

## ASSOCIATION RULES FOR LAYOUT DESIGN AND PROMOTION STRATEGY

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### Abstract

Promotion strategies play an important role facing competition. In order to determine the strategy, transaction data pattern analysis can be done. The association rule method can find the pattern. In this study, the association rule method is used for analysis customer transaction data. The result of association rule shows customer's buying pattern. However, the patterns are vulnerable to change every period. Then, further processing is carried out using Overall Variability of Association Rules (OCVR) so that the results are consistent throughout the period without being prone to changing rules because of the high level of variability. The results of OCVR are used for determining promotion strategies and store product layout suggestions. Some recommendations based on association rules analysis are moving some sections close to associated sections and use of rarely purchased product for price discount offer. Related to triggering impulse buying, mini snack section is exchanged with biscuit section, in order to create impulse buying for other products in front of it, namely Cold drinks, Ice cream, and Frozen Food.

**Keywords:** *Association rule, OCVR, Promotion Strategy, Product Layout*

### 1. Introduction

Running a mini market or a store in urban areas has its challenges. One of the challenges is competition with surrounding stores. Consequently, a store needs a competitive promotion strategy and a convenient store layout. The store strategy and layout have to meet customer behavior. Data mining is an alternative approach to understand customer behavior. Customer behavior can be approached by delving their transaction data. In this paper, a data mining model named as association rule is employed to find customer behavior. Based on mining results, promotion strategy and store layout can be generated.

Data mining is defined as observational data set analysis. Its aim at finding unknown relationships and resume the data in a novel structure that can be understood and useful for the data owner (Hand, Mannila, and Smyth 2001). One of the data mining models is affinity analysis. This model is the investigation of attributes or properties that "go together" (Larose 2005). Affinity analysis is known also as market basket analysis. This model quantifies relationship between attributes. The relationships are in the form of association rule. The association rules form is "If antecedent, then consequent".

In a mini market, customer behavior change over time. Papavasileiou and Tsadiras (2011) proposed an analysis known as OCVR (Overall Variability of Association Rules). This method aims at obtaining rules that are not susceptible to period changes because customers have high shopping habit variability. The results of this analysis can provide suggestions in the form of product promotion efficiency and product layout rearrangement.

#### 1.1 Objectives

Retail X is a mini market that has not implemented promotions. Product layout is also not arranged properly. So, it is necessary to implement knowledge-based on consumer shopping cart transaction data. The association rule method is used to find customer behaviors. Each month may have various customer spending pattern, so we conduct further analysis using OCVR to obtain efficiency association rules which are implemented throughout the period. The purpose of this research is making product promotion strategies and product location re-layout based on the OCVR results.

## 2. Literature Review

### 2.1. Association rule or market basket analysis

Association Rule is a data mining technique introduced by Agrawal et al., (1993). This method is the process of finding relationships (associations) between data in a database. Association rules are written in "If and then" statements. This is illustrated in the following equation:

$$X \rightarrow Y \quad (1)$$

The meaning is "if X then Y", this is called a rule expression. The expression "X" is called the antecedent, and the expression "Y" is called the consequent (Bermúdez, Rodríguez, and Abad 2016). Association rules have been applied to various sectors such as marketing, banking, medical data, crime data, and satellite data (Bramer 2016).

Association rule is also known as Market Basket Analysis (MBA) or affinity analysis. MBA is a process of finding associations between each product in a collection of consumer purchase transaction data (Han, Kamber, and Pei 2012). Same as previous equation, MBA in the association rules can be termed "if you buy product X, you will also buy product Y". The following are specific criteria for carrying out the Market Basket Analysis process as a measure of the value of the rules:

1. **Support** : This measure of goodness aims to measure the level of dominance of the appearance of the item set in the transaction data set (Gunadi & Sensuse, 2012). The support value is formulated as follows.

