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IMPLEMENTATION OF MARKET BASKET ANALYSIS AS A MARKETING IMPROVEMENT STRATEGY FOR LOCAL PAPER CHEMICAL PRODUCERS IN THE PAPER INDUSTRY (CASE STUDY AT PT. AKL)

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Abstract

The development of global demand for pulp and paper industry products both domestically and for export is still promising, including tissue paper products, packaging paper and so on. Another industry that is growing along with the growth of the paper industry is paper chemicals or additives used in the paper-making process. In business, data mining is used to find patterns and relationships in data to help make better business decisions. Data mining techniques using association rules such as market basket analysis can help find sales trends, develop smarter marketing campaigns, and accurately predict customer loyalty. From the research results, the most sold products at PT. AKL is Epostrong Final/CT/FG. Experiments with a minimum support value of 0.05 and a minimum confidence value of 0.05 obtained seven association rules that can be used as a reference to determine which products have the opportunity to increase sales because the resulting association rules are ideal with a lift ratio value > 1 so that they have the potential to be used. Based on the final association rules, with a support value of 1.4%, a confidence value of 100% and a lift ratio value of 3.227, it is obtained that if you buy a bustrong 20D and a bustrong 11G, you will buy calciperse. Thus, based on the association rules obtained, PT. AKL can maximize the utilization of data mining applications so that by promoting product combinations, it will increase more sales opportunities.

Keywords: Data Mining, Sales, Paper Chemical, Apriori, Fp-Growth

INTRODUCTION

Globalization has had a major impact on today's business environment. This provides benefits for both the customer and the business owner. The business market space has become widely available, influencing customer demand and behavior. It also opens up more business opportunities for business owners to venture into. This is beneficial to those who take this opportunity but may put pressure on those who remain the same. To succeed in such a challenging environment, businesses need to compete with others and find ways to make their presence significant. Knowing one's customers, especially their preferences, will be one of the best strategies to survive in this challenging environment.

The effects of the devaluation of one’s country currency, make companies concentrate more on exports rather than imports; this also leads to a greater potential to be in demand on the foreign market. From manufacturing companies’ perspectives, the products and services offered now are cheaper for foreign customers, so companies could easily reach potential

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markets through online channels in a less costly way and thus increase their competitive advantage against their competitors [1].

The development of global demand for pulp and paper industry products, including tissue paper, packaging paper and so on, both domestically and for export is still promising. With the increasing trend of e-commerce transactions, the demand for paper for paper and cardboard packaging will continue to grow. Therefore, through various policy instruments, the government encourages comparative advantage to become a competitive advantage. The pulp and paper industry itself is one of the sectors whose development is prioritized according to Government Regulation Number 14 of 2015 concerning the Master Plan for National Industrial Development. In the Asian region, Indonesia ranks third for the pulp industry and fourth for the paper industry. Meanwhile in the world, Indonesia's pulp production ranks tenth and the paper industry ranks sixth. This gain is obtained from the pulp production capacity which has reached 11 million tons per year and 16 million tons per year for paper [2].

Other industries that have also grown along with the growth of the paper industry are paper chemicals or additives used in the pulp and paper industry process itself, one of which is PT. AKL. PT. AKL is a foreign investment company established in 2010 specializing in the production, development and distribution of water-soluble polymers with an annual capacity of 30,000 metric tons. Products PT. AKL is widely used in various industries such as paper, ceramics, textile, and water treatment and is distributed worldwide. Products PT. AKL has been sold mainly in Indonesia and China. Recently started exporting to Malaysia, India and Thailand. As a competitive manufacturer, this enables PT. AKL to sell its products either to end users directly, or through agents. Production facilities integrated with R&D and Application Testing Center is one of the main selling points of PT. AKL to enable providing a fast response to customer input.

The papermaking process is made from cellulose fiber with the addition of other additives to improve the quality of the paper produced according to the desired grade. Pulp for papermaking can be made from virgin fiber by mechanical or chemical processes or by re-pulping of recovered paper or recycled paper. Among the additives used in paper making are dry strength agents and wet strength agents. Dry strength agent is a chemical to increase paper strength such as crack, tensile, and compressive resistance. While wet strength agent is a chemical used to increase the strength of paper in wet conditions [3]. The use of this additive can increase dry strength by 75 percent and wet strength by up to 30 percent based on increased dry strength and about 50 percent based on dry strength on untreated paper [4], [5].

In the current information age, the importance of data resources can be imagined, and the importance of using data resources means that data mining has also emerged. Data mining is a tool for obtaining valuable knowledge and information. Making good use of association rules and related algorithms can help countries make better predictions and provide decision support [6]. In the current situation, all industries are in a relatively equal stage, must make good use of data resources, use apriori algorithm to mine association rules, formulate marketing strategies, promote sales growth and slow down the loss of national GDP [7].

