Layout Design and Product Bundling Strategy Using Overall Variability of Association Rules (OCVR) Method

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Abstract

Alfazzamart is a minimarket that sells various daily needs. For several months, the number of transactions per month at Alfazzamart fluctuated. Alfazzamart owners want to achieve sales targets so that profits increase. This is a challenge for employees to determine the right product bundling strategy and product layout according to buyer behavior. Therefore, this research was conducted to provide product bundling strategies and layout suggestions based on buyer behavior. This study uses the OCVR method to determine consistent purchasing patterns in each period. Based on this method, the results of the OCVR method are used as a reference in product bundling and product layout. Data processing was carried out following CRISP-DM. Based on the findings of this study, 17 bundling packages were obtained that could be implemented. Bundling package offers can be made by placing the product on the promo shelf or by the cashier offering product bundling recommendations directly. In addition, regarding the proposed change in product layout, it can be done by bringing noodle products closer to snack and soft drink products, swapping the location of bread products with syrup, bringing wafer products closer to candy products, and bringing toy products closer to ice cream so that empty shelves can be filled with accessories.

Keywords : Minimarket; Market Basket Analysis; OCVR; Product Bundling; Product Layout

INTRODUCTION

The ever-evolving era affects various fields in a country. One of the visible impacts in the trade sector is the spread of minimarkets that are easy to find in cities and villages. The increase in the number of mini-markets certainly makes trade competition more stringent. Moreover, coupled with advances in technology have resulted in minimarkets not only competing with retail businesses in the vicinity but also having to compete with marketplaces. Therefore, a minimarket must have a promotional strategy that can attract buyers.

Minimarket bundling strategies can be designed using buyer behavior. This is also done by the marketplace to attract impulse purchases (Wahyuni & Rachmawati, 2018). This can be done by analyzing buyer behavior into knowledge with data mining. Data mining is the process of obtaining knowledge from a collection of data. Data mining can be done in a mini market which usually has transaction data for each period. The data is converted into knowledge to determine the products that can be offered to buyers. This analysis can be done with Market Basket Analysis (MBA). Market Basket Analysis analyzes buyer behavior by making associations between products. Therefore, the results of this knowledge can be considered in designing product bundling strategies and product layouts (Agarwal, 2014).

Product bundling can attract buyers (Nugroho et al., 2023). Product layout can also influence purchasing decisions (Masibbuk et al., 2019). Both are expected to be able to give a good influence on sales. Therefore, it needs the right design. Designing product bundling and product layouts in MBA can use the Apriori algorithm. The apriori algorithm was proposed by R. Agarwal and R. Srikant to find frequent itemsets. However, the fact is that each period of buyer behavior can change as shown in Figure 1. Therefore, Papavasileiou & Tsadiras introduced the Overall Variability of Association Rules (OCVR) (Papavasileiou & Tsadiras, 2011). This method provides a solution to buyer behavior data with high variability so that a consistent strategy can be found.

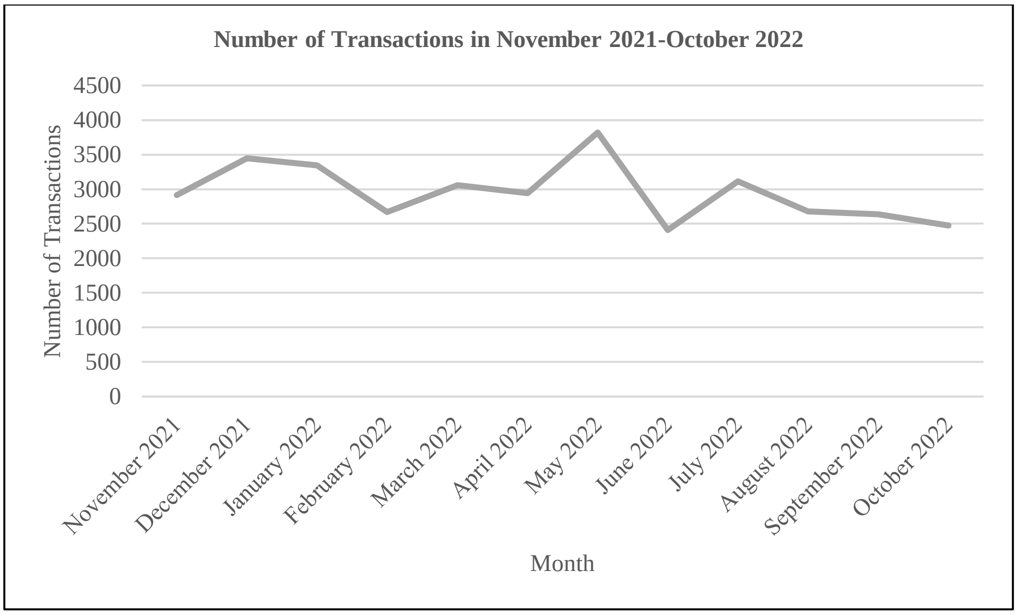

Figure 1. Number of Transactions in November 2021-October 2022

Therefore, the OCVR method is expected to assist minimarkets in designing product layouts and product bundling. One of them is Alfazzamart which is a minimarket in Jabung, Ganwarno, Klaten which was established at the end of 2019. The owner of Alfazzamart wants to achieve sales targets so that profits will increase. Figure 1 shows that the number of buyer transactions per month fluctuates. Moreover, Alfazzamart's operations are still managed by its employees, such as determining product bundling and product arrangement. Both of these can be given a fixed standard to attract buyers. It is hoped that the proposal to standardize product arrangement and product bundling based on buyer behavior is expected to be able to increase Alfazzamart sales.

