v3i1.4127
E-ISSN : 2988-585X (Online)

Implementation of Apriori Algorithm to Analyze Sales Transaction Patterns in Official E-Commerce

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Article Info

Article history:

Received June 2, 25
Revised Jun 29, 25
Accepted Jun 30, 25

Keywords:

Apriori Algorithm
FP-Growth
Product Association
E-Commerce
Data Mining
RapidMiner

ABSTRACT

Consumer behavior has changed dynamically as a result of Indonesia's e-commerce boom, particularly with regard to fashion goods purchases. Nevertheless, the majority of companies have not made the best use of transaction data when creating focused marketing campaigns. The incapacity to methodically identify consumer buy trends from intricate and substantial transaction data is one of the primary obstacles. In order to detect recurrent purchase patterns based on product combinations that are frequently bought together at the Qeela Official store, an online fashion retailer, this study intends to utilize the Apriori algorithm, more especially the FP-Growth approach. 20,000 transactions from January to April 2024 are included in the data, which was sampled into 10,000 transactions based on RapidMiner system constraints. The FP-Growth method is applied, data is transformed to binary format, attributes are converted to binominal, and association rules are formed with minimal support parameters of 0.001 and minimum confidence of 0.5. Strong association patterns, like SHORT PARASUT → SHORT CARGO with a lift of 3.197 and a confidence of 82.1%, are evident from the results. The information offers a solid foundation for choices about stock management, automatic suggestions, cross-selling implementation, and product bundling tactics. It has been demonstrated that the data mining technique is pertinent and useful for enhancing the operational and marketing efficacy of e-commerce enterprises, particularly in the fiercely competitive fashion sector.

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1. INTRODUCTION

In the digital era, buying and selling activities have undergone a significant transformation as information technology advances. E-commerce is growing rapidly because it offers accessibility, ease of payment, and a wide variety of products [1]. This shift has also had an impact on consumer behavior, as system recommendations and digital platform usability are now taken into consideration when making purchases rather than just price and product quality. One of the biggest markets, Shopee, offers a wide range of goods, such as Qeela Official, a fashion retailer that sells apparel for both men and women, including t-shirts, sportswear, and jeans.

As transaction activity and competition between sellers on this platform increase, businesses are required to develop data-driven strategies to accurately understand consumer purchasing patterns. This strategy is needed not only for marketing, but also for stock management and recommendation systems that are responsive to customer needs [2]. Factors such as price, location, promotion, and physical evidence are also part of consumer considerations in making decisions [3], so systematic processing of transaction data is a strategic necessity.

In the context of e-commerce, the ability to understand consumer behavior patterns is a key factor in building competitive advantage. One of the analytical approaches used is data mining, which is the process of discovering new patterns or knowledge from large data sets [4]. This technique allows businesses to find hidden information that can be used as a basis for making business decisions. One of the popular data mining methods is the association algorithm, especially Apriori, which is able to identify relationships between products in transactions through analysis of support and confidence values [5].

However, the Apriori algorithm has efficiency limitations when applied to large-scale data. To overcome this, the FP-Growth (Frequent Pattern Growth) method is used which does not require the process of generating candidate items and is able to speed up the search for itemsets that often appear in transactions [6]. This method is very suitable to be applied to e-commerce data that tends to be large and varied. The results of this process are association patterns that can be used to develop strategies such as product bundling, cross-selling, and dynamic recommendations that are relevant to customer behavior [7].

A variety of previous studies have proven the effectiveness of the Apriori algorithm in identifying transaction patterns. In the culinary sector, this algorithm helps develop a more optimal buffet menu [8] and determine superior packages based on customer preferences [9]. In the optical field, this algorithm is used to develop a marketing strategy for eyeglasses based on product associations [10], while in the laptop accessories sector, associations between products are used as the basis for more attractive sales bundles [11]. However, most of these studies are still limited to the offline sector, have low product variety, and have not discussed the application of association algorithms in the context of more complex and dynamic fashion e-commerce [12].

In addition, not many studies have utilized tools such as RapidMiner in processing large-scale transaction data, as well as integrating additional evaluation metrics such as lift ratio or conviction to assess the quality of the generated association rules [13]. Considering these gaps, this research aims to develop and implement an Apriori algorithm-based system using the FP-Growth method on Qeela Official sales transaction data on Shopee. The dataset used consists of 20,000 transactions during the period January to April 2024 [14].