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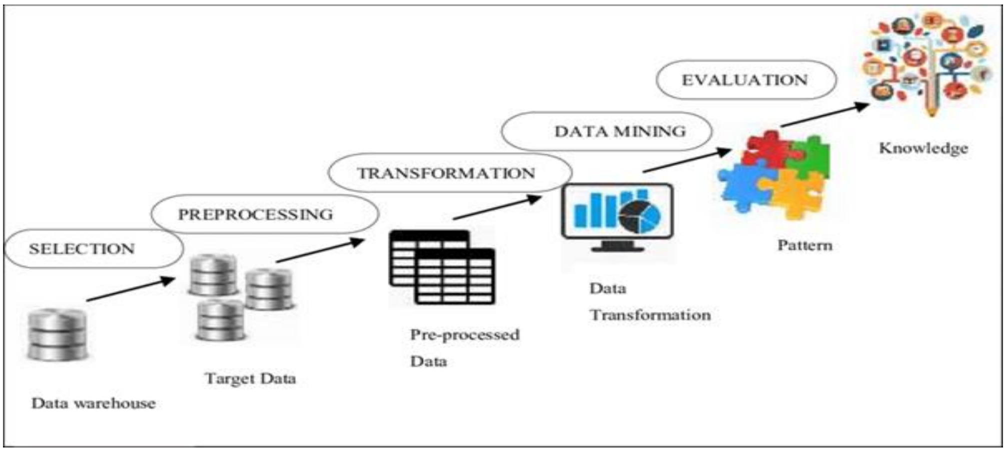
The availability of a database of records of purchase transactions of customers in a supermarket or elsewhere has encouraged the development of techniques that automatically find associations of products or items stored in these databases. An example is data about transactions collected from barcode scanners in supermarkets. Market basket databases like this contain a very large number of records. Each record lists all items purchased by a customer in a single purchase transaction. These managers can use this information to create supermarket layouts, for example, so that the arrangement of these items can be optimal with each other or can also be used for promotional purposes, buyer segmentation, product cataloging or viewing shopping patterns [8], [9], [10]. In marketing a product there are several factors that will greatly affect sales, one of which is a strategy in sales. With a good strategy a product will sell quickly, but if the strategy used is not right then a product will decline in terms of sales [11], [12], [13], [14], [15].

Data Mining is an analysis step of the knowledge discovery process in a database or knowledge discovery from a database called Knowledge Discovery in Database (KDD). Knowledge can be in the form of valid data patterns or relationships between data (which were not previously known) [12]. Data Mining is a combination of a number of computer science disciplines which is defined as the process of discovering new patterns from very large data sets, including methods that are slices of artificial intelligence, machine learning, statistics, and database systems. Data Mining is aimed at extracting (taking the essence) knowledge from a set of data so that a structure can be understood by humans and includes database and data management, data processing, model and inference considerations, interest measures, complexity considerations, post-processing of the found structures, visualization [4].

Figure 1: Knowledge Discovery in Database Process (KDD) [16]



Mining Frequent Item set towards finding associations and correlations among items in very large transaction and relational data sets [16]. With massive amounts of data continuously being collected and stored, many industries are becoming interested in mining these patterns from their databases. The discovery of interesting correlation relationships among many business transaction records can assist in many business decision-making processes, such as catalog design, cross-marketing, and shopping behavior analysis. In some applications,

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transaction databases must be mined frequently to analyze customer behavior. In such applications, data mining efficiency can be a more important factor than the complete accuracy of the results. In addition, in some applications the problem domain may be vaguely defined. The few missing marginal cases that have a level of trust and support at the boundary line may have little effect on the quality of the solution to the real problem. Leaving imprecise results can actually significantly increase the efficiency of the applied mining algorithm [6].

A common example of frequent item set mining is market basket analysis in supermarkets. This process analyzes the buying habits of the customer by finding associations between the different items that the customer places in the 'shopping cart'. The discovery of associations like this can help retailers develop marketing strategies by gaining insight into what items are frequently purchased together by customers [8].

RESEARCH QUESTIONS

The objectives of this research are as follows: 1) to determine the pattern of purchasing goods based on the tendency of consumers to buy products by looking at products/items that meet minimum support and minimum confidence and lift ratios; 2) to provide information and recommendations as a decision support system to local paper chemical producers in developing marketing strategies to increase sales.

METHODOLOGY

There is a technique in data mining called Market Basket Analysis (MBA) or also known as Association Rule Mining (ARM) which is a technique for finding jointly purchased items based on customer buying behavior. Apriori is the most classic and quite important algorithm in Frequent Itemsets Mining (FIM). The Apriori algorithm is an algorithm for mining association rules developed by Agrawal and Krishnan in 1994. After that, various improved association rule algorithms based on the Apriori algorithm have also been generated. Similar algorithms are more efficient, such as FP-Growth, LCM, and so on, Apriori is still the most widely used and implemented in commercial products for data mining because it is considered a more established algorithm. The main key in the Apriori algorithm process is to make several iteration stages in the database. It was also explained that each iteration produces a frequency pattern which is calculated by scanning the database to get support for each item. After the support for each item is obtained, items that have support above the minimum support are selected as high-frequency patterns with a length of one or often called 1− itemset.