$$Support(X) = \frac{Count(X)}{Count(T)} \quad (2)$$

$$Support(Y) = \frac{Count(Y)}{Count(T)} \quad (3)$$

$$Support(X \Rightarrow Y) = \frac{Count(X \cap Y)}{Count(T)} \quad (4)$$

2. **Confidence** : This measure of goodness aims to measure the relationship between items or a measure of the trust level of a rule. The confidence value is formulated as follows.

$$Confidence(X \Rightarrow Y) = \frac{Support(X \cap Y)}{Support(X)} \quad (5)$$

3. **Lift Ratio** : This measure of goodness aims to measure the strength of the formed association rules, namely by measuring the amount of opportunity for item/itemset Y to appear if given item/itemset X. The lift ratio is formulated as follows.

$$Lift(X \Rightarrow Y) = \frac{Confidence(X \Rightarrow Y)}{Support(Y)} \quad (6)$$

Andari et al. (2009) used an MBA for minimarket layout using the ARC method. Kaur & Kang (2016) discuss data mining techniques, namely association rule mining, and provide new algorithms that can help to check customer behaviour and help increase sales. Halim et al. (2019) redesigned the arcade game place using the MBA method, retail layout theory. Walenna and Pramudyo (2019) redesigned the layout of student cooperatives based on customer shopping patterns, assuming the stock is available and without moving shelves.

The Apriori Algorithm is one of the algorithms used to apply the Market Basket Analysis methodology. The main characteristic of the Apriori Algorithm is that all subsets of frequent item sets are also members of frequent item sets (Virgiawan and Mukhlash (2013). Halim et al. (2017) built a sales application system for processing and presenting sales data based on the MBA and developed with the Apriori Algorithm. This application provides a view of the level of sales of certain products based on sales trends with other products so that they can provide promotional decisions. Kurniawan et al. (2018) designed an application to process and re-record existing transaction data with MBA references and developed it with the Apriori Algorithm as an analysis of consumer shopping behavior.

### 2.2. Overall Variability of Association Rule (OCVR)

OCVR is one of post-mining methods for association rules. OCVR is proposed by Papavasileiou & Tsadiras (2011). The goal is to find the best rules with consistency between periods of high variability. This indicator is applied to shopping cart analysis assuming high variability. Changes in the value of confidence, lift for each rule that is formed every period indicate that not all of these rules are consistent with the high variability assumption. OCVR analysis introduces a data processing

equation to determine the variability index value of changing confidence and lift parameters. The following is the equation for calculating the variability index as follows.

$$CV = \frac{S}{\bar{X}} \quad (7)$$

Where :

$CV$  : Variability Index  
 $S$  : Standard Deviation  
 $\bar{X}$  : Average

The variability index above is carried out in confidence and lift values for each rule so that there are two equations, namely the Index Variability Confidence (CVC) equation, and the Index Variability Lift (CVL) equation. Then the two equations are used to build the OCVR equation as follows.

$$OCVR = \frac{CVC + CVL}{2} \quad (8)$$

The OCVR results illustrate the overall degree of variation of the association rules and play a role in streamlining consumer behavior patterns. So, it is expected that the resulting marketing/promotion strategy based on the OCVR analysis can increase customer interest. Nugrahanto et al. (2017) conducted a two-year analysis of real transaction data for retail companies. The application of MBA and OCVR with three variables succeeded in selecting a rule with a high and consistent value for the measure of goodness for two years. Alfira & Khasanah (2020) implement OCVR as an analysis of consumer spending patterns with high spending variability so that a more accurate rule is formed to be used as the right marketing strategy.

