Original Article

Design Planogram for the Priority Shelf Based on Customer Behaviour by Applying the Merchandising Decision Model

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Abstract

Intelligent and strategic product arrangements in retail stores can increase sales and maximize profits. However, shelf operations management is increasingly challenging with a large variety of products available on limited retail shelf space or what is commonly known as the shelf space allocation problem (SSAP). Retailers must plan shelf space by considering two factors namely appropriate allocation of products on shelves and customer preferences. From the customer shopping behavior analysis, this research aims to redesign retail planograms based on product allocation on priority display shelf space by applying a merchandising decision model. Multilevel association rule mining was used to determine the relationship between categories, subcategories, and product items by utilizing customer shopping basket data. The study presented is a planogram design for priority display shelves based on customer preferences, which can be implemented to maximize profits for retail owners and increase consumer satisfaction.

Keywords: Customer Behaviour, Data Mining, Multilevel Association Rule, Retail.

1. Introduction

When shopping, customers' choices are strongly influenced by in-store factors, especially when purchases are unplanned and when the product they are looking for is not available (Suher & Hoyer, 2020). In this context, more than simply displaying merchandise, bright product arrangements on shelves can increase demand and, ultimately, the store's financial performance (Bianchi-Aguiar, et al., 2018). This is because a strategic and appropriate product layout can enable consumers to reach more products easily, thereby providing profits for retailers. One way to increase sales is to place products at eye level or slightly below eye level (van Herpen, et al., 2016) and displaying products in window stores (Zheng & Li, 2018). In addition, an appealing product display as well as good layout may attract consumers to walk passed many display and browse more products. Purwantoro (2019) highlights that an appropriate and attractive product layout may enable consumers to determine their interest in shopping. Thus, the product layout is normally builds an image as wished by the retailer (Ladhari, Rioux, Souiden, & Chiadmi, 2019). Lee, Kim, Seo, & Hight (2015) state that a practical layout impacts organizations in determining strategies related to differentiation, low costs, or speed of response. So, the arrangement of goods in modern retail outlets must consider factors such as the nature of goods, level of needs, and consumer shopping habits, and other than decorative aspects (Sari, 2018).

Flamand, Ghoniem, & Maddah (2016) state that optimizing the layout and allocating shelf space are needed to maximize customer visibility and encourage product purchases. The placement of shelves for products on display influences product sales. In addition, placing complementary products close to each other allows for cross-selling of products (Ozcan & Esnaf, 2013). According to Behera and Mishra (2017), displaying complementary products or similar brands close together tends to influence customers to buy these complementary products other than products purchased. This shows that the layout of retail products depends on consumer behavior or shopping patterns. Therefore,, understanding customer shopping behavior and preferences can help to determine the best retail product layout strategy to increase product sales (Hasan & Mishra, 2015). With a large variety of products and consumer purchasing behavior patterns, selecting product shelves to display is one of the vital aspect in retail (Czerniachowska & Subbotin, 2021).

Product diversity and product allocation on display shelf space are two essential things in the retail business (Timonina-Farkas, Katsifou, & Seifert, 2020). These two things can influence consumers' purchasing. The amount of display shelf space is becoming limited as the number of product variations continue to increase to meet the consumer desires. Hübner & Schaal (2017) requires retailers to implement display space management in their retail outlets. Space management is a concept or product display plan based on the flow of consumer shopping habits to maximize profits and improve service to end consumers (Chan & Ip, 2011). According to Levy and Weitz (2009), space management involves two sources of decisions: the allocation of store space to display categories and brands as well as locations of goods categories in the store .

Shelf space planning is becoming increasingly challenging as more products available in the same limited space. It has become an active area of research in retail operations management under the term of Shelf Space Allocation Problem (SSAP). SSAP investigates the retailer's task of selling different products and allocating them to limited shelf space. The goal is to determine the appropriate shelves and shelf segments to place products on and the suitable shelf space for each product to maximize retailer profits. From a retailer's perspective, the shelf space allocation process is based on two factors. On the one hand, they must allocate products on the appropriate shelves. On the other hand, they must consider customer preferences because the increasing demand, customer loyalty, and shopping satisfaction are influenced by the proximity of the product to the product.

In retail stores, optimizing profits from product sales is the retailer's goal, which can be achieved with the help of planograms. In practice, a planogram is a blueprint for retailers to develop their merchandising plans. It is can pinpoint where each product should be physically displayed and how many surfaces the product should accommodate. Planograms are normally created separately for each category, the space of which is determined in advance at the macro or upstream level. There are space planning software systems that can help retailers with this activity. So, a planogram is a graphic representation of the arrangement of physical products on store shelves that helps retailers know the exact position of products on the shelf and arrange the number of surfaces. Planograms often promote symmetry and aesthetics, increasing customer satisfaction while shopping. In retail either traditional or modern store, available space is a limited resource (Bianchi-Aguiar, Silva, Guimarães, Carravilla, & Oliveira, 2018).

This research aims to redesign the planogram based on product allocation on priority display shelf space, which is known for identifying customer behavior using the association rule mining method. Product allocation is adjusted to the relationship between categories, sub-categories, and product items by applying a merchandising decision model to increase sales and maximize profits for the retail owner. The relationships between categories, sub-categories, and items are obtained from multilevel association rules. The Multilevel association rule method is an association rule for detecting relationships between small groups of things in large volumes of data. In Multilevel association rule mining, items are categorized based on the level of the concept hierarchy so that the search for associations from combinations of items is carried out in stages in each hierarchical category (Prajapati & Garg, 2017).