The term k itemset is the term for a set consisting of k items. While the second iteration will produce 2−itemset which each set has two items. In its use, the Apriori algorithm can reduce the number of candidates whose support must be calculated by pruning. This pruning is what makes the Apriori algorithm perform well. In addition to having good performance, the Apriori algorithm also has weaknesses. Some researchers conclude that the weakness in the Apriori algorithm lies in the scanning process that must be carried out at each iteration so that it will take a long time and large computational capabilities. This Apriori algorithm deficiency is no longer found in similar new algorithms, such as FP-Growth for example. They also said that

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the Apriori algorithm still needs to be researched and developed again in relation to the field of data mining. FP-Growth is an alternative algorithm that is quite effective for finding the most frequently occurring data set (frequent itemset) in a large data set. FP-Growth has a speed in displaying results compared to Apriori, but fails to produce a high confidence value. FP-Growth has the advantages of recognizing an object non-linearly, making it easier to map input into a result without knowing the actual process, strong in parallel processing and the ability to tolerate.

Association rules want to provide information in the form of an "if-then" or "if-then" relationship. This rule is calculated from probabilistic data. In a recommendation system, such as when a person sees an item, it will be recommended to buy another item that is usually purchased by other customers together.

From the large number of rules that may be developed, it is necessary to select rules that are sufficiently strong in the level of dependence between items in the antecedent and consequent. To measure the strength of this association rule, confidence and lift ratio are used. In addition to support, there is another measure that measures the level of uncertainty in the "if-then" or "if-then" rules, namely the confidence of the rules. Confidence is the ratio between the number of transactions covering all items in the antecedent and consequent to the number of transactions covering all items in the antecedent.

Determining what is contained in the frequent item set is related to the concept of support. The support of a rule is the number of transactions that contain items in both antecedent and consequent. It is called support because it measures the level of data support for the validity of the developed rules. Usually support is expressed in the form of a percentage or sometimes it can also be expressed in the number of occurrences [6].

To get the support value for item a, it can be obtained as follows:

$$\text{Support (A)} = \frac{\text{Number of transactions containing item A}}{\text{Total transactions}}$$

Meanwhile, to get support from two items, namely item A and item B, it is as follows:

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

After obtaining the minimum support, the minimum confidence is as follows:

$$\text{Confidence (A, B)} = \frac{\text{Number of transactions containing item A and B}}{\text{Number of transactions containing item A}}$$

One of the better ways to see whether the association rule is strong or not is to compare it with a benchmark value, where it is assumed that the occurrence of the consequent item in a transaction is independent of the occurrence of the antecedent in an association rule.

The estimated value of the confidence benchmark of a data against a rule can be calculated by:

$$\text{Confidence benchmark} = \frac{\text{Number of transactions with items in consequent}}{\text{Number of transactions in the database}}$$

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Lift is a ratio number that shows how many chances of finding an attribute that appear together with other attributes compared to all occurrences of the attribute being met. Lift shows the level of rule strength on random occurrences of antecedent and consequent based on their respective supports. This will provide information about the improvement and increase in the probability of the consequent based on the antecedent.

$$\text{Lift Ratio} = \frac{\text{Confidence}}{\text{Confidence benchmark}}$$

The lift ratio value > 1 indicates the benefits of the rule. The larger the lift ratio value, the greater the strength of the association

RESULTS

Transaction Data

The analyzed data is taken from the transaction data of PT. AKL in October 2021-March 2022. Further analysis using the rapid miner application.

Table 1: Transaction Data Set

TID	ITEM	TID	ITEM
T1	Calciperse, Bustrong 11G	T37	Calciperse
T2	Calciperse, Bustrong 11G	T38	Epostrong, Bustrong 11G
T3	Calciperse	T39	Epostrong, Bustrong 11G
T4	Bustrong 20D	T40	Epostrong
T5	Bustrong 20D	T41	Bustrong 20D
T6	Epostrong	T42	Epostrong
T7	Bustrong 20D	T43	Bustrong 20D
T8	Bustrong SH12N	T44	Bustrong SH12N
T9	Calciperse	T45	Calciperse
T10	Epostrong	T46	Calciperse
T11	Epostrong	T47	Calciperse
T12	Epostrong	T48	Epostrong, Bustrong 11G
T13	Bustrong 20D	T49	Epostrong, Bustrong 11G
T14	Bustrong 20D	T50	Epostrong
T15	Epostrong	T51	Calciperse
T16	Epostrong	T52	Burstrong 20D
T17	Bustrong 20D	T53	Bustrong SH12N
T18	Bustrong SH12N	T54	Calciperse
T19	Epostrong	T55	Calciperse
T20	Epostrong	T56	Bustrong 11G
T21	Calciperse	T57	Epostrong, Bustrong 11G
T22	Calciperse	T58	Epostrong
T23	Calciperse	T59	Bustrong 20D
T24	Calciperse	T60	Bustrong 20D