### 3. Methods

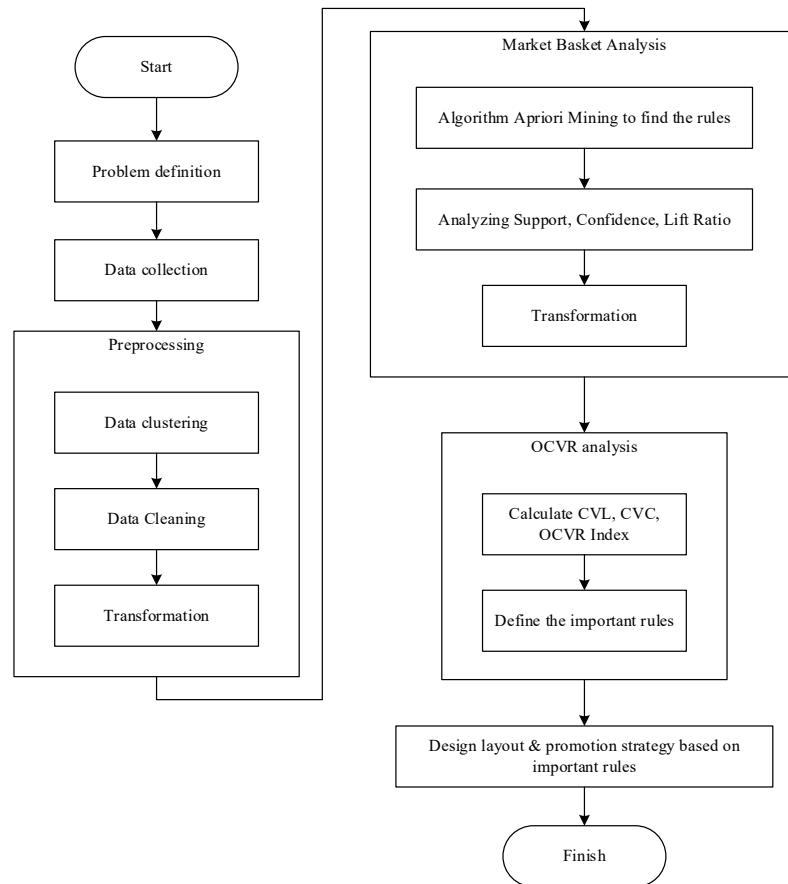
The research object was carried out at Retail X. This study used sales transaction data from January 1 to July 31, 2020. The number of transactions for 7 months was 13017 transactions. The research conducted is to find the association rules (rule) in one month of transaction data and each period is every week. So that there are 4 periods (weeks) of processed data using the Apriori Algorithm assisted by R software. Number of transactions are shown in Table 1.

**Table 1.** Number of transactions and items each month

Month	Week	# Transaction	# Item
1	1 - 4	1834	1952
2	5 - 8	1628	1746
3	9 - 12	1982	2187
4	13 - 16	1828	1950
5	17 - 20	1963	2082
6	21 - 24	1901	2023
7	25 - 28	1881	1999

The above table shows the number of transactions for each period (month) from January to July 2020. From the transaction data, mining is processed to produce association rules with a minimum value of certain support and confidence parameters using the Apriori Algorithm. The resulting rules are then processed with OCVR analysis to find the best and consistent rules with high variability. The results of the OCVR analysis are used to determine promotion strategies and effective product layout arrangement.

This research starts with problem definition to determine research objectives. It is followed by data collection and preprocessing. Data Preprocessing consists of data clustering, cleaning and transformation. Then, market basket analysis or association rule method is used to find the data pattern. The data patterns define the rules based on support, confidence and lift ratio. The pattern is then streamlined using OCVR analysis. The analysis output is then used for designing the product layout and promotion strategy. The research flow chart is shown in the figure 1.



**Figure 1.** Research flow chart

## 4. Data Collection

### 4.1. Transaction Data

The transaction data used is the data from January to July wherein those months' data has been recapitulated in the cashier database using excel documents. The data obtained are transaction time, number of transactions per day, type of product, product price, number of products in a transaction, and total amount paid. The transaction data used are shown in the table 2.

**Table 2.** Transaction data for January-July 2020

InvoiceNo	Description	Quantity	InvoiceDate	UnitPrice
1	Biscuits	1	1/1/2020	8300
1	Mineral water	1	1/1/2020	4700
1	Soft drink	1	1/1/2020	2500
.....	.....	.....	.....	.....
.....	.....	.....	.....	.....
13017	Ice cream	1	7/31/2020	4000
13017	Soft drink	2	7/31/2020	5000

## 5. Results and Discussion

### 5.1 Preprocessing Data

Before processing the data using R software, data preprocessing is required. The data are classified based on each product type. Then, the unnecessary data are removed. Next, the selected data is transformed in order to match with the R software requirement. The transformed data are shown in the table 3.

