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Optimizing Inventory with Frequent Pattern Growth Algorithm for Small and Medium Enterprises

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ABSTRACT

The success of a business greatly depends on its ability to compete and adapt to the changing dynamics of the highly competitive retail sector. Ineffective inventory management often leads to issues such as stock shortages or excess inventory. Therefore, the implementation of appropriate inventory management techniques, including data mining techniques like association rule mining, is crucial in addressing these issues. The aim of this research is to identify patterns in product placement and purchasing using the Frequent Pattern Growth algorithm. Before the Frequent Pattern Growth algorithm is applied, the dataset is first analyzed and preprocessed. The research results in 24 association rules, comprising rules with two itemsets and frequently occurring three itemset rules. It is found that the highest support value for two itemset association rules is 10%, with a corresponding confidence level of 56%. Meanwhile, for three itemset rules, the highest support value reaches 67%, with a matching confidence level of 67%. Another key point is that all three of these rules have a confidence level of 100%. Therefore, it can be concluded that association rules generated by the Frequent Pattern Growth algorithm often serve as valuable guidance for decision-making in product sales for small and medium-sized retail businesses..

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1. INTRODUCTION

Inventory control or merchandise control is an important aspect that must be managed properly so that the business can run smoothly and efficiently. The development of information technology began to be utilized by competition between business owners, so developers must find the right strategy to meet the needs and provide satisfaction to customers [1–3]. One of the strategic innovations in business is to look for connections or linkages between different product sets so that they can be packaged and sold simultaneously. This innovation solves sales and inventory problems because product mismatches increase sales. However, finding relationships between goods is difficult due to large product problems, especially when merchants have thousands of products. This causes problems for store owners in determining the decision to choose a product package to be marketed according to the diversity of consumer desires for inventory management [4, 5]. Data mining algorithms may be utilized to look for patterns in inventory data, one of which is by applying the Association Rule technique. The Association Rule method that can be applied to this study is the analysis of market baskets [6, 7]. One of the challenging data analysis methods is the association rule technique. Data mining involves statistical and mathematical techniques to explore and find hidden patterns in large data sets [8–10]. Data mining aims to get valuable and useful information from data to make business decisions [11]. Data mining can be applied to various data types, such as customer data, inventory, transactions, marketing, and other data. The data mining process includes several steps, such as data preprocessing, selection of the right data mining method, method execution, evaluation of results, and interpretation of results [12, 13]. Some commonly used data mining techniques include classification, regression, clustering, association, and ranking models [14, 15]. Each of these techniques has a different purpose and can be applied to different data types. Data mining in business can help optimize inventory management, improve product efficiency, improve customer experience, and make more accurate business decisions [16].

Analysis of market baskets is one data mining technique [17–19]. Analysis of market baskets is an analytical method to determine customer patterns in shopping at supermarkets by identifying the relationship or relationship of what items are in the shopping cart. The purpose of analyzing market baskets is to discover customer habits in buying goods simultaneously. The analysis of the market baskets method in this study was conducted using the algorithm called Frequent Pattern Growth (FP-Growth) [20–22]. The two parameters used by FP-Growth are support and confidence [23, 24]. The confidence parameter measures how strongly one item is related to another item in the constructed association rule. In contrast, the support parameter measures the proportion of combinations of items discovered in the database [25, 26]. The result of a combination of items formed and meeting the minimum support and minimum confidence requirements is called the list of association rules [27]. FP-Growth can find the frequency of itemsets with only small access to the original database, and its approach is the most efficient. In addition, FP-Growth can also avoid problems if the number of prospective itemsets is too large. FP-Growth uses a tree-specific prefix (FP-Tree) to organize data [28, 29].

Several previous studies related to the use of the FP-Growth algorithm, such as those conducted by L, Ardiantoro, and N, Sunarmi to analyze the playing patterns of badminton players, one of the popular sports in Indonesia, the processed data collection was carried out by dividing the playing field into various game areas [30]. Hu, Song Liang, et al. used a frequent-pattern growth algorithm to analyze the stability of public transportation trips with the association rule mining method [31]. Further research was conducted by Erkan akr et al., utilizing the Association Rule method on a priori and FP-Growth algorithms to analyze accident rates on ships, resulting in five Association Rule possible causes of accidents [32].