Various kinds of algorithms have been used to enforce multilevel association rules in retail product layout, such as the Apriori, FP-Growth, Eclat, and K-Apriori algorithms. Many studies have compared these algorithms to find the best one. Khan et al. (2017) investigate the application of market basket analysis to increase sales and marketing using apriori, FP growth, and Eclat algorithms. The results show that FP Growth is better than Apriori and Eclat in terms of time and memory usage for large data sets. However, Eclat outperforms FP-Growth and Apriori based on runtime and memory space for small and medium datasets. These results are is the same as Syahrir and Merdadi (2023) who compared the traditional Apriori, FP-Growth, and TPQ-Apriori algorithms. Additionally, Heaton (2021) stated that FP-Growth or Eclat should to be the most frequently used itemset applications. In his research, these two algorithms had similar performance, although FP-Growth showed slightly better performance than Eclat. Another paper also recommends FP-Growth for many cases (Borgelt, 2012). So this research uses the FP-Growth Algorithm.

Using a data mining approach, Chen and Lin developed a product allocation model on display shelf space based on the relationship between categories, sub-categories, and product items (Chen & Lin, 2007). Nafari and Shahrabi developed the model Chen and Lin created by adding the product's price elasticity variable (Nafari &

Shahrabi, 2010). Another allocation model was developed by Murray et al. product facing displays are arranged based on the orientation of the product arrangement by considering the width and height of the display shelf space, and the allocation is based on the interaction of selling prices between products in one product category (Murray, Talukdar, & Gosavi, 2010). Based on the research that has been conducted, this research uses a product allocation model on Chen and Lin's display shelf space. The scope of the research focuses on the relationship between categories, sub-categories, and product items. The results demonstrated are in the form of a planogram design that can be applied to maximize profits for retail owners and increase consumer satisfaction by implementing a merchandising decision model.

In addition, Rhavi and Bagat (2017) studied sales strategies based on consumer shopping behavior. His research has tested three merchandising and pricing factors with hypermarket consumer purchasing behavior. Then Rhavi and Bagat (2017) suggest several other merchandising strategy variables, one of which was planograms, for future consumer behavior studies. So, this research has filled the theoretical research gap by determining a planogram design based on consumer shopping behavior. This research also has filled the practical knowledge gap in the Bianchi-Aguiara et al. (2021) that state the most of the literature on shelf space planning assumes that shelf design (such as the number of shelves, layers, height, etc.) is predetermined. Bianchi-Aguiara et al. (2021) recommend that future research needs to explore the rules of other relevant businesses, such as pre-defined family product lines or complementary product combinations. So, the novelty of this research has filled the theoretical research gap and practical knowledge gap, which were creating a planogram design based on consumer behaviour and planning shelf space by determining a series of family sequences, which are then called categories and sub-categories, and identifying product combinations that can be purchased simultaneously.

2. Previous Work

An essential goal of retailing is to sell merchandise. Merchandising is a process that includes several activities carried out by retailers, such as planning, buying, and selling goods to customers for their benefit. It is also an essential component of managing store operations. Merchandise control includes outlining strategies and procedures to achieve predetermined goals. The goals span the micro level to corporate strategy, including product selection, storage, and reordering (Mann & Jha, 2013).

Regardless of store layout or shelf space capacity, product selection decisions based on deterministic or probabilistic consumer choice models focus on substitution and complementarity effects between products (Flamand, Ghoniem, Haouari, & Maddah, 2018). Shelf space management problems typically refer to predetermined product selection and focus on allocating shelf space within a limited number of shelves. Thus, a professional shelf planner must create a planogram that provides specific surfaces and locations for each product on the shelf (Duesterhoeft, 2020).

Retail shelf design and shelf space allocation are two isolated research streams in retail planning. While the former focuses on optimizing decisions at the shelf level, the latter focuses on decisions at the product level (Karki, 2019). Considering that this research covers both of these streams of literature, we have summarized some of the primary research in each and the related gaps that form the basis of this research.

Several previous studies discuss shelf space allocation (Karki, 2019). Zhaoa et al. (2016) researched a combined optimization model for shelf space allocation and display location with multi-item restocking. Bianchi-Aguiara et al. (2018) presented an article on a new mixed-integer programming formulation for the Shelf Space Allocation Problem by considering two innovative features emerging from trading rules: hierarchical product groups and display direction. Dujak et al. (2017) study the conditions of retail shelf space management in Croatia to help food producers and small retailers make navigation easier through category management. According to them, retailers should decide on shelf space allocation at the segment level based on market share (via the consumer decision tree method) to maximize sales and minimize consumer confusion within categories. Those researchs did not calculate the estimated profit per shelf and the probability of cross selling profit.

Karki (2019) discusses Joint Rack Configuration and Shelf Space Allocation (JRC-SSA) to determine the optimal retail shelf layout and decisions on placement and number of product locations. The results show that the angle of the shelf influences product decisions; high-impulse products are placed at the front near the end caps on 90˚ shelves, and the same products are now placed at the back in acute angle shelves. The results show retailers can achieve up to a 10.1% increase in profits through JRC-SSA compared to traditional 7-foot shelves in a 90˚ orientation. This research presents rack configuration and shelf space allocation standards to increase sales but does not show the overall shelf design.