**Table 3.** Transformed data transaction result for January

Transaction	Items		
1	Mineral water	Biscuits	Soft drink
2	Gas		
3	Biscuits	Biscuits	Honey
.....	.....	.....	.....
.....	.....	.....	.....
1833	Body cleaning tools	Cold drink	Soft drink
1834	Gallon		

### 5.2 Association Rules Parameter

In this research, some parameters are determined by experiments in order to form rules. There is minimum support, and minimum confidence, there are shown in the table 4.

**Table 4.** Minimum determination of association rule parameters

Alternative	Min. Support	Min. Confidence	Summary of Rules
1	0.1	0.1	Formed but undefined rules
2	0.01	0.2	Formed and lift value > 1

Based on the above table, the second alternative is used because using the alternative can define rules and have a value of lift more than 1. This means that the results of the rules have benefited so that they can be used.

### 5.3 Market Basket Analysis

In this paper, Market Basket Analysis or Association Rules method is used to find associations between data in a database. The rules generated every month using Apriori Algorithm function are shown in the table 5 to 12.

**Table 5.** Results of the association rules mining for January

No	Left hand side (Lhs)	Right hand side (Rhs)	Support	Confidence	Lift	Count
[1]	{Instant noodles, Dishwashing}	{Detergent}	0.010	0.679	9.24	19
[2]	{Detergent, Instant noodles}	{Dishwashing}	0.010	0.528	10.67	19
[3]	{Brewed tea}	{Sugar}	0.016	0.484	5.11	30
....	....	....	....	....	....	...
[80]	{Cooking oil}	{Soy sauce}	0.010	0.202	7.013	19
[81]	{Snacks}	{Mineral water}	0.024	0.201	1.215	45

There are 81 rules formed using the Apriori Algorithm function for January transaction data. For example, the first rule generated is **IF** buy Instant Noodles, Dishwashing **THEN** buy Detergents. Its support value is 0.010 with a confidence value of 0.679, and a lift ratio of 9.24. The number of transactions which is containing these rules in January is 19 transactions.

**Table 6.** Results of the association rules mining for February

No	Left hand side (Lhs)	Right hand side (Rhs)	Support	Confidence	Lift	Count
[1]	{Liquid Milk, Wafers}	{Snacks}	0.012	0.704	4.848	19
[2]	{Mini Snack, Liquid Milk}	{Snacks}	0.014	0.697	4.802	23
[3]	{Liquid Milk, Wafers}	{Mini Snack}	0.011	0.667	5.019	18
....	....	....	....	....	....	...
[120]	{Detergent}	{Snacks}	0.020	0.211	1.450	32
[121]	{Detergent}	{Sugar}	0.019	0.204	1.793	31

**Table 7.** Results of the association rules mining for March

No	Left hand side (Lhs)	Right hand side (Rhs)	Support	Confidence	Lift	Count
[1]	{Detergent, Bar soap}	{Instant noodles}	0.010	0.700	5.719	21
[2]	{Detergent, Sugar}	{Instant noodles}	0.011	0.647	5.286	22
[3]	{Instant noodles, Bar soap}	{Detergent}	0.010	0.600	6.928	21
....	....	....	....	....	....	...
[119]	{Instant noodles}	{Sugar}	0.025	0.202	2.252	51
[120]	{Soft drink}	{Mini Snack}	0.012	0.200	1.548	24

**Table 8.** Results of the association rules mining for April

No	Left hand side (Lhs)	Right hand side (Rhs)	Support	Confidence	Lift	Count
[1]	{Rice, Cooking oil}	{Sugar}	0.012	0.880	6.998	22
[2]	{Soy sauce, Cooking oil}	{Sugar}	0.015	0.818	6.506	27
[3]	{Rice, Sugar}	{Cooking oil}	0.012	0.733	10.561	22
....	....	....	....	....	....	...
[115]	{Sachet Milk}	{Sugar}	0.011	0.200	1.590	20
[116]	{Sugar}	{Egg}	0.025	0.200	2.710	46