Based on several previous studies that have used the same algorithm, namely Frequent Pattern Growth, on LPG gas sales data, but only utilized data for 5 weeks and involved 15 consumers. On the other hand, the research conducted by L. Ardiantoro and N. Sunarmi to identify game patterns did not include Support and Confidence values but divided the playing field into different areas. There is also another study with a similar goal, although it uses a different algorithm. The current ongoing research adopts a different approach by using a larger dataset, comprising 140 transactions involving various consumers and analyzed products, not just a single item. In this study, we also analyze high-frequency patterns and have set Support and Confidence values. The results include combinations of up to 3-itemsets that provide more detailed insights into the relationships between products or elements in the store's inventory. Therefore, this research has advantages in terms of using a larger dataset, applying Support and Confidence values, and conducting a more in-depth analysis of product combinations. This research can contribute to further studies on the use of the FP-Growth algorithm in analyzing sales data. Additionally, it provides valuable insights for store owners in managing their inventory to make informed decisions to enhance sales.

2. RESEARCH METHOD

This research adopts a quantitative approach that aligns with the method of analyzing numerical data, with its main focus on the collection, analysis, and interpretation of numerical data as the primary method in conducting this research, including the implementation of the FP-Growth algorithm.

2.1. Data Set

The object of research studied in this study is data on the supply of goods (clothing) in the Bengkulu City area in 2022 with a total sampling data of 140 transactions. The data was obtained directly from the shop owner, and the data was processed using a spreadsheet program.

2.2. Research Steps

This research uses one of the FP-Growth algorithm data mining methods, also known as the association technique, with the stages of research in Figure 1.

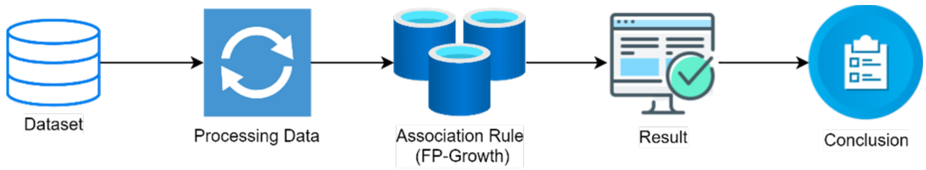

Figure 1. Stages of research

The research object studied in this study is data on the supply of goods (clothing) in the Bengkulu City area in 2020, with a total sampling data of 140 transactions. These data are data on goods sales transactions. The research conducted an analysis process using the rule data mining methodology with the FP-Growth algorithm as a measurement parameter adjusted to the scope of the research. The stage of data collection is finding information about the data to be used. Researchers collect sales data in the form of notes and move them in a number processing application (Ms. Excel). Sales data were obtained from January to March 2020. Then, the initial data processing is carried out to select the attributes needed in data processing. Then, the selected dataset is processed by applying the FP-Growth algorithm to find frequent itemsets and association rules. The frequent itemset and association rules generated are then evaluated to determine the strength of the correlation (lift ratio).

2.3. Association Rule Mining

1. Dataset analysis
   Dataset analysis determines the most frequent itemset with a predetermined support value. In this case, researchers set a minimum support of 0.02 or 2% because the value tends to be small after seeing and analyzing the amount of transaction data. Search results from the highest frequent itemset value using the following Equation. The support value of the highest frequent itemset is obtained using Equation (1) [33].

$$Support(A) = \frac{\Sigma \text{ Contain A}}{\Sigma \text{ Total Transactions}} \times 100 \tag{1}$$

   The value containing A is the value of one goods item in the transaction. To get the support value of A 1-itemset, divide the value containing A by the total amount of all transactions. To obtain the percentage value, multiply the result of the division by 100. Thus, we can obtain the support value of the proportion of all A values from the entire transaction.
2. Establishment of Association rules with Minimum support
   The association rules formation stage is carried out to select data that has met the support frequent itemset for merging. Non-compliant items set will be deleted, and those that meet the iteration will be used for the next process [33]. The value of the 2-itemset is obtained using the Equation (2):

$$Support(A \cap B) = \frac{\Sigma \text{ Contain A and B}}{\Sigma \text{ Total Transactions}} \times 100 \tag{2}$$

   A value containing A and B is the value of the two items of goods in the transaction, which meets the support value set at 1-itemset (0.2%) that does not meet will be eliminated and will not follow the next step to get the support value of 2-itemset which is dividing the value containing A and B by the total amount of all transactions. To obtain the percentage value, multiply the result of the division by 100.

$$Support(A \cap B \cap C) = \frac{\Sigma \text{ Contain A,B and C}}{\Sigma \text{ Total Transactions}} \times 100 \quad (3)$$

The value containing A, B, and C is the value of the three items of goods in the transaction, which meets the support value set in the 2-itemset (0.2%); that does not meet will be eliminated and will not follow the next stage to get the 3-itemset support value by dividing the value containing A, B, and C by the total amount of all transactions A. To obtain the percentage value, multiply the result of the division by 100.