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T25	Epostrong, Bustrong 20D	T61	Epostrong
T26	Epostrong	T62	Epostrong
T27	Bustrong 20D	T63	Bustrong 20D
T28	Bustrong 20D	T64	Bustrong SH12N
T29	Epostrong	T65	Epostrong
T30	Epostrong	T66	Epostrong
T31	Bustrong 20D	T67	Calciperse, Bustrong 11G
T32	Bustrong SH12N	T68	Calciperse
T33	Epostrong	T69	Calciperse
T34	Epostrong	T60	Calciperse
T35	Calciperse, Bustrong 11G, Bustrong 20D	T71	Calciperse
T36	Calciperse		

In order to be read by rapid miner, the transaction data format is converted into a binary matrix format. Binary matrix format is changing the data format from primary data in the form of sales data to binary 1 and 0 data. Binary matrices are very useful in analyzing data mining where the use of binary matrices uses tropical rank and determinant rank [17].

Table 2: Transaction Data in Binary Matrix Format

No. Transaksi	calciperse 2000	epostrong final	bustrong SH12N	bustrong 11G	bustrong 20D
1	1	0	0	1	0
2	1	0	0	1	0
3	1	0	0	0	0
4	0	0	0	0	1
5	0	0	0	0	1
6	0	1	0	0	0
7	0	0	0	0	1
8	0	0	1	0	0
9	1	0	0	0	0
10	0	1	0	0	0
11	0	1	0	0	0
12	0	1	0	0	0
13	0	0	0	0	1
14	0	0	0	0	1
15	0	1	0	0	0
16	0	1	0	0	0
17	0	0	0	0	1
18	0	0	1	0	0
19	0	1	0	0	0
20	0	1	0	0	0
21	1	0	0	0	0
22	1	0	0	0	0
23	1	0	0	0	0
24	1	0	0	0	0
25	0	1	0	1	0
26	0	1	0	0	0
27	0	0	0	0	1
28	0	0	0	0	1
29	0	1	0	0	0
30	0	1	0	0	0
31	0	0	0	0	1
32	0	0	1	0	0
33	0	1	0	0	0
34	0	1	0	0	0
35	1	0	0	1	1
36	1	0	0	0	0

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Table 2. Transaction Data in Binary Matrix Format (continued)

No. Transaksi	calciperse 2000	epostrong final	bustrong SH12N	bustrong 11G	bustrong 20D
37	1	0	0	0	0
38	0	1	0	1	0
39	0	1	0	1	0
40	0	1	0	0	0
41	0	0	0	0	1
42	0	1	0	0	0
43	0	0	0	0	1
44	0	0	1	0	0
45	1	0	0	0	0
46	1	0	0	0	0
47	1	0	0	0	0
48	0	1	0	1	0
49	0	1	0	1	0
50	0	1	0	0	0
51	1	0	0	0	1
52	0	0	0	0	1
53	0	0	1	0	0
54	1	0	0	0	0
55	1	0	0	0	0
56	0	0	0	1	0
57	0	1	0	1	0
58	0	1	0	0	0
59	0	0	0	0	1
60	0	0	0	0	1
61	0	1	0	0	0
62	0	1	0	0	0
63	0	0	0	0	1
64	0	0	1	0	0
65	0	1	0	0	0
66	0	1	0	0	0
67	1	0	0	1	0
68	1	0	0	0	0
69	1	0	0	0	0
70	1	0	0	0	0
71	1	0	0	0	0

Support and Confidence

Calculation Support value calculation for 1 item set:

$$\text{Support (A)} = \frac{\text{Number of transactions containing item A}}{\text{Total transactions}}$$

$$\text{Support (Calciperse 2000)} = \frac{22}{71} x100\%$$

= 31%

The calculation results for each item can be seen in the following table:

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Table 3: Total Support for Each Item

Item	Quantity	Support
CALCIPERSE 2000	22	31%
EPOSTRONG FINAL/CT/FG	27	38%
BUSTRONG SH12N	6	8%
BUSTRONG 11G	11	15%
BURSTRONG 20 D	17	24%

Calculation of support and confidence for 2 item sets:

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

$$\text{Support (Calciperse 2000, Bustrong 11G)} = \frac{4}{71} x\ 100\%$$

= 5.6%

$$\text{Confidence (A, B)} = \frac{\text{Number of transactions containing item A and B}}{\text{Number of transactions containing item A}}$$

$$\text{Confidence (Calciperse 2000, Bustrong 11G)} = \frac{1}{22} x\ 100\%$$

= 18.2%

The calculation results for each combination of 2 itemset can be seen in the following table:

Table 4: Support and Confidence of Combination of 2 Item sets

Item	Support	Confidence
CALCIPERSE 2000, BUSTRONG 11G	5.6%	18.2%
EPOSTRONG FINAL/CT/FG, BUSTRONG 11G	8.5%	22.2%
BUSTRONG 11G, EPOSTRONG FINAL	8.5%	54.5%
BUSTRONG 11G, CALCIPERSE 2000	5.6%	36.4%

Calculation of support and confidence for 3 item sets:

$$\text{Confidence (A, B, and C)} = \frac{\text{Number of transactions containing item A, B, and C}}{\text{Number of transactions containing item A}}$$

$$\text{Confidence (Calciperse 2000, Bustrong 11G, Bustrong 20D)} = \frac{1}{71} x\ 100\%$$

= 1.4%

$$\text{Confidence (Calciperse 2000, Bustrong 11G, Bustrong 20D)} = \frac{1}{4} x\ 100\%$$

= 25%

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The calculation results for each 3 itemset combination can be seen in the following table:

Table 5: Support and Confidence 3 Itemset Combination

Item	Support	Confidence
CALCIPERSE 2000, BUSTRONG 11G, BUSTRONG 20D	1.4%	25%
CALCIPERSE 2000, BUSTRONG 20D, BUSTRONG 11G	1.4%	50%
BUSTRONG 11G, BUSTRONG 20D, CALCIPERSE	1.4%	100%

Calculation of Lift Ratio Value

$$\text{Confidence (Calciperse 2000, Bustrong 11G)} = \frac{4}{22} x\ 100\%$$

$$= 18.2\%$$

$$\text{Confidence benchmark} = \frac{\text{Number of transactions with items in consequent}}{\text{Number of transactions in the database}}$$

$$\text{Confidence benchmark} = \frac{11}{71}\ x\ 100\%$$

$$= 15.50\%$$

$$\text{Lift Ratio} = \frac{\text{Confidence}}{\text{Confidence benchmark}}$$

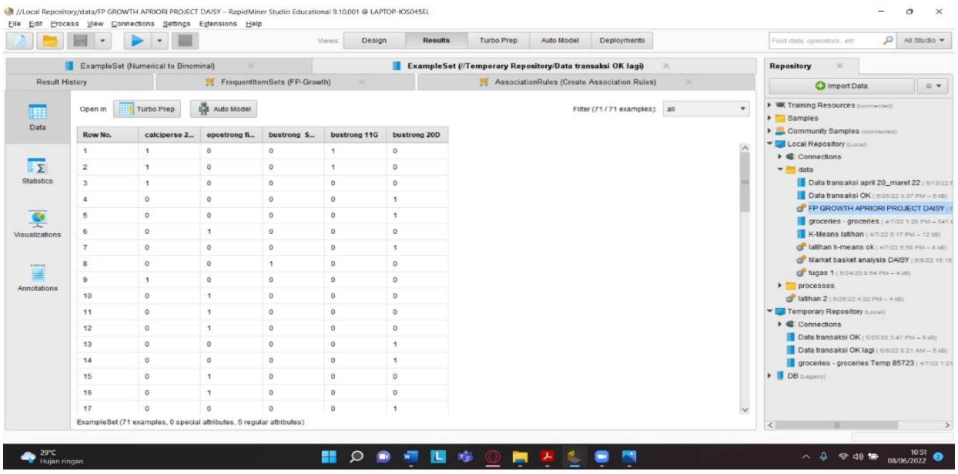
$$\text{Lift Ratio} = \frac{18.6}{15.50}$$

$$= 1.174$$

Implementation using Rapid Miner

Application Phase One: Input transaction data in binary matrix format by calling Excel data.

Figure 2: Transaction Data in Binary Matrix in Rapid Miner



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Phase two: Numerical data is converted into binomials, where data that were originally 1 and 0 become true and false so that the FP-Growth model can read them.

