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Product Sales Promotion Recommendation Strategy with Purchase Pattern Analysis FP-Growth Algorithm

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Abstract: The development of retail business technology is related to the need for management to meet customer demands using technological assistance. This study aims to provide an analysis related to purchasing patterns of PT. X in the city of Sumbawa Besar as a retail company that sells and distributes daily consumer goods. The purchase transaction database that is stored as a company archive asset can be used to process information that is useful in increasing customer purchases and product promotions. The algorithm used is Frequent Pattern – Growth which is one of the algorithms in data mining that is used to find relationships in large data based on the number of occurrences of these data relations. The Association Rule Mining method is used in the retail business sector which is also known as Market Basket Analysis. The test application used is Rapidminer 9.10. The stages of the research include: data collection, data preparation, implementation of the FP-Growth algorithm, analysis of results and conclusions. The data used is sales transaction data within 3 months of 7,772 transactions with a total product purchase of 137,334 products consisting of 1,211 types of product variations. The results of the tests carried out produced 819 rules with filtering to 85 strong rules. The results of grouping strong association rules based on the combination and number of products information that is expected to be used as product promotion recommendations.

Keywords: Frequent Pattern-Growth, Market Basket Analysis, Customer Purchase Pattern, Association Rules, Data Mining

INTRODUCTION

The development of retail business technology is related to the need for management to meet customer demands by using technology assistance. Joseph Pistrui and Dimo Dimov in Harvard Business Review (Joseph Pistrui & Dimo Dimov, 2018) explain the change in the role of managers from directive to instructive which is in line with technological developments that require managers to do work creatively by implementing technological assistance in information search and processing to support management activities. Therefore, the company's management strategy to survive in business competition and retain customers is the ability to develop various management strategies, increase sales and implement appropriate marketing (Mustakim et al., 2018). To help make effective sales strategic decisions, it is necessary to optimize the use of information technology on existing sales transaction data (Takdirillah, 2020). The transaction database that has been stored as a company archive asset can be used for processing information that is useful in increasing product sales and promotions (Anggraeni et al., 2019).

This study aims to provide an analysis related to the sales pattern of PT. X in Sumbawa Besar City, West Nusa Tenggara. PT. X is a retail company that sells/ distributes daily consumer goods including soaps, detergents, margarine, dairy based foods, ice cream, cosmetic products, tea based beverages and fruit juices in stores in the area. The results of the analysis carried out from the research are expected to provide an overview of the knowledge of product purchasing patterns which are expected to become recommendations for determining marketing strategies at the management level in the company. Research (Elisa, 2018) explains that similar research allows managers to develop interventions aimed at influencing buying behavior, including stimulating overall demand, promoting a particular product category, or offering promotional offers for the sale of products that tend to increase sales. In addition, research (Alfiqra & Alfizi, 2018) also explains that research results play

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an important role in predicting consumer behavior so that shopping cart data analysis can be carried out, grouping sales product data, product catalog design in sales promotions and analysis of sales product layout in a store.

LITERATURE REVIEW

Data Mining is a process that uses statistical techniques, mathematics, artificial intelligence, and machine learning to extract and identify useful information and related knowledge from various large databases (Zulham et al., 2021). The purpose of data mining is to find relationships or patterns that can provide benefits to related parties (Fahruddin, 2019). The results of data mining analysis in the form of relationships or patterns on sales can be used as decisions in product stock inventory strategies, apply discounts and help identify products that are purchased together (Supriyono et al., 2021). A well-maintained sales database can be used with a wide variety of mapping, grouping and association searches that can be used in preparing better marketing strategies.

Association rule is a method of analysis of the behavior of customers, specifically a particular group (Fitrianah & Zain, 2021). The Association Rule Mining method is a pattern of data linkages in the database and in the retail business field known as Market Basket Analysis (Bunda, 2020). Muzakir and Adha in research (Abdullah, 2018) explained that market basket analysis is one of the methods in data mining that determines the products that customers buy simultaneously based on the consumer transaction data. Sudirman et. al. also explained that Market Basket Analysis is a modeling method based on the idea that when a consumer buys a certain set of goods, the buyer has a higher or lower probability of buying another set of products (Sudrajat & Ermatita, 2021). The purpose of analyzing the buyer's basket on product sales transactions in a market is to be able to find out which products are purchased simultaneously (Supriyono et al., 2021)(Nurmayanti et al., 2021)(Suharjo & Wibowo, 2020). The results of the analysis can provide an overview of consumer behavior by relating to the influence of certain variables. According to Margareth Rouse in research (Lawrence et al., n.d.) that shopping cart analysis is one of the data mining techniques, namely association rules used by retailers or sellers to increase product sales by analyzing product purchase patterns by customers.