**Table 9.** Results of the association rules mining for May

No	Left hand side (Lhs)	Right hand side (Rhs)	Support	Confidence	Lift	Count
[1]	{Cooking oil, Brewed tea}	{Sugar}	0.011	0.846	7.619	22
[2]	{Cooking oil, Tea Bag}	{Sugar}	0.013	0.833	7.504	25
[3]	{Soy sauce, Cooking oil}	{Sugar}	0.012	0.821	7.397	23
....	....	....	....	....	....	...
[90]	{Snacks}	{Soft drink}	0.017	0.200	1.944	34

**Table 10.** Results of the association rules mining for June

No	Left hand side (Lhs)	Right hand side (Rhs)	Support	Confidence	Lift	Count
[1]	{Brewed tea}	{Sugar}	0.013	0.421	4.329	24
[2]	{Soy sauce}	{Detergent}	0.011	0.42	5.509	21
[3]	{Floor cleaner}	{Dishwashing}	0.011	0.351	6.952	20
....	....	....	....	....	....	...
[72]	{Snacks, Mini Snack}	{Wafers}	0.015	0.5	6.942	29

**Table 11.** Results of the association rules mining for July

No	Left hand side (Lhs)	Right hand side (Rhs)	Support	Confidence	Lift	Count
[1]	{Dishwashing, Bar soap}	{Detergent}	0.011	0.778	11.830	21
[2]	{Biscuits, Snacks}	{Wafers}	0.011	0.636	7.019	21
[3]	{Biscuits, Mini Snack}	{Wafers}	0.012	0.611	6.740	22
....	....	....	....	....	....	...
[63]	{Snacks}	{Biscuits}	0.017	0.201	3.036	33

**Table 12.** Results of the association rules mining for January-July

No	Left hand side (Lhs)	Right hand side (Rhs)	Support	Confidence	Lift	Count
[1]	{Clothes softener}	{Detergent}	0.016	0.531	6.994	211
[2]	{Brewed tea}	{Sugar}	0.017	0.521	5.000	219
[3]	{Snacks, Wafers}	{Mini Snack}	0.015	0.517	4.572	198
....	....	....	....	....	....	...
[71]	{Wafers}	{Instant noodles}	0.018	0.200	1.738	237

#### 5.4 Overall Variability of Association Rule (OCVR)

Furthermore, from all the rules that are obtained, the next process is OCVR analysis. The first thing to do is to find which rules have the same association rules every month. Then, Lift Variability Index (CVL) and Index Variability Confidence (CVC) are calculated. In this research, OCVR limit value is not prone to change every period with low variability. The value is between 1% to 30%. There are eleven rules which have OCVR value more or equals to 30%. Consequently, these rules can be used for generating marketing/promotion strategies. The results of OCVR analysis are shown in the table 13.

**Table 13.** OCVR value calculation

No	Left hand side (Lhs)	Right hand side (Rhs)	CVC	CVL	OCVR
1	{Shampoo}	{Detergent}	22%	19%	20%
2	{Biscuits, Wafers}	{Mini Snack}	18%	27%	22%
3	{Clothes softener}	{Detergent}	25%	19%	22%
4	{Mini Snack}	{Wafers}	12%	32%	22%
5	{Wafers}	{Mini Snack}	21%	22%	22%
6	{Bar soap}	{Detergent}	8%	38%	23%
7	{Wafers}	{Snacks}	19%	31%	25%
8	{Biscuits}	{Wafers}	19%	33%	26%
9	{Snacks}	{Wafers}	22%	32%	27%
10	{Dishwashing}	{Detergent}	13%	46%	29%
11	{Brewed tea}	{Sugar}	25%	36%	30%

#### 5.5 Layout Design and Promotion Strategy Analysis

Based on OCVR analysis, promotion strategies are generated. There are three strategies recommended.