Czerniachowska and Hernes (2021) conducted research aimed at developing a model for allocating shelf space for specific products. They propose that retailers can apply provisions for product appearance on shelves based on packaging type, brand, price, shape, and size by considering additional allocation parameters such as capping and nesting. In addition, Hübner et al. (2021) examined shelf segment dimensions and product allocation, which can determine the number of surfaces for each product, the number of shelves and sizes, and the number of shelf segments. They show that integrating shelf dimensions into product allocation results in profits up to 5% higher than benchmarks available in the literature. These studies did not involve designing a planogram and calculating profit estimates.

Mishra and Mishra (2016) discuss the reasons and how to design planograms for visual merchandising in local supermarkets. They highlighted the internal problems faced by local retailers, including stock and sales analysis. So, planograms are implemented to make stores more attractive and avoid customer complaints and monotonous and boring layouts. At the operational level, creating detailed planograms is an exciting focus to study. However, the planogram design in this research was not based on customer behavior as in this research. Flamand et al. (2016) recommend integrated planning of layout decisions and tactical shelf space allocation to increase customer flow in stores, product visibility to buyers, and average retailer profits.

3. Research Methods

3.1 Data and Assumption

The data mining-based procedure proposed for product selection and allocation is implemented in this study in a retail store. The database was obtained from ABC Mart. The database includes transaction records containing the transaction date, transaction code, product code, product item name, selling price, number of items purchased, and total transactions. There are 9686 historical shopping data obtained for one month. To carry out the analysis, several additional assumptions have been made as follows:

1. All shelves are assumed only to have two different sizes: a shelf measuring 336 x 150 cm (width x height) with four layers placed in the middle and a wall shelf measuring 336 x 210 cm with seven layers. Figure 1 illustrates a top view of the rack in this implementation.
2. This study ignores the height and depth of the product and only considers the surface width of the product.

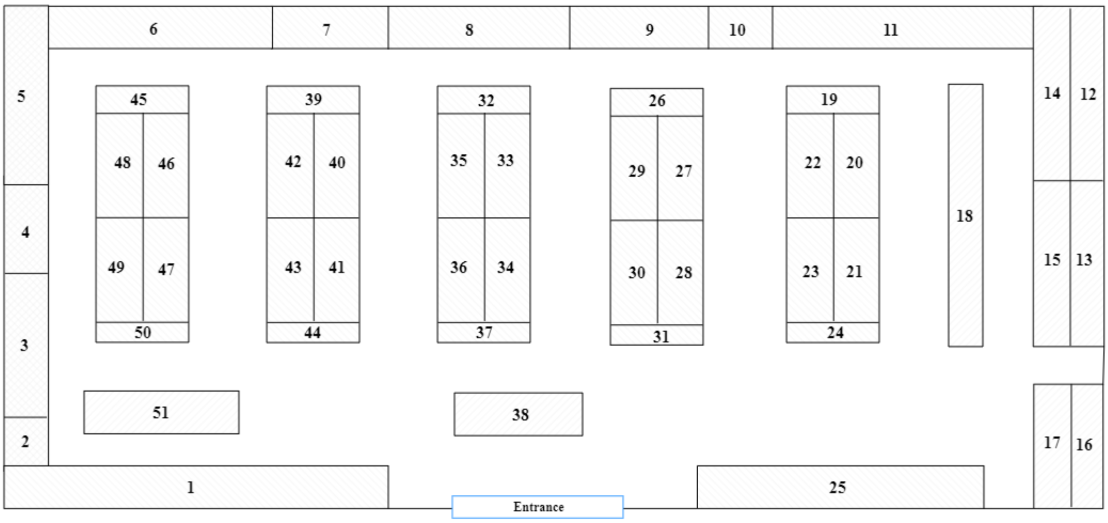

Figure 1. shelf layout

3.2 Grouping Product Items into Family Product-Based

All product items in a retail store are grouped into appropriate product families. In this case, products were grouped into several more specific categories by dividing them into two types, namely essential products and additional products, and classifying them based on type or similarity. So, from all products available, these products were grouped into 24 categories and 102 sub-categories. These categories are classified into food and beverage (FnB) and non-FnB, with 12 categories each.

3.3 Planogram

3.3.1 Multilevel Association Rule

After the data has been converted into a format that can be read by the FP-Growth algorithm, the multilevel association rule method was used to search for associations of product categories, subcategories, and items found for product selection and allocation on the shelves. There are 9686 transaction data used in this research. It is important to note that more variety of product items and transaction data used, the more difficult it would be to search for combination associations. Minimum support reduction is used in multilevel association rule mining. The lower the level of abstraction, the smaller the corresponding minimum support and minimum confidence. Minimum clearance and conviction for subcategories and items are set to very low thresholds. Product category, subcategory, and item minimum support are assigned to 5%, 2%, and 2% respectively. Minimum confidence for product categories, subcategories, and items is 25%.