Figure 3. Leadership and Non-Leadership Roles

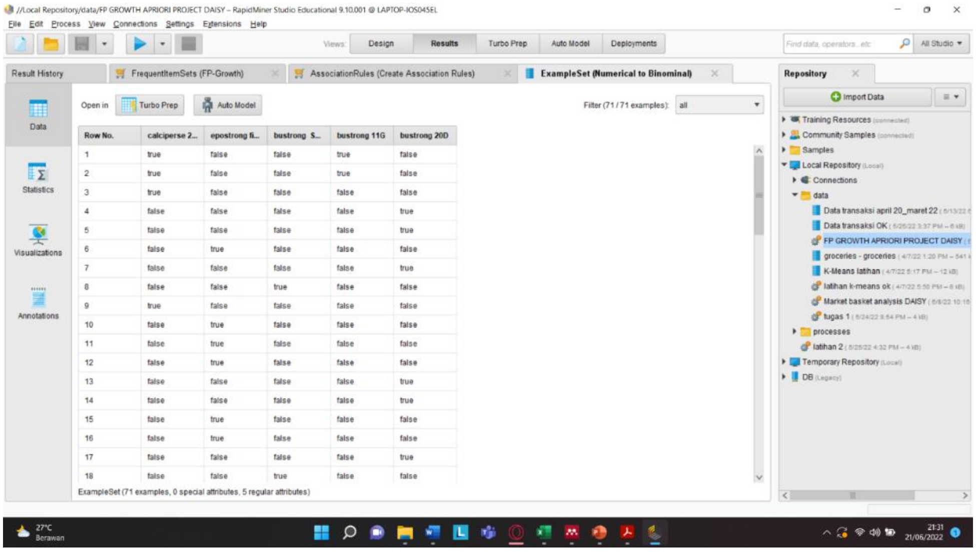
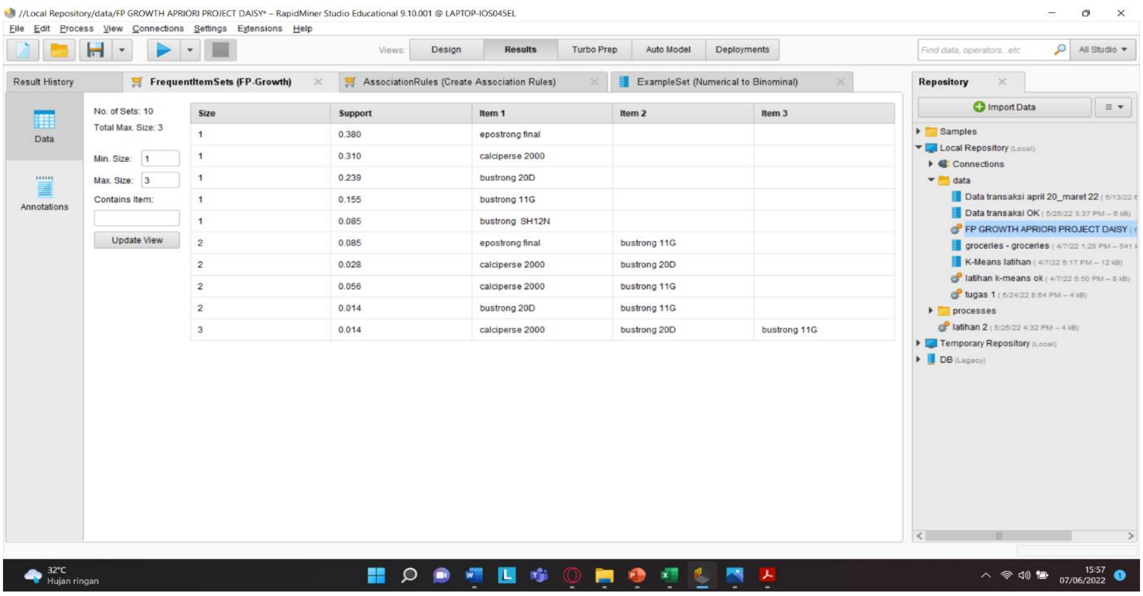


Figure 3. Leadership and Non-Leadership Roles.

Phase 3: The number of frequencies of each item is calculated by changing the support value

Figure 4. Frequent Item set FP-Growth Support 0.05



Phase 4: Create association rules by determining the confidence value.