The algorithm used is Frequent Pattern (FP) – Growth discovered by Jiawei Han, Jian Pei and Yiwen Yin published in research (Han et al., 2000). The FP-Growth algorithm is one of the algorithms used to find association relationships in large data based on the number of frequency occurrences of these data relationships. Research (Astuti & Leonard, 2012) explains that the FP-Growth algorithm reduces the size of the dataset by representing the frequency of occurrence of the item set called Frequent Pattern Growth. The performance study of FP-Growth algorithm by Jiawei Han, Jian Pei and Yiwen Yin in research (Han et al., 2000) shows that FP-Growth method is efficient and scalable for mining both long and short frequent patterns, and is about an order of magnitude faster than the Apriori algorithm and also faster than some recently reported new frequent pattern mining methods. The novelty in this research is the amount of sales data used in this study has not been widely used in other studies. The total sales transaction data in 3 months was 7,772 transactions with a total of 137,334 product purchases consisting of 1,211 types of product variations. It is hoped that the results of the study can explain variations in the association model so that it can be a reference and the first step for further research related to the application of data mining in marketing activities.

The frequent item set will later be used as a reference for formulating the association rules generated by the market basket analysis model (Natasuwarna, 2019). The application used for testing is Rapidminer 9.10. The Rapidminer 9.10 application was developed by Raft Klinkenberg, Ingo Mierswa, and Simon Fischer in 2001 (Natasuwarna, 2019). The Rapidminer 9.10 application has been widely known in implementing data mining so that it is considered capable of completing data testing to get the desired results.

METHOD

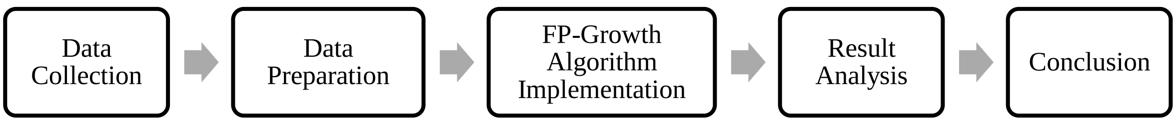

Fig. 1 Research Method

The implementation of the research is divided into several steps as shown in Figure 1. Each step described as follow:

Data Collection

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The first step is to collect research data. The sales database used is the company's sales database from January to March 2019. The total sales transaction data in 3 months was 7,772 transactions with a total of 137,334 product purchases consisting of 1,211 types of product variations. Product Purchase Data in January - March 2019 can be seen in table 1.

Table 1. Product Purchase Data in January – March 2019

No.	Month	Number of Transactions	Number of Product Purchases
1	January	2,608	49,795
2	February	2,479	41,782
3	March	2,685	45,757
	Total :	7,772	137,334

Data Preparation

The second stage is preparing the feasibility of the data for testing using the FP-Growth algorithm. Data preparation is done on transaction data, product data and transaction data initialization to binomial data type. The initialization of transaction data and the initialization of product data can be seen in table 2 and the initialization of transaction data into binomial transaction data according to the needs of data testing can be seen in table 3.

Table 2. Initialization of Transaction Data and Product Data

	No.	Code Name	Initialization
Initialization of Transaction Data	1	20xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx001	T0001
	2	20xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx002	T0002
	3	20xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx003	T0003
	. . .	. . . . . .	. . . . .
	7,770	20xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx605	T7770
	7,771	20xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx603	T7771
	7,772	20xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx600	T7772
Initialization of Product Data	1	Axe Acne Protexxxxxxxxxxxxxxxxxxxxxxxxxxx	P0001
	2	Axe Bw Black xxxxxxxxxxxxxxxxxxxxxxxxxxx	P0002
	3	Axe Bw Dark xxxxxxxxxxxxxxxxxxxxxxxxxxxx	P0003
	. . .	. . . . . .	. . . . .
	1,209	Zwitsal Kids xxxxxxxxxxxxxxxxxxxxxxxxxxxxx	P1209
	1,210	Zwitsal Natuxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	P1210
	1,211	Zwitsal Oil Nxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	P1211