3.3.2 Estimating the frequent item set profits

Customer shopping transaction data was used for association rule mining in this research. The association rules obtained determine frequently purchased products and combinations of products often purchased together. Profits from the selected product mix can be obtained by estimating the gross margin of the frequent itemset (Chen & Lin, 2007). This study maximizes profits by arranging selected products on appropriate shelves. Profit estimates come from individual product sales and the effects of cross-selling with other products. To find out the transaction margin for various items that frequently occur in transactions, Brijs et al. (2000) developed a profit allocation method. The technique used to calculate the profit from a set of frequently occurring items is explained as follows (Chen & Lin, 2007):

T_n	items included in the n^{th} transaction
F_I	the collection of all frequent itemsets of T_n
X	a frequent itemset in the n^{th} transaction
X_{max}	the maximal frequent itemset in the n^{th} transaction
Y_{max}	the second maximal frequent itemset in the n^{th} transaction
Θ_{Tn} (X)	the probability of selecting X in T_n to allocate gross margin,

$$\Theta_{Tn}(X_{\max}) = \frac{Support\ (X_{max})}{\Sigma_{\forall Y_{MAX}}\ Support\ (Y_{max})} \quad (1)$$

Support(X)	support of X
T_n\X	items included in the n^{th} transaction after excluding X frequent itemset.
m(X)	product profits in frequent itemset X.
M(X)	summation of m(X)

The process for calculating a frequent itemset's profit in this research is explained as follows:

1. Input the transaction database, gather frequently occurring item sets, and calculate the item's gross margin.
2. For each transaction T_n in transasction database,
   (a) if X = T_n, the profit m(X) is the profit of product multiplies numbers bought in transaction record T_n. Set M(X) = M(X) + m(X).
   (b) otherwise, the profit m(X) from frequent itemsets Xmax in Tn based on the probability $\Theta_{Tn.}$ Set M(X) = M(X) + m(X). Repeat this step, if T_n\X still ha frequent itemsets.
3. Return M(X) for all frequent itemsets.

There is limited data provided by the company regarding profits, so this research only calculates the average profit on the priority shelf. The average profit per shelf space was calculated as follows:

- For the *k*th category

$$\mathrm{PC_k} = \frac{1}{|\mathrm{SC}_k|} \left(\sum\nolimits_{j \in IC_k} \frac{P_j}{f_j}\right) \quad (2)$$

- For the *l*th subcategory

$$\mathrm{PS_l} = \frac{1}{|\mathrm{IS}_l|} \left(\sum\nolimits_{j \in IS_l} \frac{P_j}{f_j}\right) \quad (3)$$

- For the *j*th item

- $$\mathrm{PI_j} = \frac{1}{|\mathrm{IFI}_i|} \left(\sum\nolimits_{j \in IFI_i} \frac{P_j}{f_j}\right) \quad (4)$$

$\mathrm{PC_k}$	the average profit per shelf space for the k^{th} category
$\mathrm{PS_l}$	the average profit per shelf space for the l^{th} subcategory
$\mathrm{PI_j}$	the average profit per shelf space for the j^{th} selected item
SC_k	the set of subcategories included in the k^{th} category
IS_l	the set of items included in the lth subcategory
IFI_j	the set of items included in the ith frequent itemset
fj	the product facing length of item j
pj	the profit of the jth selected item

3.3.3 Shelf Space Allocation

This section adopted an allocation procedure to determine the product layout on shelf space. This paper proposed shelf space allocation procedure by considering the shelf level and the relationships among categories, subcategories, and product items. he retailers typically adopt a grid display to allocate shelf space. Ozgormus (2015) stated that grid layouts are commonly used in the grocery sector because customers usually plan their purchases before visiting the store. Author think that it could also be implemented in the retail sector. So, this study adopted a grid view in a retail sector. Grid structures are usually rectangular, allowing shoppers to search for products quickly and optimizing floor space (Czerniachowska & Subbotin, 2021). The design of the grid view in this research as shown in Figure 1.

In this study, the way of product allocation was adopting from Chen & Lin, (2007). So the product allocation on each shelf is divided into three levels: high-profit, medium-profit, and low-profit products. Thus, the profit weights at the top, middle, and bottom shelf levels are assumed to be 2/6, 3/6, and 1/6, respectively. The shelf space allocation procedure does ignore the length and depth of the shelves or products but only considers the surface width. The proposed shelf space allocation approach places products on shelves based on average profit, the relationship between categories, and shelf profit weight. Products with higher profits are placed on shelves with a higher profit weight to increase sales and profits. Additionally, products that have more excellent support are placed closer together. The following are several principles of shelf space allocation procedures, according to Chen and Lin (2007):

a. Placing frequent categories as close as possible or on the same shelf.
b. Placing frequent subcategories as close together as possible or on the same shelf.
c. Placing product items in the same frequency item set and the same category as closely as possible or on the same shelf.
d. Placing product items from the same category in the same area.
e. Placing product items from the same subcategory on the same shelf.
f. Products with higher profits are allocated to shelves with higher weights.

4. Results and Discussion

4.1 Frequent and Combination Item Based on Customer Preferences

In this research, customer shopping preferences were identified quantitatively using one of the data mining techniques, namely multilevel association rule mining with the FP-Growth algorithm. In studying buyer preferences, this technique can find relationships between various items in a customer's shopping basket, often called Market basket analysis (Artsitella, Apriliani, & Ashari, 2021); (Halim, Octavia, & Alianto, 2019). This technique has been widely used in multinational companies because it has proven helpful in understanding customer purchasing patterns and preferences (Isa, Kamaruzzaman, Mohamed, Ramlan, & Puteh, 2018). The output results obtained are the trends in customer preference patterns in the form of frequent and combination item sets in association rules.