3. In determining the confidence value with this, the researcher sets a confidence value of 0.8% to form strict rules so that they can generate rules or patterns of subsequent transactions. To determine the value of confidence that is obtained using the Equation (4):

$$Confidence = P(A \mid B) \frac{\text{Number of Transactions Contains A and B}}{\text{Number of transactions Ad}} \times 100 \quad (4)$$

Confidence value is based on minimum support and minimum confidence values that have met highly frequent items [34–36].

3. RESULT AND ANALYSIS

3.1. Data Analysis

The data analysis process is carried out to find patterns of similarity of items purchased based on data on daily purchase reports. Sales report data every day at first is just ordinary information then after processing, it will be very useful information for future business progress and improvement. Therefore, researchers will test the results of using apriori and FP-Growth to find the relationship between purchasing patterns. In this research process, clothing sales data with a total transaction of 140 and items used. The transaction data has been made in tabular form, as shown in Table 1.

Table 1. Tabulation Results Data

No	Transaction Code	Items Thing			
		K	RI	...	G
1	TR210105.001	1	0	...	0
2	TR210105.002	1	1	...	0
3	TR210105.003	0	0	...	0
4	TR210105.004	0	0	...	0
5	TR210105.005	0	0	...	0
6	TR210105.006	0	0	...	0
7	TR210105.007	0	0	...	0
8	TR210105.008	0	0	...	0
9	TR210105.009	0	0	...	0
10	TR210105.010	0	0	...	0
...	...	...		...	...
131	TR210205.006	0	0	...	0
132	TR210205.007	0	0	...	0
133	TR210205.008	0	0	...	0
134	TR210205.009	0	0	...	0
135	TR210208.010	1	0	...	0
136	TR210208.011	0	0	...	0
137	TR210208.012	0	0	...	1
138	TR210208.013	0	0	...	0
139	TR210208.014	0	0	...	0
140	TR210208.015	0	0	...	0

Based on Table 1, real data with the product names of Kaos (K), Rok Include (RI), and even imported dresses (Gaun Impor/GI) are organized into tabular data. Real transaction sales data of the products are converted into binary data, namely the numbers 1 and 0. If a product is purchased, it is categorized as 1, and if not purchased, it is categorized as 0.

3.2. High-Frequency Pattern Analysis

In high-frequency pattern analysis, this process aims to find combinations of items that meet the minimum requirements of the support value. With a formula using Equation (1), results that meet the goods transaction data in Table 2 are obtained.

Table 2. Goods Transaction Data

No	Transaction Code	ItemsThing
1	TR210105.001	K
2	TR210105.002	RI, K
3	TR210105.003	KL
4	TR210105.004	LS, SC, SCP
5	TR210105.005	CAK
6	TR210105.006	DK, CKN, CK
7	TR210105.007	RB, CK
8	TR210105.008	BK, BF
9	TR210105.009	HL
10	TR210105.010	PS
...	...	...
138	TR210108.013	PS, CK, TP
139	TR210108.014	KN, PS, RB
140	TR210108.015	EJ, K, SI

The above is sales transaction data (clothing) that will be used to perform association rules to obtain effective results in determining sales and placement of goods. Each transaction consists of one or several items recorded with a transaction code and arranged in a list. For example, the first row in Table 2 shows transaction code "TR210105.001" with one item "K" purchased. In contrast, the second row shows transaction code "TR210105.002" with two items, "RI and K." Each item in the table will be added up to determine the frequency of occurrence of each item. Thus, it will be known how many times each item has been sold within a certain period of time. To obtain association rules for the items, an initial step is to calculate the high-frequency value with a predetermined minimum support value of 2%. Based on this value, items that do not meet the frequency requirement will be eliminated as they do not meet the minimum support value. The result of the frequency count can be seen in Table 3.