Based on previous research gaps, this study aims to develop and implement an Apriori algorithm-based system using the FP-Growth method on Qeela Official sales transaction data at Shopee. This approach was chosen due to its ability to process large-scale and complex transaction data to find product combinations that are often purchased together [15]. It is anticipated that this study would yield reliable and commercially significant association rules that can serve as the foundation for the creation of marketing tactics including product bundling, cross-selling, automated suggestions, and more effective stock planning. In the cutthroat and ever-changing fashion e-commerce sector, this study offers a useful contribution to the application of data mining techniques to facilitate data-driven decision making.

2. METHOD

The flow of the research method carried out is as shown in Figure 1 which starts with Literature Study, Data Collection, Data Preprocessing, Application of Apriori Algorithm, Analysis and Recommendations, Conclusions and Suggestions.

Figure 1. Research Stage

2.1. Research Design

This research uses a descriptive quantitative approach by applying the Apriori algorithm based on the FP-Growth method to analyze consumer purchasing patterns. The transaction data used comes from the fashion store “Qeela Official” on the Shopee e-commerce platform. The purpose of this research is to identify product combinations that are often purchased simultaneously by customers during the period January to April 2024.

2.2. Research Objects and Data

The data used are 20,000 sales transactions obtained from the store's internal recording system. Due to processing limitations in RapidMiner, a random sampling of 10,000 transactions was conducted as a representation of the data to be analyzed. The dataset has been formatted in the form of binary tabulation (1 and 0) to indicate the presence of products in each transaction.

2.3. Tools and Software

The analysis was conducted using RapidMiner Studio software that supports the implementation of FP-Growth as well as the data visualization process. In addition, Microsoft Excel was used for initial data validation and supporting processing.

2.4. Data Analysis Method

The method used is the FP-Growth algorithm as a development of Apriori to find frequent itemset without the need to explicitly generate candidates. Stages in the analysis include:
1. Pre-processing: transformation of numerical data to binominal form (true/false), data normalization, and transaction data cleaning.
2. FP-Growth implementation: the minimum support parameter was set at 0.001 (0.1%) and minimum confidence at 0.5 (50%), based on iterative testing on highly variable data structures.
3. Association Rules Creation: using the Create Association Rules operator in RapidMiner with the measurement of evaluation metrics such as support, confidence, and lift ratio to determine the strength of the relationship between products.
4. Frequent itemset determination: using the minimum itemset value = 3 as an initial limit to detect more specific patterns.

2.5. Evaluation Criteria

Evaluation of association rules is done by considering three main metrics:
1. Support: the frequency of combination of items in the whole transaction.
2. Confidence: the probability of item B occurring if item A has already been purchased.
3. Lift: a measure of the strength of the association relative to a random event.

A lift value > 1 is considered a strong indicator that the combination did not occur by chance and can be utilized for business strategies such as product bundling, cross-selling, and automated recommendations

3. RESULT AND DISCUSSION

3.1. Data Collection

The data in this study were obtained from monthly sales transaction reports that occurred at the Qeela Official store, an official store operating on the Shopee e-commerce platform. The data used includes customer transaction history during the period January 1, 2024 to April 30, 2024 with 26,539 raw data collected. The data collection process is carried out as follows:
1. Downloading transaction reports from the Shopee Seller Centre seller dashboard in excel file format.
2. Direct interviews with shop owners, to gain a contextual understanding of the products sold, category groupings, and ongoing promotional strategies.
3. Data validation was conducted to ensure that all data was free from duplication and only contained successful transactions (completed/payment successful).

3.2. Preprocessing Data

Before the analysis process is carried out using the Apriori algorithm, the data that has been collected from Qeela Official needs to go through a preparation and preprocessing stage. This aims to ensure that the data is clean, consistent, and in the input, format required by the algorithm.

From the large amount of data, the columns taken to be used as datasets for the Apriori algorithm analysis include only 2 columns, namely

1. Order No., is a transaction number that represents the buyer's code which is then the column name is converted into order code.
2. SKU Reference Number, is a unique reference code for the product, the reason this column is taken instead of the Product Name column is because it is simpler and more targeted. which then the column name is turned into a product.