Based on the data processing results, 11 associations among categories were obtained with a minimum support parameter value of 5% and a minimum confidence parameter value of 25%. All product category associations that appear in the association are Food and Beverage categories, including confectionaries, modern snacks, breakfast foods, condiments, groceries, drinks, instant foods, jam, and bread. This is because the retail type is a family mart whose customers' needs are groceries, food, and beverages. The associations formed can be seen in Table 1.

Table 1. Results of Category Associations

No	Premises	Conclusion	Support	Confidence	Lift
1	Breakfast Foods	Modern Snacks	0.080	0.308	1.061
2	Modern Snacks	Jam & Bread	0.090	0.310	2.586

No	Premises	Conclusion	Support	Confidence	Lift
3	Confectionary	Drinks	0.060	0.310	2.586
4	Condiment	Instant Foods	0.070	0.333	3.030
5	Confectionary	Modern Snacks	0.070	0368	1.270
6	Confectionary	Breakfast Foods	0.070	0.368	1.417
7	Condiment	Groceries	0.080	0.381	1.361
8	Drinks	Modern Snacks	0.050	0.385	1.326
9	Drinks	Confectionary	0.060	0.462	2.529
10	Instant Foods	Condiment	0.070	0.636	3.030
11	Jam & Bread	Modern Snacks	0.090	0.750	2.586

The support parameters in Table 1 show combinations of categories that appear frequently with a percentage of 5% of the total number of transactions. Meanwhile, the confidence parameter shows the level of confidence in the emergence of the follower (Y) category (also called consequent) in transactions that contain the predecessor (X) category (also called antecedent) or vice versa, with a minimum of 25%. Association rules with a lift ratio of more than 1 indicate a profit. The higher the lift ratio value, the greater the strength of the association. Meanwhile, a negative lift or less than one means that the rules formed are weak, so purchasing certain items did not tend to purchase other items based on associations (Hemalatha, 2012)

Moreover, the association in Table 1 has the terms antecedent and consequent. Antecedent to represent the "if" part or predecessor category, and consequent to represent the "then" part or follower category. For example, in rule 1, if a customer buys a product in the breakfast category, the possibility that the customer will buy a product in the modern snack category is 8% of the total transactions, with a confidence level of 30.8%. So even though there are two or more rules involving the same category, the position of the antecedent (premises) and consequent (conclusion) categories will be different, resulting in different support, confidence, and lift values.

Of the 11 associations formed (Table 1), it can be seen that the best association rule is based on the highest lift value (Rizaldi & Adnan, 2021), namely the association between the categories "instant foods" and "condiments." This association has a lift value of 3,030 with a confidence value of 63.6% and a support value of 7%. According to Valle et al. (2018), researchers can rank association rules from best to weakest based on the highest to smallest lift value. So, the association rule that has the smallest lift value is the association between the "breakfast foods" category and the "modern snack" category with a lift value of 1.061.

In addition to product categories, this research identifies multi-level association rules to determine product sub-category preferences. This analysis provides information regarding sub-category associations based on previously formed category associations. Of the 11 category associations formed, 54 sub-category associations were formed. The best sub-category association rule based on the highest lift value is the association between the sub-category of "sauce" and "instant noodles" with a lift value of 9.091, followed by the sub-categories "cereal" and "candy" with a value of 5,357.

Table 2 Results of subcategory associations

No	Premises	Conclusion	Support	Confidence	Lift
1	sauce	instant noodles	0.030	1.000	9.091
2	sereal	candy	0.030	0.750	5.357
3	wafer	biscuits	0.050	0.500	4.167

No	Premises	Conclusion	Support	Confidence	Lift
…	…	…	…	…	…
54	liquid milk	chips	0.040	0.286	1.587

Then, the lowest level of the data set hierarchy in identifying multi-level association rules is product items. This analysis found 4 product item associations based on two subcategory associations with the highest lift values: the association between the sauce subcategory and instant noodles. And between cereal and candy. The four product item associations produced are "Indofood extra spicy chili sauce" with "Pop mie cup soto ayam," "del monte tomato" with "Indomie chicken garlic," "Nestle koko crunch," with "Yupi sea world," and "Yupi gummy fangs" with "Simba cho chips cho." Knowledge related to product item associations will be a reference in managing display shelf space allocation and planogram design. After multilevel association rule data mining, the gross profit margin of frequent and combination item sets is calculated using the approach in section 3.3.2. The results of the profit estimation are also taken into consideration in redesigning the store layout and planogram design.

4.2 Redesign Store Layout

It is widely known that layout plays a vital role in customer experience in retail stores. Store layout can influence in-store traffic patterns, shopping atmosphere, behavior, (Krasonikolakis, Vrechopoulos, Pouloudi, & Dimitriadis, 2018), and operational efficiency. The author linked store layout design to customer preferences and interests (Bermudez, Apolinario, & Abad, 2016). Store layout design is identified as a determining factor for in-store loyalty (Triantafillidou, Siomkos, & Papafilippaki, 2017).

Traditionally, the layout of the sales floor is determined based on the store manager's expertise. Products are distributed across the sales floor primarily based on their functional similarity. While these criteria may effectively reduce search time and, possibly, customer cognitive load, they do not utilize factual customer purchasing behavior derived from historical data.