Table 3. Calculation of Minimum Support Value

No	Items Thing	Frequency
1	K	8
2	RI	12
3	KL	2
4	LS	4
5	SC	2
6	SCP	3
7	CAK	10
8	DK	3
9	CKN	2
10	CK	17
11	RB	4
12	BKN	3
13	BF	10
14	HL	10
15	PS	6
16	KN	5
17	STX	16
18	LK	25
19	CKJ	3
20	JV	5
21	B	6
22	BK	9
23	RKN	3
24	TP	3
25	EJ	4
26	BS	2
27	SI	3
28	SM	1
...	...	...
40	KD	1
41	STS	1
42	SCO	1
43	BH	1
44	CVM	1
45	BI	1
46	DKS	1
47	TI	1
48	GD7	1
49	CKR	1
50	TK	2
51	SVS	2
52	SS	1
53	J	1
54	CT	1
55	DHK	1
56	H	1
57	GI	2

Based on Table 3, it can be seen that in 140 data transactions, there are 57 items of goods that have been calculated minimum support value. It is known from 57 data that there are 27 items of goods that meet the minimum value of support with a value exceeding 2.8 the number of transaction frequencies. Furthermore, the data in Table 3 will be sorted by the number of transaction frequencies from the largest to the smallest according to priority, as in Table 4.

Table 4. Item Meets Minimum Support Value

No	Items Thing	Frequency	No	Items Thing	Frequency
1	LK	25	15	LS	4
2	CK	17	16	RB	4
3	STX	16	17	CKJ	3
4	RI	12	18	BKN	3
5	CAK	10	19	SCP	3
6	BF	10	20	SI	3
7	HL	10	21	SMI	3
8	BK	9	22	LX	3
9	K	8	23	LB1	3
10	PS	6	24	ST0	3
11	B	6	25	RKN	3
12	JV	5	26	TP	3
13	KN	5	27	DK	3
14	EJ	4			

Table 4 shows that LK is the item with the most transactions, which is 25 items of goods; the more transactions or items in the database, the more effective FP-Growth will be to extract the association rule. Furthermore, the data in Table 4 will be made a frequent Pattern (FP) Tree.

3.3. Frequent Pattern (FP) Tree Creation

The data that has been processed is then used as a table for Transaction data that meets support items, and those that do not meet will be deleted automatically [37–40]. Then, sort items by priority seen from the largest frequency value and eliminate items that do not meet the minimum support. The minimum support item used is ≥ 0.2. Transaction data from 140 to 124 with 57 items to 27 items is then sorted according to priority, as shown in Table 4, and becomes a transaction in Table 5.

Table 5. Transactions According to Priority

No	Transaction Code	Items Thing
1	TR210105.001	K
2	TR210105.002	RI, K
3	TR210105.004	LS, SCP
4	TR210105.005	CAK
5	TR210105.006	CK, DK
6	TR210105.007	CK, RB
7	TR210105.008	BF, BK
8	TR210105.009	HL
9	TR210105.010	PS
10	TR210105.011	KN
...	...	...
122	TR210208.013	CK, PS, TP
123	TR210208.014	PS, KN, RB
124	TR210208.015	K, EJ, SI

Furthermore, the data sorted according to priority will be formed into an FP-Tree tree. Starting from Null, and will be followed by the itemset in the transaction until all transactions are formed into a tree, as shown in Figure 2.