METHODS

This research analysis uses CRISP-DM guidelines which consist of a business understanding phase, data understanding phase, data preparation phase, modeling phase, evaluation phase, and deployment phase (Larose, 2010). The first step of the business understanding phase includes identifying the purpose of doing data mining. After getting the right goal, you can carry out the data understanding phase by selecting Alfazzamart transaction data to be used in data mining. Then proceed with the data preparation phase by cleaning the unused data variables and transforming the data by changing the data format so that it can be used during the modeling phase. Then the modeling phase performs transaction data processing with the MBA. MBA uses the apriori algorithm in each period. After getting the rule results per month, check the lift value in the evaluation phase, if the lift value is less than 1 it will affect product layout changes with ARC (Walenna & Pramudyo, 2019). Finally, the deployment phase in this research is only limited to the proposed layout and product bundling strategy. The product bundling strategy can be obtained by analyzing the results of the rules on OCVR while the proposed layout changes are based on OCVR and ARC. All these steps can be shown in the form of a flowchart in the Figure 2.

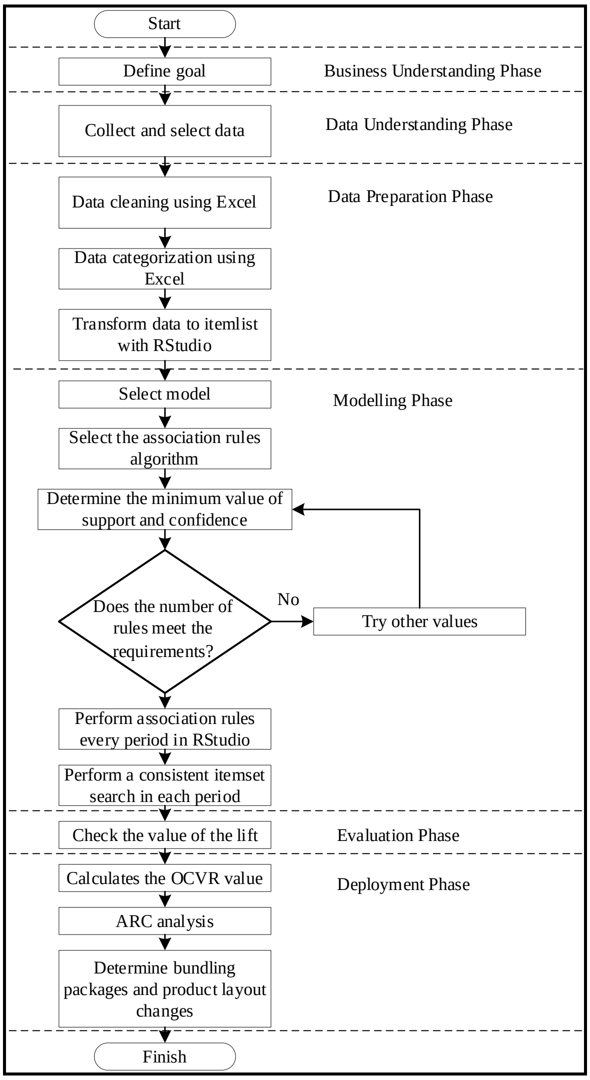

Figure 2. Flowchart of CRISP-DM

RESULT AND DISCUSSION

The results of this research analysis are the results of data mining with the steps following CRISP-DM. The six steps of CRISP-DM are all carried out but in the deployment phase, they only arrive at a proposal. Processing data mining research from start to finish using the same device. So, there is no difference factor that affects the processing results.

1. Business Understanding Phase

The purpose of this data mining is to provide layout suggestions and product bundling strategies for Alfazzamart based on buyer behavior. However, based on Figure 1, it shows that the behavior of Alfazzamart buyers is always changing. This results in the behavior of buyers in the past period not necessarily the same as the behavior of buyers in the next period. So, to avoid changes in buyer behavior the OCVR method is used. The proposal is expected to attract buyers so as to increase sales each period.

2. Data Understanding Phase

Based on the business understanding phase of this research, the data that can be used is buyer transaction data (Alfiqra & Khasanah, 2020). The data used is transaction data for Alfazzamart buyers for the period November 2021-October 2022. During that period 35511 transactions occurred. Details of the number of transactions are shown in Table 1 as follows.

Table 1. Details of Transaction Amount

Month	Number of Transactions
November 2021	2915
December 2021	3446
January 2022	3346
February 2022	2671
March 2022	3059

April 2022	2943
May 2022	3820
June 2022	2409
July 2022	3115
August 2022	2677
September 2022	2635
October 2022	2475

Figure 3 shows an example of the Alfazzamart transaction data structure. The data will be changed during the data preparation phase.