As for after selecting the columns used, there are steps taken to clean up the funds by deleting empty rows and duplicate entries in the dataset. The following dataset items are used in table 1.

TABLE I DATASET ITEMS

Code	*Product*
240301UVX6KVWH	CARGO PENDEK
240301US1N4E5N	CARGO PENDEK
240301V9CXR39D	CARGO PENDEK
240301U1CSPN35	SWEATPANTS
240301UREHV4AM	SWEATPANTS

3.3. Data Transformation

Before the FP-Growth algorithm is applied, a series of processes are carried out to organize transaction data in a format suitable for association analysis. The initial stage is the preparation of the transaction format, where the raw data consists of two main attributes: order code as the identity of the transaction and product as the list of items purchased in the transaction. This data is then converted into a transactional format, where each row represents one transaction that lists the products purchased simultaneously. The following data format after being changed according to the transaction format is shown in Figure 2.

	kode_pesanan	produk
0	240301000JBGVU	[SWEATPANTS]
1	24030100BEEBKK	[SWEATPANTS]
2	24030100BVPP80	[CARGO PANTS, CARGO PANTS, CARGO PANTS]
3	24030100D9H3KN	[SWEATPANTS, SWEATPANTS]
4	24030100FE8V82	[SWEATPANTS JUMBO]

Figure 2 Transaction Format Data

The next step is to transform the data into a binary format (binary encoding) to facilitate the processing of the Apriori algorithm. In this format, each row represents one transaction, while each column is a representation of the available products. A value of 1 indicates that the product was purchased in that transaction, while 0 indicates otherwise. This transformation is a standard format in market basket analysis, especially when using software like RapidMiner, which requires a boolean attribute structure to calculate support, confidence, and lift metrics.

In this study, 16 products were identified in the cleaned data, including: Cargo Pants, Short Cargo, Crewneck, Sporty Dress, Jogger Cargo, Onset Cargo Crewneck, Onset Crop Zipp X Swc, Onset Doraemon X Jogger Sweatpants, Onset Sweatpants + Crewneck, Short Parachute, Reject Jogger, Short Short pants, Sweatpants, Sweatpants Jumbo, Training Strip, and Zipp Doraemon. The original product names are used as column labels to be descriptive and facilitate the process of interpreting the analysis results, especially in developing bundling strategies and recommendation systems based on association results. The following display of binary data format is shown in Figure 3.

	kode_pesanan	CARGO PANTS	CARGO PENDEK	CREWNECK	DRESS SPORTY	JOGGER CARGO	ONESET CARGO CREWNECK	ONESET CROP ZIPP X SWC	ONESET DORAEMON X JOGGER SWEATPANTS
0	240301000JBGVU	0	0	0	0	0	0	0	0
1	24030100BEEBKK	0	0	0	0	0	0	0	0
2	24030100BVPP80	1	0	0	0	0	0	0	0
3	24030100D9H3KN	0	0	0	0	0	0	0	0
4	24030100FE8V82	0	0	0	0	0	0	0	0

Figure 3 Binary Format Data

After the transformation process was complete, the dataset was finalized by filtering out only transactions that contained at least two products, as single transactions were not relevant in the association analysis. The final dataset amounted to 20.000 unique transactions and was imported into RapidMiner for further analysis using the FP-Growth algorithm.

3.4. Application of Apriori Algorithm

This stage is the core of the transaction data analysis process using the Association Rule Mining method. In this research, RapidMiner Studio software is used to implement the association analysis approach with the help of workflow-based visual operators. Although the research title refers to the Apriori algorithm, in practice, the FP-Growth algorithm is used because it has higher efficiency in finding frequent itemsets on large-scale data, without having to explicitly form candidate itemsets. The workflow built in RapidMiner to implement the association algorithm is shown in Figure 4.