1. Promoting products at discounted prices.

The mini market can use the results of the OCVR analysis as a reference for discounted promotional strategies. In this way, if the products that comply with the rules are bought simultaneously, there will be a discount on products that are not sold or are less attractive to consumers.

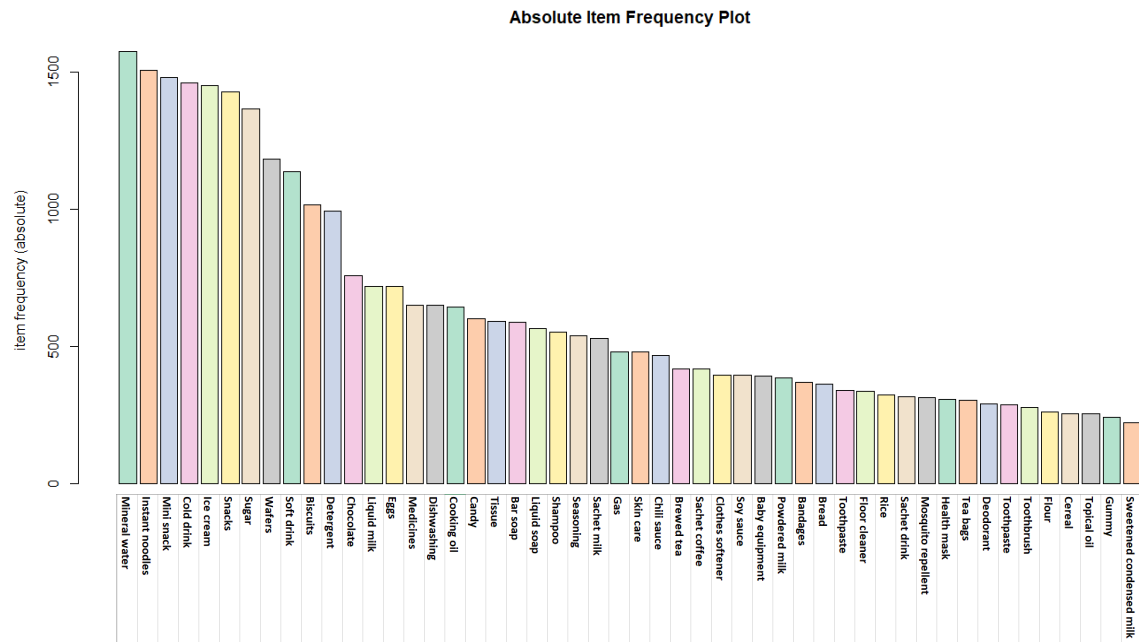


Figure 2. Frequent itemsets for January-July

There are 50 types of products that are often bought together with other types of products. The products and its buying frequency are shown in the figure 2. The products that are rarely purchased from the 50 types of products, namely sachet drink, mosquito repellent, and so on, can be used as a reference for products that are submitted as price discount offers. For example, every purchase of shampoo at the same time as detergent will get a discount on toothbrushes.

## 2. Promoting products by product bundling

The next strategy is product bundling or at affordable prices for products that have been classified separately. For example, product bundling in rule 11 is the result of OCVR, which means offering affordable price redemptions for product bundling of powdered tea, sugar, and products with minimal purchases but a kind, namely tea bags.

## 3. Develop a product promotion catalogue

Mini market may publish promotional catalogues according to the results of MBA analysis to reach a wider community so that they get to know more about this new mini market and attract buyers. In its preparation, the products being promoted are by the proposed discount and product bundling strategies in the previous description.

Based on OCVR analysis, a product layout design is proposed. According to Andari et al. (2009), rules are used as a reference for laying out by setting minimum confidence of 30% of the resulting rules. The product layout is carried out by paying attention product association. In this paper, if there are association rules that have high confidence, then the products are recommended to place close together. Products that affect many other products are placed on back shelves or in areas that are not immediately visible to customers when they first enter. This is done to stimulate impulse buying for other products in front of it. This research suggests some recommendations.