88811113015						
11/11/2021					TUNAI	
	BARANG	QTY	TOTAL			
	99901032	POLYTEX SPON	1			2,500
	1001000	BAYCLIN REGULAR	1			2,600
	301643	MODERN MASKER	3			3,000
	TOTAL		5			8,100
88811113016						
11/11/2021					TUNAI	
	BARANG	QTY	TOTAL			
	17101003	NISSIN WALENS	1			7,900
	5601000	BELFOODS FAV	1			26,000
	15903001	SARI GANDUM	2			4,000
	TOTAL		4			37,900
...	...	...	...	...	...	...
55530106371						
30/10/2022					TUNAI	
	BARANG	QTY	TOTAL			
	11205002	INDOMILK UHT CHO	1			18,000
	TOTAL		1			18,000

Figure 3. Examples of Forms of Transaction Data

3. Data Preparation Phase

The data preparation phase of this research includes data cleaning and data transformation. The data preparation phase is carried out so that the raw data matches the Modeling phase. The data preparation phase was carried out using Microsoft Excel and RStudio software. The first thing to do is to convert the transaction data file in the form of .htm (Figure 3) to .csv so that the process of data cleaning and data transformation can be continued.

a. Data cleaning

Data cleaning is done by deleting some data that is not needed during the modeling phase. Unused data deletion using Microsoft Excel software. Based on Figure 3 shows several variables contained in Alfazzamart transaction data. The data that will be used in the modeling phase include INVOICE and ITEM. There are several variables that are not needed at the modeling stage, so that transaction data variables are deleted, including transaction date, item id, quantity, and total price. Table 2 below shows the results of cleaning Alfazzamart transaction data.

Table 2. Result of Cleaning Data

INVOICE	ITEM
88811113015	POLYTEX SPON
88811113015	BAYCLIN RESUGARR
88811113015	MODERN FACE MASK
88811113016	NISSIN WALENS
88811113016	BELFOODS FAV

88811113016	SARI GANDUM
88811113017	TOLAK ANGIN CAIR
…	…
55530106371	INDOMILK UHT CHO

b. Transformation Data

Data transformation is done by product categorization. Categorization is carried out as a consideration in making changes to product layout not only per brand but includes similar products according to category. There are 72 product categories in Alfazzamart. The results of cleaning the data in Table 2 are categorized so that the contents of the ITEM variable change from brand name to product category. The following is presented in Table 3 which is the result of grouping product categories in Alfazzamart transaction data.

Table 3. Result of Grouping Product Categories

INVOICE	ITEM
88811113015	Household appliance
88811113015	Deterjent
88811113015	Face mask
88811113016	Biscuit
88811113016	Frozen food
88811113016	Biscuit
…	…
55530106371	Soft drink

The final process of the transformation is carried out by changing Table 3 of the product categorization results into an item list that is sorted and adjusted according to INVOICE. The form of the itemlist data is the final result of data preparation and is ready for the modeling stage. This is done because the arules library only requires an itemlist to run the a priori algorithm. The following Figure 4 is an example of coding from the data transformation process of transaction data at Alfazzamart.

```
#Menggabungkan transaksi sesuai invoice no
library(plyr)

#november
df.itemlist_nov <- ddply(dataset_nov, c("INVOICE"), function(df1)paste(df1$ITEM, collapse = "," ))
```

Figure 4. Coding Data Transformation to Itemset in RStudio

The data itemlist form is the final result of data preparation and is ready for the modeling phase in RStudio with the library (arules). This is because the library (arules) only requires an itemlist to run the a priori algorithm. The following Table 4 results from the data transformation process of transaction data at Alfazzamart.

Table 4. Results from The Data Transformation Process

No	Itemset
1	Shaver,Skincare,Toothbrush,Deodorant,Medicine
2	Cigarette
3	Tissue
4	Instant seasoning,Cooking oil,Wafer
5	Wafer,Skincare,Soap
…	…
35511	Wafer

4. Modeling Phase

The modeling phase is the stage of running association rules using RStudio. Prior to this, the minimum support and minimum confident values were determined by trial (Sharma et al., 2018). Determination of the minimum support and minimum confidence values is carried out in order to find values that produce a lot of rules but not too many.

a. Determination of value

In the first determination, the minimum support value is 0.2 and the minimum confidence is 0.3. The result is that no rules are formed at this minimum value. Then the second determination with a minimum support value of 0.02 and a minimum confident value of 0.4 produces 3 rules that always appear every period. In the next determination with a minimum support value of 0.02 and a minimum confidence value of 0.3 it produces 24 rules that always appear every period. The last determination with a minimum support value of 0.03 and a minimum confidence value of 0.3 produces 10 rules that always appear every period. Based on the results of these rules, a minimum value of 0.03 and a minimum confidence of 0.3 were chosen because it has quite a lot of options but will be concise because there are several iteration rules. Table 5 shows the results of determining the minimum support and confidence values.