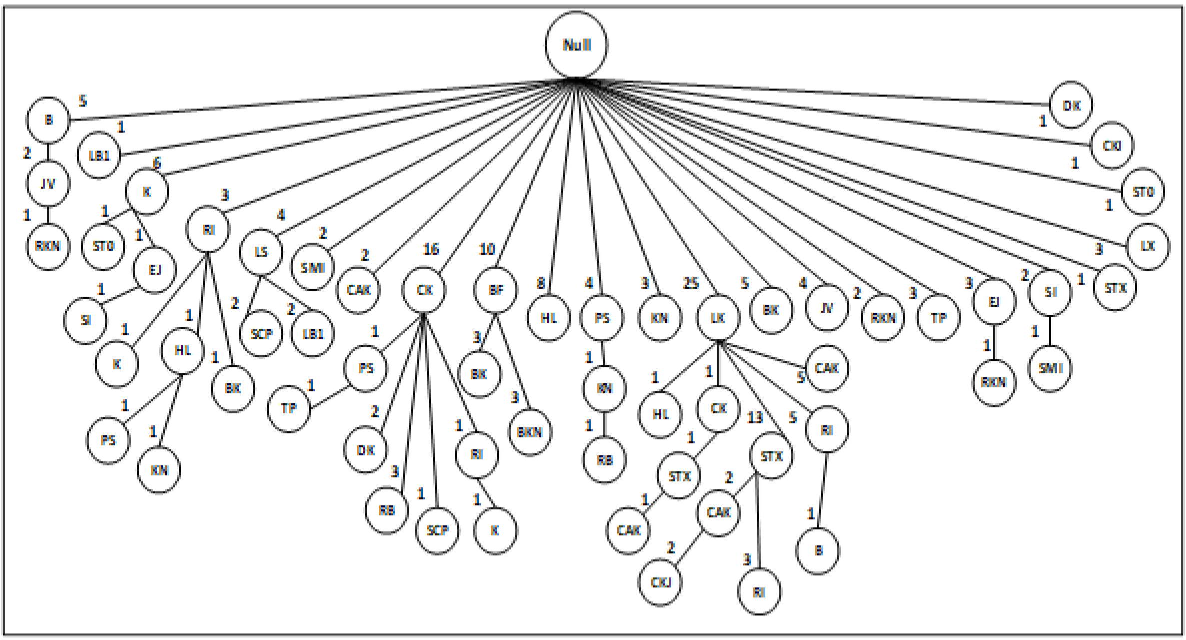

Figure 2. Results of the establishment of the frequent pattern tree of goods

3.4. Application of FP-Growth Algorithmitle

To apply the FP-Growth algorithm to item data, the first process that will be done is to find frequent itemsets by creating an FP-Tree pattern. Next, the pattern is formed, then we have to determine the Conditional Pattern Base, look for the Conditional FP-Tree pattern, and finally, the Frequent Itemset pattern [41, 42] in completing the formation of the Association rule on the use of FP-Growth through stages as Figure 3.

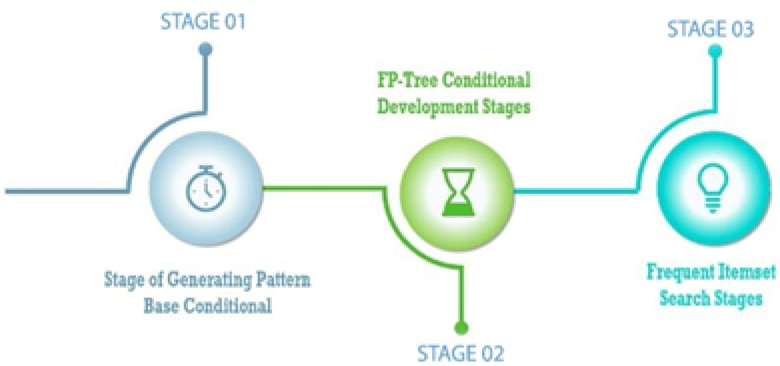

Figure 3. FP-Growth implementation stages

From the stages in Figure 3, to complete the FP-Growth stage, calculations will be carried out starting from the Conditional Pattern Base Generation, then the Conditional FP-Tree, and the Frequent Itemset stage.

a. Stage of Conditional Pattern Base Generation
pay attention to FP-Tree. At this stage, the FP-Growth algorithm will break down the FP-Tree results in Figure 2. Based on each suffix and produce, as stated in Table 6, the item name will be used as a code for the next step.