So, the redesign of the store layout needs to be carried out based on customer preferences, which are known from the results of the category associations formed (as in Table 1). In this research, the layout was redesigned to make it easier for customers and increase the possibility of cross-selling and triggering impulse purchases. Figure 1 represents the results of the shop layout redesign.

The Jam & Bread category is one of the categories that has the highest support and confidence values. So, this category is placed on the front shelf close to the ice cream in order to increase ice cream sales. Apart from that, Jam & Bread is associated with Modern Snack, so the confectionary is placed on the shelf between Jam & Bread and Modern Snacks. Since the research was conducted at a family mart type store, it is natural that grocery category items are one of the best sellers and contribute 35% of the store's gross profit, so they are placed at the front close to the entrance to display lots of appropriate promotions and increase sales.

Then, the condiment and instant foods categories were placed close together but in opposite directions or back-to-back. This aims were to ensure that customers do not just walk in one aisle but in other aisles to see the display of products in other categories. The condiment and instant foods categories also have the highest lift values, so these two categories are priority categories for planogram design.

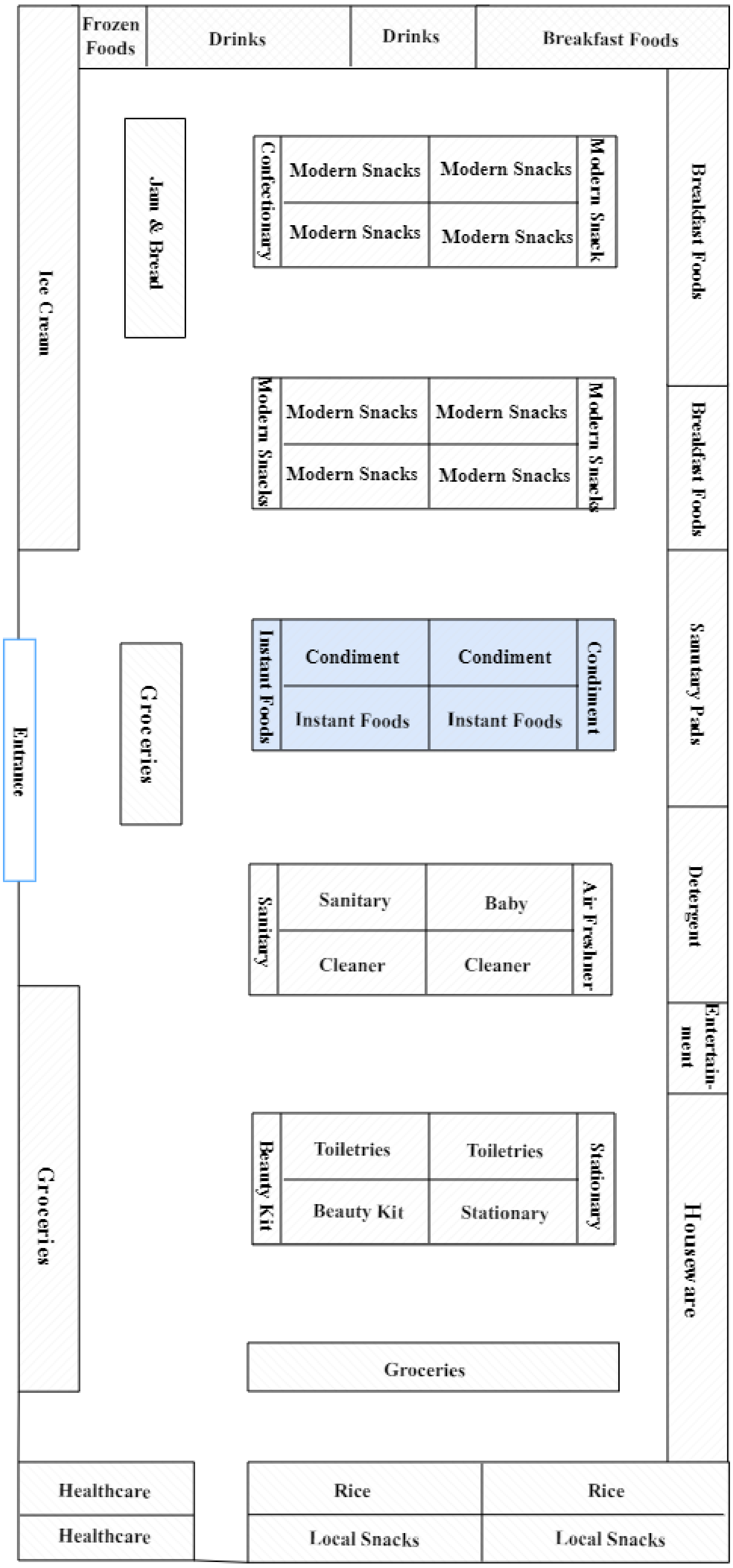

Figure 2. Redesign Store layout from top view

4.3 Planogram Design for The Priority Shelf

The planogram design in this study is limited to priority shelves based on the highest category association lift value. In the previous design it was discovered that the category that had the most significant lift value was the association of condiment and instant foods categories. Thus, the design is now changed to planogram design, which is the focus of this category.