Table 5. Determination of Minimum Support and Confidence Values

Minimum Support	Minimum Confidence	Number of Rules
0.2	0.3	-
0.02	0.4	3
0.02	0.3	24
0.03	0.3	10

b. Association rules results

The modeling phase uses the association rules method and the apriori algorithm. Modeling is done with a minimum support value of 0.03 and a minimum confidence of 0.3. The association rules process is carried out using the RStudio software. Association rules are carried out every month. The following Figure 5 is an a priori coding with a minimum support of 0.002 and a minimum confidence of 0.3.

```
#Run apriori

#november
basket_rulesnov <- apriori(txn_nov,parameter = list(minlen = 2, sup = 0.002, conf = 0.3,target="rules"));
```

Figure 5. Coding Apriori in RStudio

The following Tables 6 to 17 are the results of the association rules each month.

Table 6. Results of Association Rules in November 2021

No	Antecedent	Consequent	Confidence	Lift
1	Sausage	Soft drink	50	1.983673
2	Jam	Bread	54.54545	16.920696
3	Pudding	Soft drink	50	1.983673
4	Cheese	Biscuit	53.84615	4.099618
5	Cheese	Wafer	46.15385	3.274565
…	…	…	…	…
500	Ice cream, Soft drink, Snack	Wafer	31.11111	2.207299

Table 7. Results of Association Rules in December 2022

No	Antecedent	Consequent	Confidence	Lift
1	Snack home made	Mie	38.88889	4.324194
2	Snack home made	Snack	44.44444	2.54063
3	Floor cleaner	Deterjent	38.88889	10.55512
4	Pudding	Biscuit	33.33333	2.536424
5	Puddinh	Snack	38.09524	2.177683
…	…	…	…	…
608	Ice cream, Soft drink, Snack, Wafer	Biscuit	44.44444	3.381898

Table 8. Results of Association Rules in January 2022

No	Antecedent	Consequent	Confidence	Lift
1	Jam	Bread	63.63636	13.83058
2	Snack home made	Snack	44.44444	2.508525
3	Frozen food	Soft drink	42.85714	1.492642
4	Toys	Ice cream	41.93548	2.007984
5	Toys	Snack	32.25806	1.820704
…	…	…	…	…
517	Ice cream, Soft drink, Snack, Wafer	Biscuit	53.84615	4.201004

Table 9. Results of Association Rules in February 2022

No	Antecedent	Consequent	Confidence	Lift
1	Sanitation	Soft drink	40	1.488579
2	Deodorant	Soft drink	36.36364	1.353254
3	Toys	Ice cream	33.33333	1.763696
4	Toys	Snack	33.33333	1.72276

5	Toys	Soft drink	42.85714	1.594906
…	…	…	…	…
416	Biscuit, Ice cream, Soft drink	Snack	53.33333	2.756415

Table 10. Results of Association Rules in March 2022

No	Antecedent	Consequent	Confidence	Lift
1	Shaver	Soft drink	53.84615	2.069965
2	Jam	Bread	77.77778	17.62963
3	Moasquito repellent	Soft drink	34.28571	1.318019
4	Baby food and milk	Snack	33.33333	1.731749
5	Toys	Ice cream	51.6129	2.487173
…	…	…	…	…
322	Biscuit, Mie, Soft drink, Snack	Wafer	50	3.713592

Table 11. Results of Association Rules in April 2022

No	Antecedent	Consequent	Confidence	Lift
1	Snack home made	Soft drink	63.63636	2.107373
2	*Cottonbuds*	Soft drink	50	1.655793
3	Jam	Butter	46.15385	97.05495
4	Butter	Jam	42.85714	97.05495
5	Jam	Bread	76.92308	13.80863
…	…	…	…	…
440	Ice cream, Soft drink, …	Candy	35.29412	3.710924

Table 12. Results of Association Rules in May 2022

No	Antecedent	Consequent	Confidence	Lift
1	Cheese	Soft drink	58.82353	1.956177
2	Snack home made	Snack	40	2.672028
3	Snack home made	Soft drink	50	1.66275
4	Egg	Mie	48	6.196216
5	Household appliance	Cigarette	37.2093	4.29537
…	…	…	…	…
141	Mineral water, Soft drink, Wafer	Snack	61.90476	4.135281

Table 13. Results of Association Rules in June 2022

No	Antecedent	Consequent	Confidence	Lift
1	Sugar	Mie	37.5	3.912338
2	Jelly	Soft drink	35.29412	1.27908
3	Stationery	Ice cream	47.61905	2.113479
4	Chocolate	Wafer	44.44444	3.245791
5	Chocolate	Snack	33.33333	1.742589
…	…	…	…	…
522	Mineral water, Soft drink, Snack, Wafer	Biscuit	45.45455	4.564394

Table 14. Results of Association Rules in July 2022

No	Antecedent	Consequent	Confidence	Lift
1	Deodorant	Soft drink	43.47826	1.495345
2	Mosquito repellent	Soft drink	35.48387	1.220395
3	Jelly	Snack	46.875	2.766335
4	Jelly	Soft drink	46.875	1.612169
5	Cotton	Mie	31.25	3.540909
…	…	…	…	…
377	Biscuit, Soft drink, Snack, Wafer	Candy	41.17647	4.934842