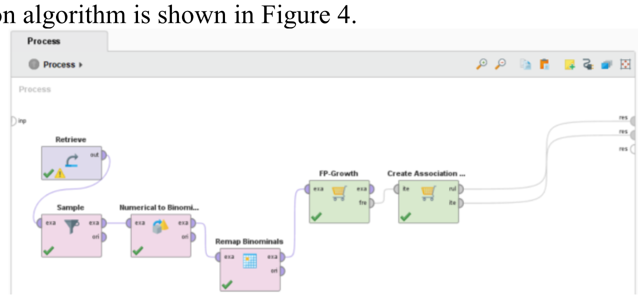

Figure 4 RapidMiner's Workflow

3.4.1. Retrieve

This operator serves to load a pre-formatted transaction dataset. The dataset contains binary data (1 and 0) to indicate product involvement in the transaction.

3.4.2. Sample (absolute)

Due to the limitation of RapidMiner which is only able to execute a maximum of 10,000 rows of data in the FP-Growth algorithm, a sampling process is carried out using the Sample operator.

Sampling is done randomly (random sampling) to ensure the data remains representative of the entire population of 20,000 transactions. Parameters used:

1. Sampling Type: Absolute
2. Sample Size: 10,000 records
3. Random Seed: 21 (to maintain reproducibility)

These sampling results are then used as the basis for exploring association patterns with the FP-Growth algorithm.

3.4.3. Numerical to Binominal

FP-Growth in RapidMiner only works on attributes of binominal type, numeric data (e.g. 1 and 0) is converted to binominal type (true/false) so that it can be recognized as the presence of products in a transaction.

3.4.4. Remap Binominals

This operator is used to ensure that all converted attributes have consistent true/false values and are ready to be processed by the FP-Growth algorithm.

3.4.5. FP-Growth

FP-Growth is the core algorithm used in this research to find frequent itemset, which are combinations of products that often appear together in customer transactions. This process aims to identify purchase patterns that have high relevance in the business context of the Qeela Official store on Shopee.

In the initial stage, the minimum support parameter is generally determined by a standardized value, such as 0.05 (5%), which means that an item combination must appear in at least 5% of all transactions to be considered significant.

However, in the context of this research, when the minimum support value was set too high (e.g. 0.05 or 0.01), not a single frequent itemset was found that met the threshold. This may be due to:
1. Limited number of transactions
2. High product variety, so the occurrence of the same combination of items is very rare
3. Customer purchasing habits are individualized and inconsistent.

Therefore, we set the minimum support value at 0.001 (0.1%). This value allows the algorithm to capture more product combination patterns that may not appear very often, but still provide valuable information for further analysis.

With a minimum support of 0.001, the FP-Growth process successfully generates a number of frequent itemset which are then used to form association rules at the next stage (Create Association Rules). The output of this operator is a list of itemset that pass the support threshold and are used as input in forming association rules that include the premise and conclusion of the product relationship.

The adjustment of find min number of itemset and min number of itemset, set to 3, allows the system to still maximize the possibility of finding patterns even when the data is not dense. In addition, the use of dummy coded columns is in accordance with the format of transaction data that has been cleaned and formed into a binary format.

3.4.6. Create Association Rules

After obtaining frequent itemset through the FP-Growth algorithm, the next step is to form association rules using the Create Association Rules operator in RapidMiner. This operator generates rules of the form "If item A is purchased, then it is likely that item B is also purchased", complete with evaluation metrics such as support, confidence, and lift.

The following are the parameters used in this process, along with their explanations listed in table 2.

TABLE 2 PARAMETER ASSOCIATION RULES

Parameter	Value	Explanation
criterion	confidence	The main criterion used to filter the rules is the confidence value. This means that only rules with confidence above a minimum threshold will be retrieved.
min confidence	0.5	That is, only rules with a probability ≥ 50% will be considered valid. This value is chosen to maintain the quality of the rules without discarding too many possible patterns.
gain theta	2.0	This parameter is used to control the sensitivity of the algorithm in measuring the strength of the relationship (gain) between items. The value 2.0 is the default and provides a balance between precision and recall.

laplace k	1.0	It is used to avoid division by zero in probabilistic calculations, especially in low-frequency datasets. This value is the standard smoothing value (Laplace correction).

3.5. *Frequent Itemset Result*

Based on the analysis of Qeela Official transaction data that has gone through sampling and pre-processing, a number of frequent itemset patterns were found that reflect the tendency of products that are often purchased simultaneously by customers. Products with the highest support value include SWEATPANTS (29.6%), SHORT CARGO (25.7%), and CARGO PANTS (24.1%). These three products are the main fashion products that show a high level of demand during the period January to April 2024). Here are some itemset with the highest support values listed in Table 3.