Besides considering customer preferences, this planogram design also considers brand scale based on Valenzuela et al. (2013). Customer patterns in in-store layout depends on the brand scale, where, based on the price level, expensive brands are at the top while cheap brands are at the bottom. Scale brands based on sales volume are arranged by placing popular brands in the middle and adjacent to slow-moving brands. Then, based on the promotional strategy, the promoted brand is in the horizontal aisle. At the same time, the store brand itself is positioned next to the famous brand and the brand being promoted (Valenzuela et al., 2013). Retailers should always focus on product locations at eye level, which is higher in adult areas and lower in children areas or locations that are easily visible (Czerniachowska & Subbotin, 2021).

In line with Chen and Lin (2007), the allocation of display shelf space combined subcategories of each category including the previous set of frequency subcategories into virtual subcategories by considering the support of the frequency subcategories. Positions for subcategories that were not included in the frequent set were retained. For the first subcategory, the average profit per shelf space was calculated used equation 3.

Then, sequential allocation of subcategories (virtual and infrequent) to shelf space concerning shelf profit weights and average profit per shelf space was carried out. Within each category, more profitable subcategories are allocated to higher-weighted shelves. The comparison of profits before and after redesign is shown in tables 3 and 4. Then, the results of shelf space allocation and planogram design for subcategories are shown in Figure 3. Similar activities was done for the allocation and planogram design of product items shown in Figure 4 and Figure 5.

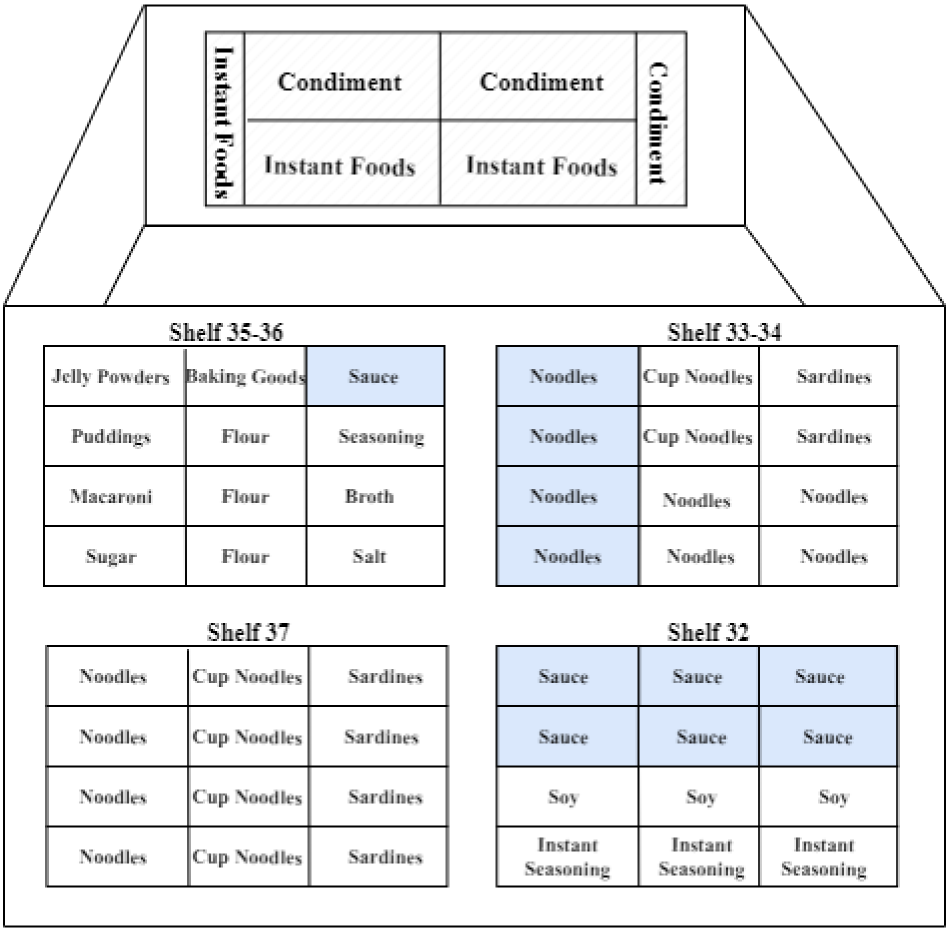

Figure 3. Planogram design for subcategory on category “condiment and instant foods”

Figure 3. Condiment and instant food shelf planogram for sub-category associations