Table 15. Results of Association Rules in August 2022

No	Antecedent	Consequent	Confidence	Lift

1	Accessories	Biscuit	46.15385	4.382979
2	Pudding	Ice cream	60	3.014634
3	Pudding	Soft drink	60	1.961905
4	Stationery	Soft drink	35.29412	1.154062
5	Butter	Jam	63.63636	106.5114
…	…	…	…	…
331	Ice cream, Soft drink, Wafer	Snack	44.44444	2.644938

Table 16. Results of Association Rules in September 2022

No	Antecedent	Consequent	Confidence	Lift
1	Cotton buds	Snack	50	2.774737
2	Cotton buds	Soft drink	50	1.589867
3	Jam	Bread	53.84615	9.216783
4	Deodorant	Skincare	30.76923	9.772011
5	Deodorant	Soft drink	30.76923	0.97838
…	…	…	…	…
432	Biscuit, Soft drink, Snack, Wafer	Candy	39.13043	3.393021

Table 17. Results of Association Rules in October 2022

No	Antecedent	Consequent	Confidence	Lift
1	Cooking oil	Instant seasoning	31.25	6.044922
2	Cooking oil	Mie	50	4.779923
3	Cooking oil	Biscuit	31.25	2.520358
4	Cooking oil	*Snack*	37.5	1.765209
5	Accessories	Bread	43.75	6.812893
…	…	…	…	…
753	Biscuit, Ice cream, Soft drink, *Snack*	Wafer	45.45455	3.0583

After knowing the results of the association rules in each month, a search for the rules that always appears every month is carried out. The search for these rules is used for further analysis with the OCVR method. The search uses coding in RStudio as shown in Figure 6.

```
#Mencari rules yang sama setiap bulan

data_novdes <- inner_join(data_commonnov, data_commondes)
data_desjan <- inner_join(data_novdes, data_commonjan)
data_janfeb <- inner_join(data_desjan, data_commonfeb)
data_fenmar <- inner_join(data_janfeb, data_commonfeb)
data_marapr <- inner_join(data_fenmar, data_commonapr)
data_aprmei <- inner_join(data_marapr, data_commonmei)
data_meijun <- inner_join(data_aprmei, data_commonjun)
data_junjul <- inner_join(data_meijun, data_commonjul)
data_julaugust <- inner_join(data_junjul, data_commonaugust)
data_augustsept <- inner_join(data_julaugust, data_commonsept)
data_septokt <- inner_join(data_augustsept, data_commonokt)
```

Figure 6. Coding Search Same Rules Every Month in RStudio

After searching, we get 24 rules that appear every month. The following Table 18 are the results of the rules that appear every month

Table 18. Rules that always appear every month

No	Antecedent	Consequent
1	Jelly	Soft drink
2	Toys	Ice cream
3	Wafer	Snack
4	Snack	Soft drink
5	Candy, Wafer	Snack
…	…	…
24	Biscuit, Soft drink, Wafer	Snack

5. Evaluation Phase

The process of evaluating the modeling stage can be seen from the requirements for more than one lift value. Based on the results of the rules that always appear in each period, there are two rules in the two periods that have a lift value of less than one. The two rules are the purchase of jelly and bottled drinks in August and mineral water, snacks and packaged drinks in September. This shows that the opportunity to purchase the product simultaneously is small. Table 19 below shows the lift value less than one with an asterisk (*).

Table 19. Check Lift Value

No	Antecedent	Consequent	August	September
			L	L
1	Jelly	Soft drink	0.991*	1.445
2	Toys	Ice cream	2.041	1.961
3	Wafer	Snack	1.833	1.691
4	Snack	Soft drink	1.410	1.285
5	Candy, Wafer	Snack	2.840	2.836
6	Bread, Snack	Soft drink	1.777	1.817
7	Snack, Tissue	Soft drink	1.635	1.378
8	Soft drink, Tissue	Snack	1.887	2.004
9	Medicine, Snack	Soft drink	1.486	1.870
10	Mineral water, Snack	Soft drink	1.834	0.984*
...	…	…	…	…
24	Biscuit, Soft drink, Wafer	Snack	2.840	2.455

Based on the lift value which is less than 1, the possibility of the occurrence of these rules is small. This shows that in August, the rules formed between jelly and bottled drinks have a small chance of happening, as well as the rules formed in September between mineral water, snacks and bottled drinks. This will affect the value of the relationship between products in consideration of the weaker product layout as seen in Explanation code 3 (Figure 7).

6. Deployment Phase

The deployment phase step in this study is only limited to providing suggestions. There are two results obtained, namely the proposed product bundling strategy based on OCVR then followed by the proposed product layout with ARC. Both can be used as a consideration in Alfazzamart's decision to sell.

a. Proposed Product Bundling Strategy

Based on the results of the search for rules that appear every month, the OCVR analysis can be continued. OCVR analysis requires S (Standard Deviation) on the confidence and lift values, $\bar{X}$ (average) on the confidence and lift values, so that the variability index CVC and CVL can be calculated.