TABLE 3 ITEMSETS EITH THE HIGHEST SUPPORT VALUE

Item	Support
SWEATPANTS	0.296
CARGO PENDEK	0.257
CARGO PANTS	0.241

In addition, there are also two-item product combinations (size 2) with lower support values, but still business significant. Some of these include:

- SHORT CARGO and CARGO PANTS (0.011)
- SWEATPANTS and JOGGER CARGO (0.005)
- SWEATPANTS and SHORT CARGO (0.003)

Although the support value is small, this is reasonable considering the characteristics of e-commerce data which tend to be varied and not too dense.

3.6. *Association Rule Result*

From the frequent itemset that have been obtained, association rules are formed using the Create Association Rules operator. This rule shows that customers who buy SHORT PARASUT have a probability of 82.1% to also buy SHORT CARGO, with more than three times the strength of association compared to random association. Processing results using the Create Association Rules operator, one association rule was found with the following evaluation metrics, listed in Table 4.

TABLE 4 HASIL ASSOCIATION RULE

Premises	Conclusion	Support	Confidence	Lift	Conviction
PENDEK PARASUT	CARGO PENDEK	0.002	0.821	3.197	4.161

3.7. *Interpretation and Business Implications*

This purchasing pattern can be utilized by store managers to strategize product bundling appropriately. Products with strong associations can be offered as a promotional package (e.g. “Buy SHORT PARASUT, get a discount for SHORT CARGO”). Products with high support such as SWEATPANTS and CARGO PANTS can also be used as the center of the promotional strategy because they fall into the category of fast-moving items.

In addition, the association rules obtained can also be used to build an automated product recommendation system within the Shopee platform, specifically on the “Frequently Bought Together” feature. From an operational perspective, these results are also useful in planning stock items so that products with high purchase rates are always available.

4. CONCLUSION

This research successfully applies the Apriori algorithm with the FP-Growth method using RapidMiner to identify customer transaction patterns at the Qeela Official store during the period January to April 2024. Although the data is complex and not dense, the minimum support parameter of 0.001 and confidence 0.5 proved to be able to generate business-relevant association rules. One of the rules found, such as SHORT PARASUT → SHORT CARGO, shows high association strength and can be used as a basis for promotional strategies. The analysis also found that products such as SHORT CARGO, CARGO PANTS, and SWEATPANTS have high purchase rates, making them prime candidates for bundling and stock management strategies. Combinations of items with low support but high confidence remain significant in the context of e-commerce product variety. These patterns can be used for cross-selling strategies, automated recommendation systems in Shopee, and more accurate stock planning and demand prediction for fashion products.

Based on the research results, there are several things that can be recommended both in terms of developing analytical methods and business strategies that can be implemented by Qeela Official. Promotional strategies can be optimized by utilizing the association rules that have been found, either through bundling products that are often purchased together or bundling based on best-selling products such as SWEATPANTS, SHORT CARGO, or CARGO PANTS, to increase purchase opportunities and average customer transaction value. In addition, cross-selling strategies can be applied consistently by displaying complementary product recommendations on the checkout page as well as inserting them in product descriptions or catalog images to psychologically encourage additional purchases. To maintain the relevance of the strategy to the dynamics of consumer behavior, transaction analysis should be conducted periodically.

Analysis results can also be integrated into broader business systems, such as ERP or CRM, and visualized through interactive dashboards such as Tableau or Power BI. This will facilitate cross-team decision-making within the organization. In addition, the effectiveness of promotional strategies designed based on the results of association analysis needs to be tested in a measurable way, for example through A/B testing methods, so that it can be seen which approach has the most impact on increasing sales and customer loyalty. From a technical perspective, the application of the Apriori algorithm can be improved by exploring the minimum support and confidence parameters more systematically to find the optimal combination.

The dataset used can also be expanded to include additional variables such as product category, time of purchase, buyer origin, and payment method, so that the association analysis becomes sharper and able to support personalization strategies and customer segmentation more effectively.

ACKNOWLEDGEMENTS

Thank you to all parties who have supported this research so that it can be completed properly. Especially, for the parents who have always supported and guided me in this research. I`m very grateful.

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