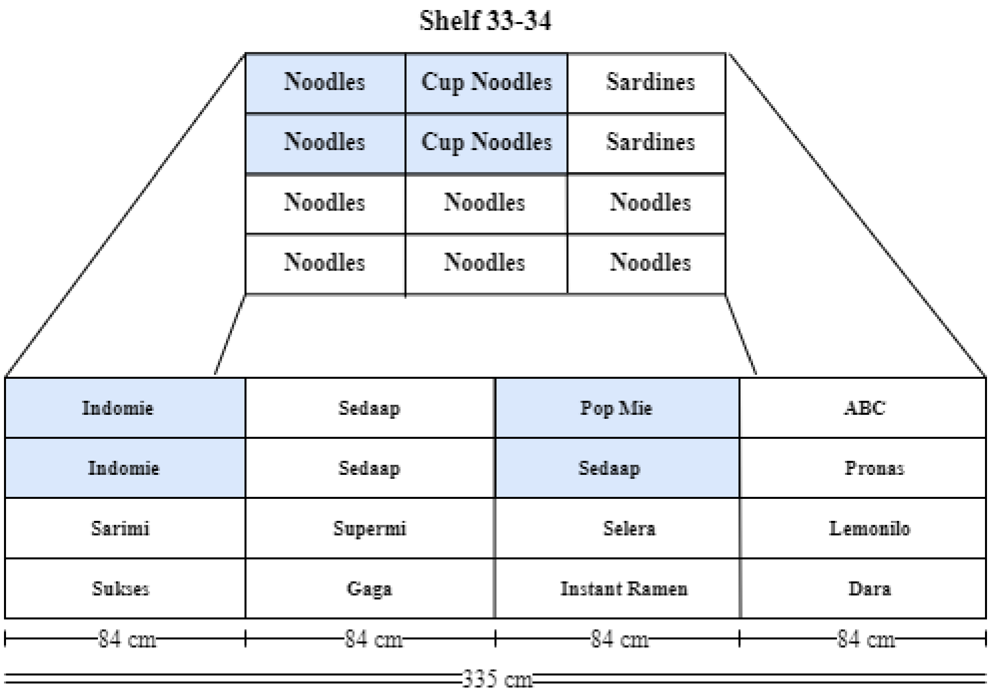

Figure 4. Planogram of product items on shelves 33-34

Table 3. Profit Comparison between current display and redesign planogram on shelves 33-34

	1	2	3	4	Average per shelf	
Average profit[1]	0.143	0.667	0.333	0.772	0.479	0.410
	0.333	0.143	0.422	1.043	0.485	
	0.500	0.316	0.200	0.500	0.379	
	0.188	0.500	0.333	0.167	0.297	

1 Calculation : (Profit of redesign / Profit of current) - 1

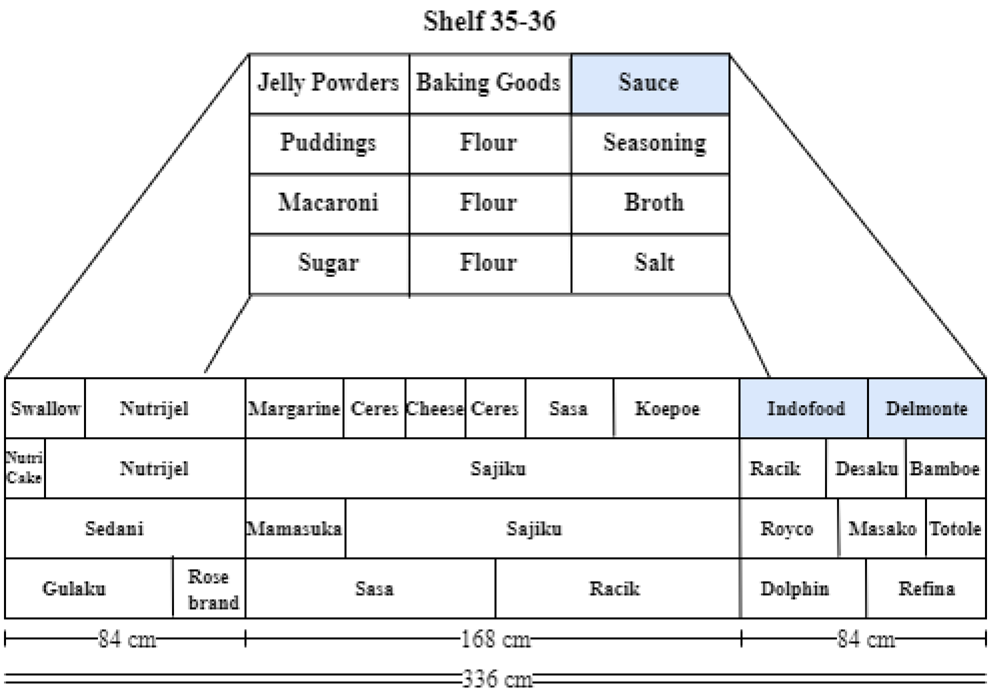

Figure 5. Planogram of product items on shelves 35-36

Table 4. Profit Comparison between current display and redesign planogram on shelves 35-36

	1	2	3	Average per shelf	
Average profit[1]	0.400	0.111	0.333	0.281	0.396
	0.406	0.547	0.230	0.395	
	0.250	0.663	0.250	0.388	
	0.579	0.667	0.313	0.519	

[1] Calculation : (Profit of redesign / Profit of current) - 1

5. Conclusions

Shelf space management is critical to maintain a competitive advantage in the retail sector. Retailers can create strategies to influence purchasing decisions by arranging appropriate and attractive store layouts by considering various customer demands and preferences. One of the ways is by utilizing transaction data to manage shelf space. This article implements a data mining-based approach to make informed decisions about which products to stock, how much shelf space to allocate to the products being stocked, and how to display them.

The results include layout design, shelf space allocation, and planogram for priority shelves. From the results of the product selection model, shelf space for each category can then be generated at the production allocation stage. Product categories, subcategories, and items with high associations can allocated as closely as possible to increase the cross-selling effect. Based on the results of calculating estimated profits per shelf and the possibility of cross selling, it is proven that redesign can increase profits by an average of 40%. The limitation of this research is the lack of data related to company profits so that product estimates can only be calculated for priority shelves. It is hoped that the calculations and results can be a reference for companies in calculating profits and the average profit per shelf space as a whole. Further research needs to ensure that companies can provide profit data so that planogram design and profit estimation can be carried out on all shelves.

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