Table 20. OCVR Calculation Results

No	Antecedent	Consequent	Confidence		Lift		CVC	CVL	OCVR
			S	$\bar{X}$	S	$\bar{X}$			
1	Snack	Soft drink	0.024	0.410	0.066	1.446	0.058	0.046	5.172%
2	Candy, Wafer	Snack	0.035	0.495	0.289	2.808	0.070	0.103	8.664%
3	Snack, Wafer	Soft drink	0.040	0.444	0.156	1.569	0.090	0.099	9.450%
4	Toys	Ice cream	0.051	0.421	0.182	2.067	0.121	0.088	10.440%
5	Biscuit, Soft drink	Snack	0.058	0.465	0.248	2.621	0.124	0.095	10.919%
6	Wafer	Snack	0.036	0.343	0.227	1.940	0.104	0.117	11.061%
7	Soft drink, Wafer	Snack	0.055	0.455	0.260	2.564	0.122	0.101	11.155%
8	Snack, Wafer	Biscuit	0.041	0.371	0.373	3.261	0.112	0.114	11.298%
9	Biscuit, Wafer	Snack	0.055	0.445	0.257	2.512	0.124	0.102	11.313%
10	Biscuit, Snack	Wafer	0.047	0.406	0.382	3.158	0.117	0.121	11.884%
11	Biscuit, Wafer	Soft drink	0.055	0.399	0.146	1.402	0.137	0.104	12.071%
12	Mie, Snack	Soft drink	0.053	0.423	0.184	1.493	0.125	0.123	12.390%
13	Biscuit, Snack	Soft drink	0.064	0.461	0.203	1.622	0.139	0.125	13.219%
14	Biscuit, Snack, Wafer	Soft drink	0.075	0.466	0.231	1.639	0.160	0.141	15.055%
15	Mineral water, Snack	Soft drink	0.068	0.446	0.246	1.577	0.152	0.156	15.400%
16	Medicine, Snack	Soft drink	0.083	0.504	0.255	1.772	0.165	0.144	15.447%
17	Soft drink, Tissue	Snack	0.068	0.403	0.343	2.270	0.169	0.151	15.988%
18	Biscuit, Ice cream	Snack	0.059	0.408	0.419	2.319	0.145	0.181	16.286%
19	Bread, Snack	Soft drink	0.075	0.474	0.290	1.676	0.159	0.173	16.606%
20	Mie, Soft drink	Snack	0.072	0.419	0.384	2.366	0.171	0.162	16.658%
21	Biscuit, Mie	Snack	0.068	0.420	0.407	2.379	0.162	0.171	16.661%
22	Snack, Tissue	Soft drink	0.085	0.480	0.270	1.689	0.177	0.160	16.818%
23	Biscuit, Soft drink, Wafer	Snack	0.090	0.537	0.517	3.034	0.167	0.171	16.890%
24	Jelly	Soft drink	0.069	0.400	0.553	1.615	0.173	0.342	25.778%

Based on the results of the modeling phase, data processing is carried out by calculating each CVC, CVL, and the resulting OCVR. Table 18 shows the 24 rules resulting in an OCVR value of 5% -26%. Therefore, all these rules are consistent every month [3].

The results of the OCVR calculations serve as a reference in making product bundling strategy proposals at Alfazzamart. Products to be bundled are products that comply with the 24 rules in Table 20 (Andari et al., 2009). OCVR values of more than 1% and less than 30% indicate that these rules are not susceptible to changes in the next period. However, there are some of the same rules, including rules no. 17 with no. 22, rules no. 12 with no. 20, rule no. 8, no. 9, with no. 10, rule no. 5 with no. 13, rule no. 3 with no. 7, finally rule no. 14 with no. 23. Because there are 7 rules that have similarities with the previous rules, they can be used as 17 rules as a reference for determining product bundling. Therefore, the proposed product bundling packages are obtained as shown in Table 21.

Table 21. Proposed Bundling Product

No	List of *Bundling* Product
1	*Snack* and Soft drink
2	Candy, wafer, and *snack*
3	Soft drink, wafer, and *snack*
4	Toys and Ice cream
5	Biscuit, Soft drink, and *snack*
6	Wafer and *snack*
7	Biscuit, wafer, and *snack*
8	Biscuit, wafer, and Soft drink
9	Mie, *snack*, and Soft drink
10	Biscuit, Soft drink, wafer, and *snack*
11	Mineral water, *snack*, and Soft drink
12	Medicine, *snack*, and Soft drink
13	Soft drink, Tissue, and *snack*
14	Biscuit, Ice cream, and *snack*
15	Bread, *snack*, and Soft drink
16	Biscuit, mie, and *snack*
17	*Jelly* and Soft drink

Based on the results of this study, it is hoped that it will be able to provide consideration for Alfazzamart as a standard for product bundling and product layout. Proposed product bundling strategies that can be implemented by implementing the 17 product bundling packages shown in Table 21. In addition, strategies to offer product bundling include:

1. You can do promos by placing product bundling on the promo shelf, you can also make discounts if you buy the bundling.
2. The cashier can offer goods that are suitable for bundling if the buyer only buys one product so that the buyer is tempted. For example: if the buyer only buys snacks, the cashier can offer bottled drinks (according to the bundling package 1 in Table 21) and if you buy both, you will get a bundling price.

b. Proposed product layout

Based on the last results of the rules that appear, each product contained in the rules is analyzed for its placement. The Activity Relationship Chart has 5 degrees of closeness to code A (Absolutely), E (Especially Important), I (Important), O (Ordinary Closeness), U (Unnecessary), and A (Avoid Closeness). There are also 8 reasons for closeness that can be used. But explanations 5, 6, and 7 in the analysis are not found.