1. Exchanging location of sugar and eggs with jelly, herbs & spices, flour and rearrangement of cardboard beverage products. So that, Sugar section is close to Brewed Tea. This is done based on the association rules  $\{Brewed\ Tea\} \Rightarrow \{Sugar\}$  contained in the OCVR results. Egg location was moved because it was in a risky area, namely next to cardboard drinks, then moving household tools to occupy the initial area of the eggs.
2. Exchanging location of detergent with cleaning equipment racks and animal repellent. So that, detergent section is close to shampoo section. This is done based on the associations formed, namely  $\{Shampoo\} \Rightarrow \{Detergent\}$  contained in the OCVR results.
3. Exchanges in the layout of mini snack with biscuits. So that the layout of mini snack needs to be moved to the biscuit section. As a stimulus for impulse buying other products in front of it.

The existing and proposed layout is shown in the figure 3.





**Figure 3. Existing and recommendation layout**

**Notations:**

A: Camphor	O: Cotton	AC: Cooking oil	AQ: Mini Snack	BE: Body Spray
B: Floor cleaner	P: Toothbrush	AD: Tissue	AR: Mineral water	BF: first aid
C: Perfuming clothes	Q: Mouth Cleanser	AE: Adult diaper	AS: Soft drink	BG: Drugs
D: Clothes Freshener	R: Scrub	AF: Baby food	AT: Milk Drink	BH: Bar Soap
E: Dishwasher soap	S: Shampoo	AG: Milk powder	AU: Egg	BI: soy sauce sauce
F: Animal Slayer	T: Baby Equipment	AH: Instant noodles	AV: Sugar	BJ: Cheese
G: Bandage	U: Liquid soap	AI: Promotional Products	AW: Drink Sachet	BK: mayonnaise
H: Body Care	V: Rice	AJ: Cold drinks	AX: Brewed Tea	BL: Margarine
I: Oil	W: Cardboard Syrup	AK: Ice cream	AY: Milk Sachet	BM: Seasoned Flour
J: Skin Care	X: Cardboard Noodles	AL: Frozen Food	AZ: Cereals	BN: Herbs
K: Chocolate	Y: Cardboard Drinks	AM: School supplies	BA: Coffee	BO: Herbs and spices
L: Candy	Z: Jelly	AN: Accessories	BB: Air freshener	BP: Flour
M: Detergent	AA: Household appliance	AO: Wafers	BC: Purifier	BQ: Tools
N: Baby diapers	AB: Canned food	AP: Biscuits	BD: Cotton Buds	BR: Toothpaste

## 6. Conclusion

This study concludes that each period has various customer spending pattern. This requires further analysis so that the resulting efficiency association rules are implemented throughout the period. This further analysis uses OCVR. The OCVR results show that there are 11 consistent rules. So that it can be used as knowledge for the promotion of discounted prices, product bundling promotions, making promotional catalogues, and efficient layout arrangements. Some recommendations based on association rules analysis are as follows.

1. Sugar section is moved close to Brewed Tea.
2. Egg location was moved because it was in a risky area.
3. Detergent section is moved close to shampoo section.

For promotion strategy, this research recommends rarely purchased product for price discount offer. Related to triggering impulse buying, mini snack section is exchanged with biscuit section, in order to create impulse buying for other products in front of it, namely Cold drinks, Ice cream, and Frozen Food.

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**Cahyono Sigit Pramudyo** is an Assistant Professor in Industrial Engineering Department at UIN Sunan Kalijaga Yogyakarta in Indonesia. He received his Bachelor degree in Industrial Engineering from Universitas Gadjah Mada and his Master degree in Industrial Engineering and Management from Institut Teknologi Bandung Indonesia. He holds a Doctoral degree from Industrial and Manufacturing Engineering at Asian Institute of Technology Thailand. His research interests are vendor managed inventory, decision support system, and simulation.