The initialization of transaction data in table 3 that will be used in the test is the initialization of transaction data for the purchased product. Initialization of product data on transactions will be marked with a binomial data type. For example, in initializing transaction 1 with transaction initials T0001, then certain products purchased will be initialized with a value of 1 and if that particular product is not purchased it will be initialized with a value of 0. Initialization of product purchases with binomial data type adjusts the request for the type of data used in testing with Rapidminer 9.10. The data that has been initialized is checked again to ensure that the data is appropriate where there are no binomial data errors so that it is ready for use at the next stage.

Table 3. Initialization of Product Transactions to Binomial Data Type

Transaction	P0001	P0002	. . .	P1210	P1211
T0001	0	0	. . .	0	0
T0002	0	1	. . .	0	0
T0003	1	0	. . .	0	1
. . . . . .	. . .	. . .	. . .	. . .	. . .
. . . . . .	. . .	. . .	. . .	. . .	. . .
T7770	0	0	. . .	0	0
T7771	0	0	. . .	1	0
T7772	0	0	. . .	0	0

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FP-Growth Algorithm Implementation

FP-Growth algorithm is one of association rule technique that can be used to determine the set of data that most often appears (frequent product set) in a data set. The development of this Apriori algorithm lies in the scanning database and the accuracy of the rules (Suharjo & Wibowo, 2020). The frequent item set will later be used as a reference for formulating the association rules generated by the market basket analysis model (Noorkholid et al., 2020). The FP Growth algorithm was chosen because it is better than the Apriori algorithm. The FP-Growth algorithm was developed from the Apriori algorithm by improving the algorithm's shortcomings (Kahar, 2021). Support is the probability that customers buy several products simultaneously from a number of transactions. It is possible for A and B to appear in the equation denoted in (1). Confidence is the probability of the occurrence of several products being purchased simultaneously where one product is definitely purchased. Confidence is the probability that B will appear when A also appears, described in (2). In addition to looking at the value of support and confidence, the lift ratio is a validation that aims to determine whether or not the association rules that have been formed are strong. The lift ratio equation is used with the formula notated in (3).

$$\text{Support}\ (A \rightarrow B) = \frac{\text{Number of Transaction contain A and B}}{\text{Number of Transaction}} \quad (1)$$

$$\text{Confidence}(A \rightarrow B) = \frac{\text{Number of Transaction contain A and B}}{\text{Number of Transaction contain A}} \quad (2)$$

$$\text{Lift Ratio}(A \rightarrow B) = \frac{\text{Confidence}\ (A \rightarrow B)}{\text{Support}\ (A \rightarrow B)} \quad (3)$$

The results of the assessment of the strength of the association are based on the positive lift ratio value formed by dividing the association's confidence value with the association's support value. The lift ratio value which is considered strong is above the value of 1 (> 1), obtained from the results of greater confidence than the event support value of all product sales transactions that occurred. FP-Growth testing is done using the Rapidminer 9.10 application. Rapidminer 9.10 application is known in data mining as an application that can assist in analyzing data mining methods. In this study, the data mining model carried out on Rapidminer 9.10 is shown in Figure 2.

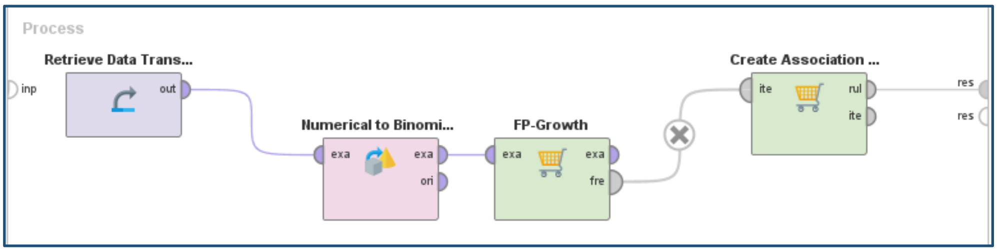

Figure 2. FP-Growth Association Analysis Model with Rapidminer 9.10 application

Result Analysis

The test results will provide rules that are formed from the pattern of product sales made by customers. In this section the rules will be selected according to the level of lift ratio that is considered strong, so that the results of the analysis carried out represent the results of association patterns that can be used for research purposes.