Table 6. Conditional Pattern Base

Code	Conditional Pattern Base
CKJ	{{LK, STX, CAK :2} {:1}}
BKN	{{BF:3}}
SCP	{{CK:1}, {LS:2}}
SI	{{K, EJ:1}, {:2}}
SMI	{{SI:1}, {:2}}
LX	{{:3}}
LB1	{{LS:2}, {:1}}
ST0	{{K:2}, {:1}}
RKN	{{B, JV:1}, {:2}}
TP	{{:3}}
DK	{{CK:2}, {:1}}
EJ	{{K:1}, {:3}}
LS	{{:4}}
RB	{{PS, KN:1}, {CK:3}}
JV	{{B, JV:1}, {:4}}
KN	{{PS:1}, {RI:1}, {:3}}
PS	{{CK:1}, {RI, HL:1}, {:4}}
B	{{LK, RI:1}, {:5}}
K	{{CK, RI:1}, {RI:1}, {:6}}
BK	{{RI:1}, {BF:3}, {:5}}
CAK	{{:2}, {LK, CK, STX:1}, {LK, STX:2}, {LK:5}}
BF	{{:10}}
HL	{{:8}, {RI:1}, {LK:1}}
RI	{{LK, STX:3}, {LK :5}, {CK:1}, {:3}}
STX	{{LK: 13}, {LK, CK :1}, {:2}}
CK	{{LK:1}. {:16}}
LK	{{:25}}

b. Stage of Conditional Development of FP-Tree
To find the Conditional FP-tree, adding up the existing support count and a larger support count will replace it with the conditional FP-tree. Support count is the number of occurrences of an itemset in all transactions in the data set. Itemsets with greater support counts are considered more important because they appear more frequently in the data set. Table 7 shows the results of the Conditional FP-Tree.

Table 7. Conditional FP-Tree

Code	Conditional Pattern Base	Conditional FP-Tree
BKN	{BF:3}	BF:3
RB	{{PS, KN:1}, {CK:3}}	CK:3
BK	{{RI:1}, {BF:3}, {:5}}	BF:3
CAK	{{:2}, {LK, CK, STX:1}, {LK, STX:2}, {LK:5}}	LK:3, STX :3
RI	{{LK, STX:3}, {LK :5}, {CK:1}, {:3}}	LK: 8, STX: 3
STX	{{LK: 13}, {LK, CK :1}, {:2}}	LK:14,
LK	{:25}	-

The Conditional FP-Tree results are determined by the count of items that meet the minimum support requirements in the Conditional Pattern Base.

c. Stage Frequent Itemset
The next step is to form a Frequent Itemset by combining sets and subsets of conditional FP-Tree with items. The results of the Frequent Itemset stage can be seen in Table 8.

Table 8. Frequent Itemset

Kode	Conditional Pattern Base	Conditional FP-Tree	Frequent Itemset
BKN	{BF:3}	BF:3	BF-BKN: 3
RB	{{PS, KN:1}, {CK:3}}	CK:3	CK-RB:3
BK	{{RI:1}, {BF:3}, {:5}}	BF:3	{BF-BK:3}
CAK	{{:2}, {LK, CK, STX:1}, {LK, STX:2}, {LK:5}}	LK:3, STX :3	{LK-CAK:8, STX-CAK:3} {LK, STX, CAK:3}
RI	{{LK, STX:3}, {LK :5}, {CK:1}, {:3}}	LK: 8, STX: 3	{LK-RI:8, STX-RI:3} {LK, STX, RI:3}
STX	{{LK: 13}, {LK, CK :1}, {:2}}	LK:14,	{LK-STX:14}
LK	{:25}	-	-

Table 8 shows the results of the Frequent itemset that has met the support of the conditional FP-tree. The results of the frequent itemset will be searched for support values using 2-itemsets and 3-itemsets. To find support values for 2-itemsets using Equation (2) and for 3-itemsets using Equation (3), the search results for support values for 2-itemsets are shown in Table 9.

Table 9. Support 2-Itemset

Code	Transaction	Total Transaction	Support (%)
BF-BKN	3	140	2
CK-RB	3	140	2
BF-BK	3	140	2
LK-CAK	8	140	6
STX-CAK	3	140	2
LK-RI	8	140	6
STX-RI	3	140	2
LK-STX	14	140	10

After trying a combination of two sets of items with a minimum support of 2%, information is obtained that eight sets of items meet the minimum standard of support. The eight set items are BKN-BKF, CK-RB, BF-BK, STX-CAK, STX-RI with 2% support, and LK-CAK, LK-RI with 6% support. Furthermore, it is known that the LK-STX combination has a support of 10%, which means that the combination is very significant in influencing the data. Using the results of the combined analysis of the two itemsets, calculations will be carried out for the 3-itemset before calculating the association rules used in making decisions by retail owners or figures. Then, three new itemsets are formed, which are shown in Table 10.