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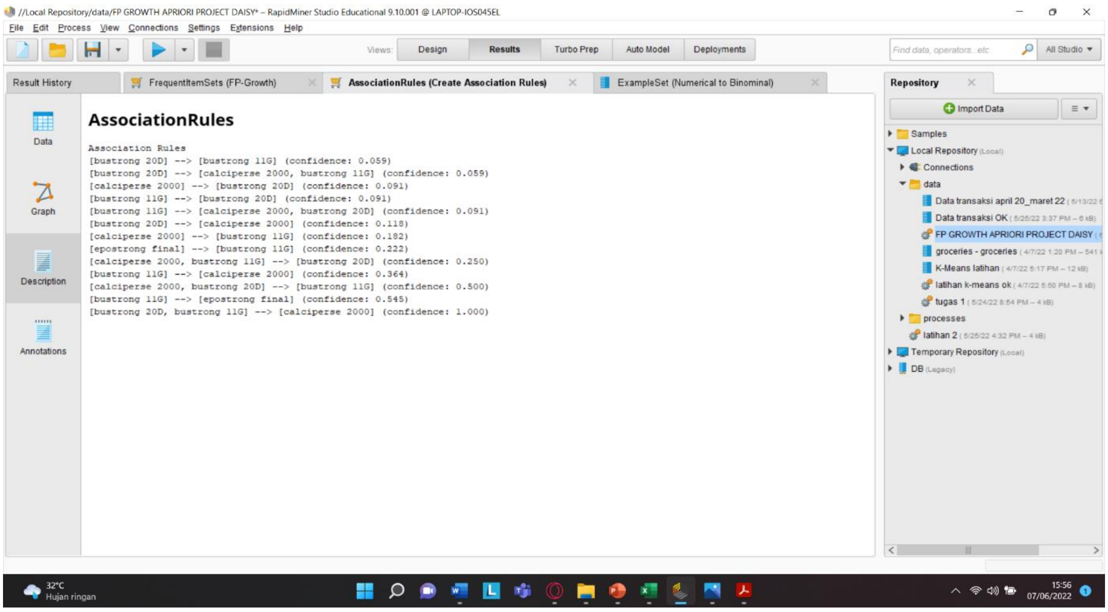
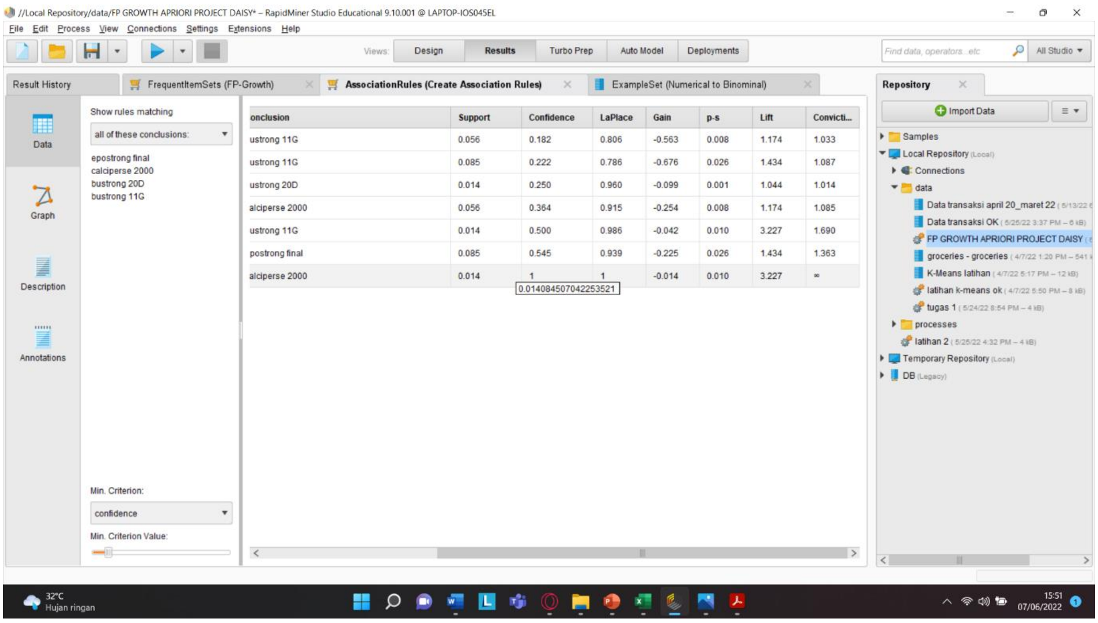
Figure 5: Association Rules with Confidence Value



Phase 5: Calculating the value of lift ratio

Figure 6: Results of Support Value, Confidence Value and Lift Ratio



The market basket analysis process can be seen in the image below:

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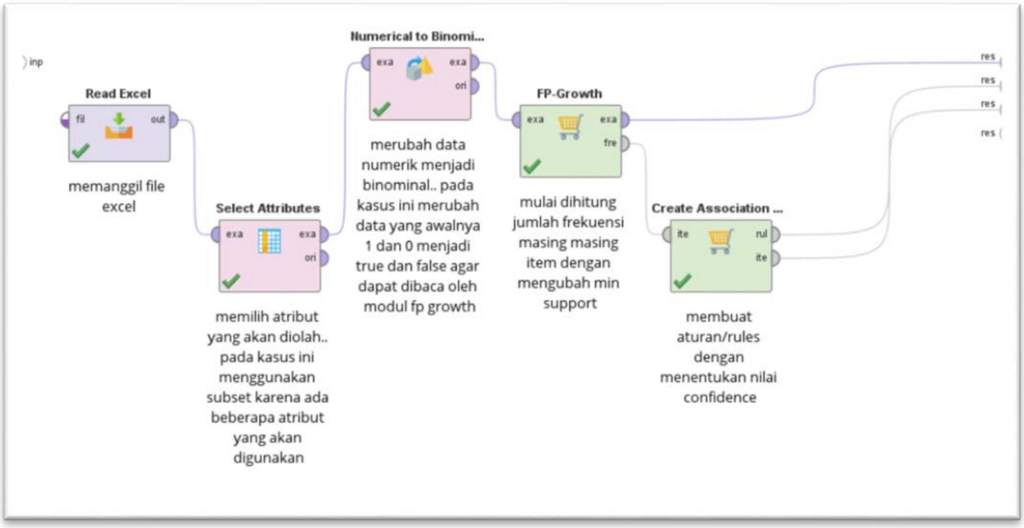
Figure 7: Market Basket Analysis Process



DISCUSSION

The results obtained from the experiments carried out are when the minimum support and minimum confidence values are greater, the resulting association rules will be less and when the minimum support and minimum confidence values are smaller, the resulting association rules will be more and more (Table 6).