Conclusion

This last stage is related to drawing conclusions from the results of test analysis on product sales pattern recognition using the FP-Growth algorithm. Conclusions are drawn from strong rules formed from pattern recognition in accordance with the minimum support and minimum confidence requirements as well as the specified minimum lift ratio.

RESULT

Association testing is carried out using the FP-Growth algorithm. The provision for the minimum support value level is 10% or 0.10 and the minimum confidence level is 80% or 0.80. Determination of the minimum support value of 0.1 (10%) is carried out by analyzing the results of experiments with Rapidminer 9.10 that the support value is closest to the original data. While the minimum confidence value of 0.8 (80%) was determined by analyzing the experimental results with Rapidminer 9.10 on the most diverse product combination variations. The maximum number of product combinations specified in the association is 5 products. The test results

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produced 819 rules with variations in the number of premise product combinations and product conclusions shown in table 4.

Table 4 shows the number of premise products which are the premise products of the associations formed to the conclusion products. Further explanation from table 4, the number of premise products is 1 product associated with 1 product conclusion totaling 72 rules. Thus, the total association formed by the 2 products as premises and conclusions is 72 rules. The number of rule 1 premise products associated with 2 conclusion products is 65 rules and 2 premise products associated with 1 conclusion product are 192 rules. The total number of associations formed by the 3 products as premise and conclusion is 257 rules. Furthermore, the number of associations for 1 premise product with 3 conclusion products is 20 rules, the number of associations for 2 premise products with 2 conclusion products is 120 rules and the number of associations for 3 premise products with 1 conclusion product is 190 rules. Thus, the total number of associations formed by the 4 products as the premise and conclusion is 330 rules. The number of product associations with 2 premise products and 3 conclusion products is 19 rules, the number of product associations with 3 premise products and 2 conclusion products is 66 products, while the number of associations with 4 premise products and 1 conclusion product is 75 products. The total number of associations formed by the 4 products as premise and conclusion is 160 rules.

Table 4. Number of FP-Growth Experiment Results Rules

Number of Premise Product	Number of Conclusion Product	Total Product Association	Amount	Number of Associates on the same Total Product
1	1	2	72	72
1	2	3	65	257
2	1	3	192	
1	3	4	20	
2	2	4	120	330
3	1	4	190	
2	3	5	19	
3	2	5	66	160
4	1	5	75	
		Total :	819	819

After getting the results of 819 rules in table 4, the rules are filtered again with the condition that the lift ratio value is above 1 (> 1). This determination is to provide results in the form of strong associations between premise products and conclusion products so that the results obtained can be more reliable and accurate. The equation used is equation (3) in the previous section. The screening results give the strongest 85 rule results with the number of combinations of association product premise and product conclusion which can be seen in table 5.

Table 5. Number of Strong Rules Result from FP-Growth Experiment Results

Number of Premise Product	Number of Conclusion Product	Total Product Association	Amount	Number of Associates on the same Total Product
1	1	2	1	1
1	2	3	3	18
2	1	3	15	
1	3	4	2	
2	2	4	16	39
3	1	4	21	
2	3	5	4	
3	2	5	12	27
4	1	5	11	
		Total :	85	85

The results of the strong rule screening are in table 5 with the condition that the lift ratio is > 1. It can be seen in table 5, that the number of associations for 1 premise product with 1 conclusion product is 1 rule. The total number of strong associations with a total of 2 products associated with 1 rule. Then, the number of associations in 1 premise product with 2 conclusion products is 3 rules and the number of associations in 2 premise products with 1 conclusion product is 15 rules. The number of strong associations formed from 3 products is 18 rules.

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Furthermore, the association of 1 premise product with 3 conclusion products is 2 rules, the number of associations of 2 product premises with 2 conclusion products is 16 rules, and the number of associations in 3 product premises and 1 conclusion product is 21 rules. So, the total number of rules formed from 4 products is 39 rules. The rules formed from 5 products totaled 27 rules with the distribution of rules with 2 premise products and 3 conclusion products totaling 4 rules, rule with 3 premise products and 2 conclusion products totaling 12 rules, and rules formed from 4 premise products and 1 product conclusion is as many as 11 rules.