This movement is based on the results of the rules in Table 20. Each rule result is analyzed with ARC (Berman & Evans, 2013). There are 6 closeness ratings and 8 explanations. Each closeness rating has its own explanation. Explanation 1 based on Permenkes No. 17 of 2020 concerning Healthy Markets which states that chemicals or hazardous substances are prohibited from being near food. Explanation 2 is a match with the results of the rules. Explanation 3 states that rules that have lift < 1 have a smaller chance of occurring. Explanation 4, 5, 6, and 7 based on grouping according to functional product (product function), purchase motivation product (buyer urgency), parquet segment product (target market), and product storability (product maintenance method) (Nur Hana Kurnia & Lestari, 2013). While Explanation 8 states that there is no related relationship. However, the results of Figure 7 show that only Explanations 1, 2, 3, 4, and 8 are used.

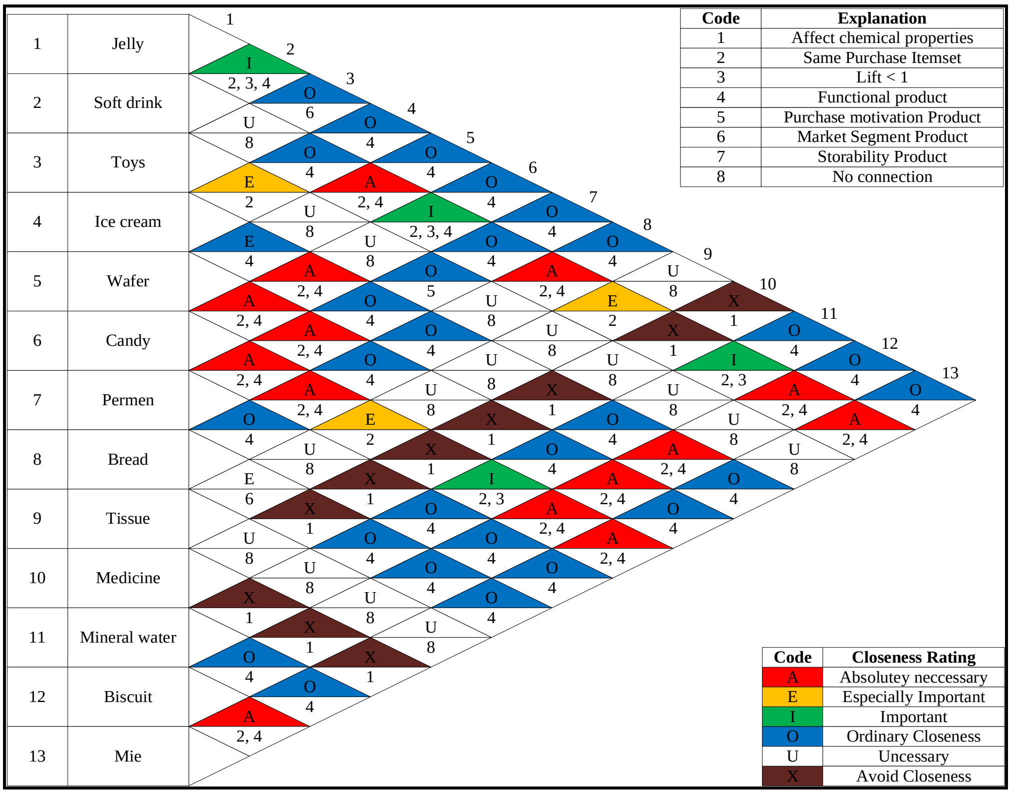

Figure 7. Activity Relationship Chart

. Based on Figure 7 shows the closeness between products analyzed by ARC. Noodle products have 3 closeness ratings with code A. Explanation code 2 indicates that noodles have the same itemset as biscuits, candies, and bottled drinks as shown in Table 20. Explanation code 4 means that noodles have the same product function as food -beverages with biscuit products, snacks, and bottled drinks. Therefore, the proximity value is really important (Absolutely necessary).

In addition, there is also a closeness rating with code E, including toys and ice cream. The explanation is the same purchase itemset, which means that toys and ice cream are an itemset relationship (shown in Table 20 rules no. 4). Products that have the same purchase itemset relationship need to be brought closer because they have the opportunity to purchase simultaneously (confidence).

The closeness rating with code I can be seen in the relationship between Jelly and bottled drinks. The code explanations are 2, 3, and 4. 2 shows the similarity of the itemset but there are drawbacks which can be seen in code 3 which shows the lift value < 1 (shown in Table 20 no. 22). This is a consideration that Jelly and bottled drinks have a small chance of purchasing together. Although both of them have the same product function relationship (code 4: functional product) as food. Therefore, the closeness rating of both is important.