Table 10. Support 3-Itemset Support

Code	Transaction	Total Transaction	Support (%)
LK→STXˆCAK	3	25	12
STX→LKˆCAK	3	16	19
CAK→STXˆLK	3	10	30
LKˆSTX→CAK	3	25	12
LKˆCAK→STX	3	25	12
STXˆCAK→LK	3	16	19
LK→STXˆRI	3	25	12
STX→LKˆRI	3	16	19
RI→STXˆLK	3	12	25
LKˆSTX→RI	3	25	12
LKˆRI→STX	3	25	12
STXˆRI→LK	3	16	19

Table 10. transaction values are the Frequent Itemset shown in Table 8. The highest value 3-itemset support results, namely CAK → STXˆLK by 30%, Combination RI → STXˆLK by 25% for STX→ LKˆCAK, STXˆCAK → LK, STX → LKˆRI, STXˆRI → LK is 19% and the smallest is 12%, then all of these itemsets meet the support value. FP-Growth method can be used in determining the choice of product item pairs. This algorithm focuses on providing product item pair choices based on sales transaction results, resulting in association rules. From the results of the frequent itemset, association rules will be formed using equation (4) to produce confidence values that can be used in decision-making by store owners. The results of association rules are shown in Table 11.

Table 11. Association Rules Final

Code	Transaction	Support (%)	Confidence (%)
1	IF buying BF, THEN buy BKN	2	8
2	IF Buying CK, THEN buying RB	2	18
3	IF Buying LK, THEN buy CAK	6	32
4	IF Buying STX, THEN buy CAK	2	19
5	IF Buying LK, THEN buying RI	6	32
6	IF Buying STX, THEN buy RI	2	19
7	IF Buying LK, THEN buy STX	10	56
8	IF buying LK, THEN buy STX and CKJ	8	8
9	IF buying STX, THEN buy LK and CKJ	13	13
10	IF buying CKJ, THEN buy STX and LK	67	67
11	IF buying LK and STX, THEN buy CKJ	8	14
12	IF buying LK and CKJ, THEN buy STX	8	8
13	IF buying STX and CKJ, THEN buy LK	13	100
14	IF you buy LK, THEN buy STX and CAK	12	12
15	IF buying STX, THEN buy LK and CAK	19	19
16	IF buying LK and STX, THEN buy CAK	12	21
17	IF buying LK and CAK, THEN buy STX	12	38
18	IF buying STX and CAK, THEN buy LK	19	100
19	IF you buy LK THEN, buy STX and RI	12	12
20	IF you buy STX, THEN buy LK and RI	19	19
21	IF you buy RI, THEN buy STX and LK	25	25
22	IF you buy LK and STX, THEN buy RI	13	21
23	IF you buy LK and RI, THEN buy STX	13	38
24	IF buying STX and RI, THEN buy LK	13	100

Table 11 shows the first association rule that if a buyer buys BF (transaction code 1), there is a 2% chance that the buyer will also buy BKN. In addition, the confidence level for this rule is 8%, which means that in 8% of transactions containing BF, the buyer also buys BKN. Other association rules are generated similarly and provide information patterns in the transaction data analyzed.

4. CONCLUSION

The results and discussion above reveal that out of 140 transactions, 24 association rules were successfully identified. There were 7 association rules with 2 itemsets and 17 association rules with 3 itemsets consistently appearing in transactions. One of the most prominent rules was CKJ→STXˆLK, with support and confidence levels of 67% each. Additionally, three other association rules, namely STXˆCKJ→LK, STXˆCAK→LK, and STXˆRI→LK, had a confidence level of 100%. In the context of previous research, the FP-Growth and Apriori algorithms have been used to analyze various aspects such as gaming patterns, accident rates, and travel stability. However, this research contributes differently by applying the algorithm to retail, particularly in inventory management and fashion product sales. This opens new opportunities to understand how these algorithms can enhance retail business operations. In conclusion, it can be inferred that the FP-Growth algorithm offers speed in data processing aided by the creation of the FP-Tree. The association rules generated from the frequent itemset algorithm can be used as valuable decision support for small and medium-sized retail businesses looking to optimize their product sales. Suggestions for further research include considering the use of more diverse datasets and testing with other algorithms in the data mining domain. This can help compare the effectiveness of the FP-Growth algorithm with alternative approaches in inventory management and sales. Future research can also focus on developing more advanced methods to support retail business operations and enhance customer satisfaction.

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