DISCUSSIONS

The test results using the FP-Growth method with a strong association lift ratio resulted in 85 rules with the level of Support and Confidence for each rule, which can be seen in Figure 4 and Figure 5. In figure 4 it can be seen that the range of support values is from 0.10 to 0.77 and the average support value is 0.36; The majority of support values are at 0.11 with 14 rules, 0.58 with 12 rules and 0.10 and 0.15 with 10 rules each; Furthermore, the confidence value in Figure 5 is in the range of values from 0.82 to 1.00 with an average of 0.97; the majority of the confidence values are at 0.97 with a total of 35 rules, a confidence value of 0.99 with a total of 19 rules and a confidence value of 0.96 with a total of 15 rules. Each rule whose support and confidence values are explained in Figure 3 and Figure 4 can be described as in Table 6.

Table 6. Description of the Strong Rules formed from the association of product sales

No.	Rules
1	If customers buy products P0173 and P0510; the tendency of customer to buy products P0922 and P1121 also occurs with the support value of events from all transactions of 10% and the level of confidence value of the same pattern of transaction events of 96%
2	If customers buy products P0173, P0834 and P0431; the tendency of customer to buy products P0838 also occurs with the support value of events from all transactions of 16% and the level of confidence value of the same pattern of transaction events of 99%
3	If customers buy products P0922, P1121 and P0834; the tendency of customer to buy products P0838 also occurs with the support value of events from all transactions of 70% and the level of confidence value of the same pattern of transaction events of 99%
…	. . . . .
83	If consumers buy products P0922, P0173 and P0834, the tendency of consumers to buy products P0838 and P1121 also occurs with the support value of events from all transactions of 58% and the level of confidence value of the same pattern of transaction events of 97%
84	If customers buy products P0922, P1121 and P0510; the tendency of customer to buy products P0173 also occurs with the support value of events from all transactions of 10% and the level of confidence value of the same pattern of transaction events of 82%
85	If customers buy products P1121 and P0510; the tendency of customer to buy products P0173 also occurs with the support value of events from all transactions of 10% and the level of confidence value of the same pattern of transaction events of 82%

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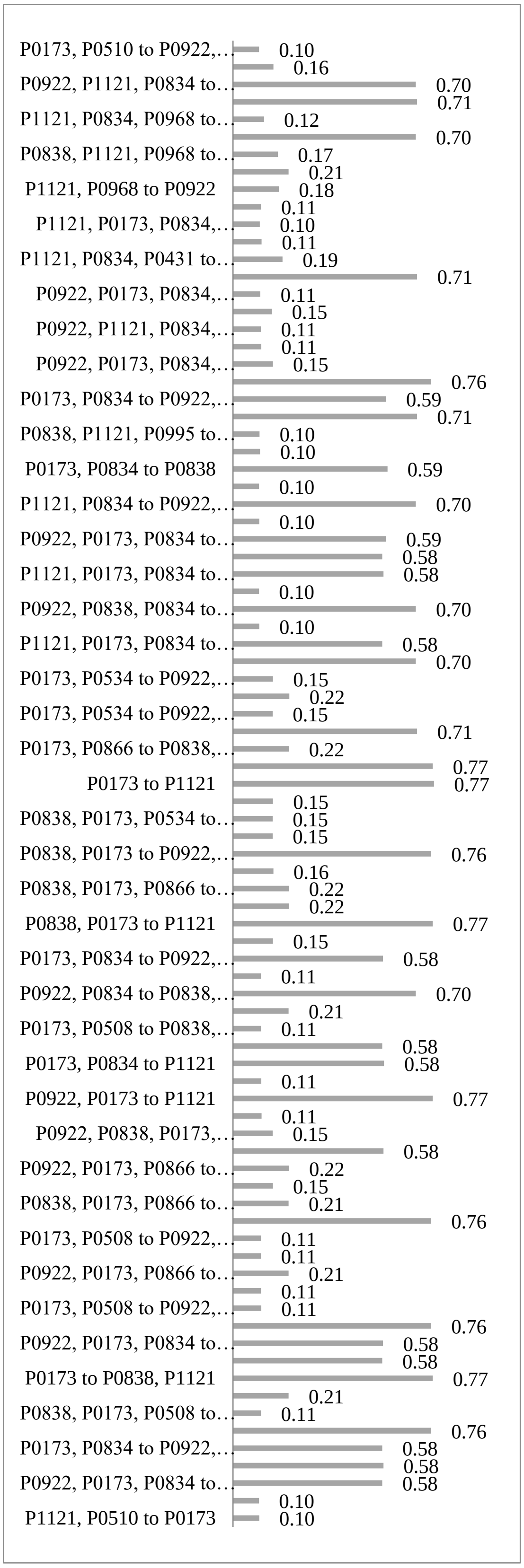