One of the closeness ratings with code O can be seen in Ice Cream and Wafers. Both have the same product function as food. Therefore, both of them have an ordinary closeness relationship.

In addition, there is also a closeness rating with code U which can be seen on Bread and Tissue. The two do not have any relationship either from the similarity of the itemset or the 4 types of product grouping. Therefore, the two are not related.

The last code is X or avoid closeness, one of which is seen in Bread and Medicine. It is hoped that the two products are not close together in order to avoid several types of drugs that can have a chemical effect on food.

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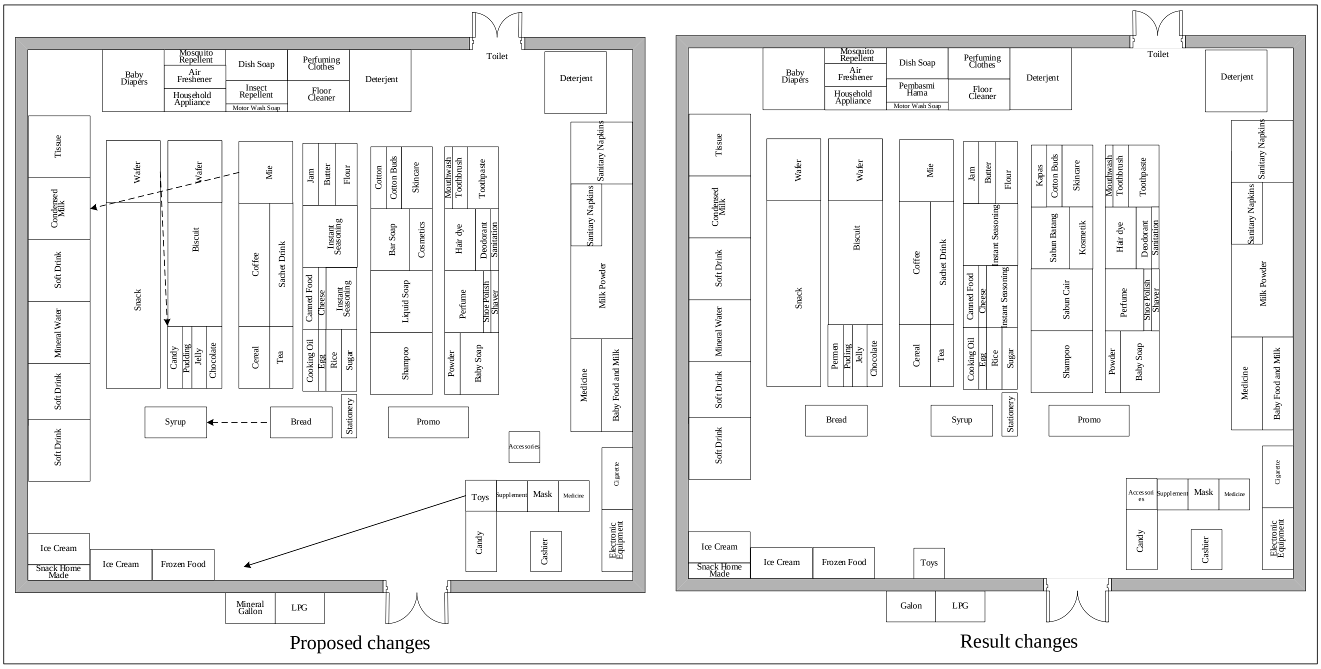

Figure 8. Proposed Changes in Product Layout and Results of Changes

The results of the ARC analysis are compared with the current Alfazzamart product layout. Based on Figure 7, it shows that there are 3 products with a closeness rating of A (Absolutely Necessary) and 1 product with a closeness rating of E which is not in accordance with the current product layout. Among them are noodle products that have an A rating related to biscuits, snacks and bottled drinks, so there needs to be a change to bring them closer together. Bread that has an A value related to snacks and bottled drinks needs to be brought closer. Wafer products that are rated A are related to candy. Finally, toy products with an E value are related to ice cream. Therefore, it can be seen in Figure 8 that the product layout plan will be moved according to the results of the ARC. The plan to move these products includes placing noodles in the area around Snack and bottled drinks by exchanging sweetened condensed milk products. Besides that, there is also an exchange of bread with syrup to be closer to snacks and bottled drinks. Wafer movement to be closer to the candy. Then move the toy closer to the ice cream cone so that the previous shelf of toys can be filled with accessories. The results of changing the product layout can be seen in Figure 8.

CONCLUSIONS

Based on this research, the proposed layout changes based on OCVR can be done by placing regional noodles around snack and bottled drinks, swapping bread and syrup, moving wafers to the side of the candy area, and bringing the toys closer to the ice cream so that the remaining area can be filled with accessories.

This research also found a product bundling strategy proposal with 17 bundling packages. Some examples can be seen in the top rules that have the highest consistent value, namely package 1. Package 1 with an OCVR value of 5.172% has a high consistent value with offering snacks and drinks. The bundling offer strategy can be carried out if the buyer purchases the product according to the package, he will get a discount. Product offers can be placed on the promo shelf and cashiers can offer product bundling offers when a buyer buys one of the products included in the bundling package.

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