Table 6: Comparison of the Number of Association Rules

Minimum Support	Minimum Confidence					
	0.05	0.1	0.2	0.3	0.4	0.5
0.05	13	8	6	4	3	3
0.1	5	5	3	2	1	1
0.2	4	4	3	2	1	1
0.3	2	2	2	1	1	1
0.4	2	2	2	1	1	1

From the table and figure below (Figure 8), it can be seen that the number of association rules significantly decreases when the minimum support is > 0.05 and the minimum confidence is > 0.05.

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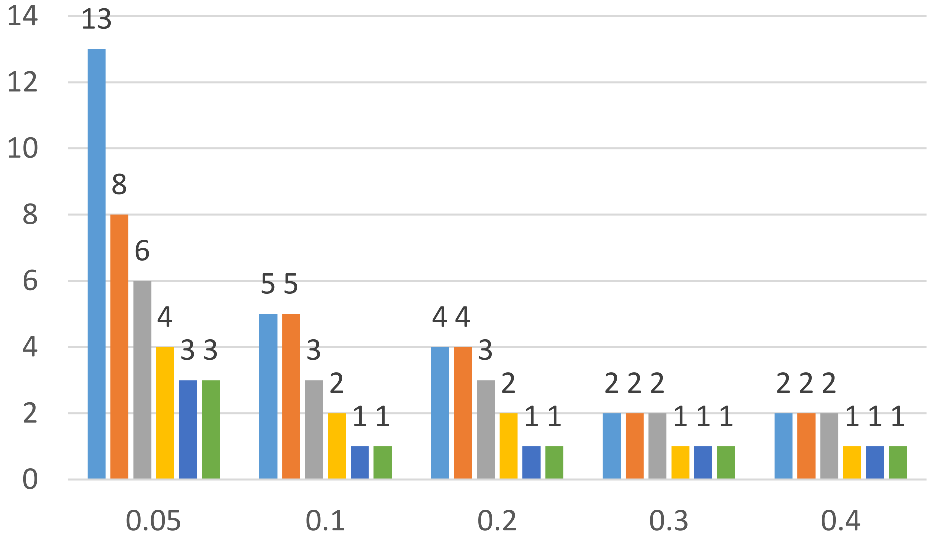
Figure 8: Comparison of Association Rules



RESULTS

Table 7: Tests on lift ratio

Premises	Conclusion	Support	Confidence	Lift
Calciperse 2000	Bustrong 11G	0.056	0.182	1.174
Epostrong final	Bustrong 11G	0.085	0.222	1.434
Calciperse 2000, bustrong 11G	Bustrong 20D	0.014	0.250	1.044
Bustrong 11G	Calciperse 2000	0.056	0.364	1.174
Calciperse 2000, bustrong 20D	Bustrong 11G	0.014	0.500	3.227
Bustrong 11G	Epostrong final	0.085	0.545	1.434
Calciperse 2000, bustrong 11G	Calciperse 2000	0.014	1	3.227

From the 13 association rules obtained, then to check whether all the association rules are valid or not, the lift ratio value is used. In the table above, there are 7 association rules with lift ratio values > 1, support values and confidence values, namely:

a) “if you buy bustrong 20D and bustrong 11G, you will buy calciperse”

b) “if you buy calciperse and bustrong 20D, you will buy bustrong 11G”

c) “if you buy bustrong 11G, you will buy epostrong final”

d) “if you buy epostrong final, then I will buy bustrong 11G”

e) “if you buy bustrong 11G, you will buy calciperse”

f) “if you buy calciperse, you will buy bustrong 11G”

g) “if you buy calciperse and bustrong 11G, you will buy bustrong 20D”

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CONCLUSION

From the results and discussion, it can be concluded several things:

1. The most sold product is Epostrong Final/CT/FG. Experiments with a minimum support value of 0.05 and a minimum confidence value of 0.05 obtained 7 association rules that can be used as a reference to determine which products have the opportunity to increase sales because the resulting association rules are ideal with a lift ratio value > 1 so that they have the potential to be used.
2. Based on the final association rules, it is found that if you buy a bustrong 20D and a bustrong 11G, you will buy calciperse. Thus, based on the association rules obtained, PT. AKL can maximize the utilization of data mining applications so that by promoting product combinations it will increase more sales opportunities.
3. PT. AKL can maximize sales opportunities by promoting product combination.

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