Fig. 3 Support Value per Rule

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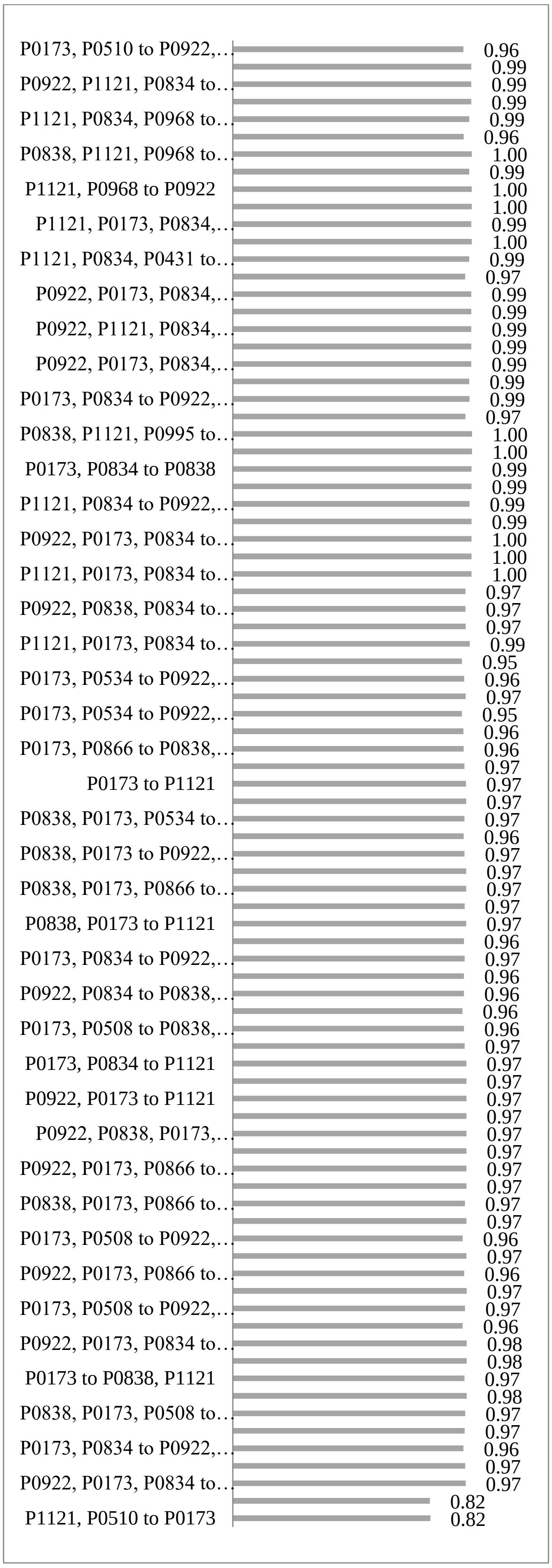

Fig. 4 Confidence Value per Rule

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CONCLUSION

The database testing stage using the FP-Growth algorithm forms 819 rules which are then selected into 85 strong rules that can be used in drawing conclusions. Strong rule based on product combinations and quantities are result of product purchase association information. The information is expected to be used as a recommendation in promoting products with several strategies, including discount, cross-selling, up-selling, product bundling and other types of promotional strategies to increase product sales.

This research is an association analysis which is part of product data analysis. The goal of a broader and more influential product promotion strategy in the field of data mining is highly expected. The hope of the researcher regarding the research is that the analysis is carried out not only on buying patterns but also on sales at certain times and moments. In addition, further analysis related to the influence of consumer demographic factors is expected to explain phenomena related to sales on the tendency to buy certain products.

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