Syntax Literate: Jurnal Ilmiah Indonesia p–ISSN: 2541-0849
e-ISSN: 2548-1398
Vol. 9, No. 9, September 2024

DEVELOPMENT OF RECOMMENDATION BUNDLING SYSTEM FOR FOOD RETAILER BASED ON DATA MINING

Bulan Rahma Fattah[1], Hartomo Soewardi[2*]
Universitas Islam Indonesia, Yogyakarta, Indonesia[1,2]
Email: 21916039@students.uii.ac.id[1], hartomo@uii.ac.id[2*]

Abstract

In retail, a major challenge is quickly selling perishable food items like cakes or pastries within a limited time. If unsold, these products lead to losses, even with discount promotions. Retailers must forecast stock accurately and develop more effective strategies to meet consumer demand within the required timeframe. One suggested strategy is bundling, where high-demand products are combined with less popular ones. However, when done manually, this approach often fails to align with consumer preferences. This study aims to develop an automated bundling system using data mining techniques. Market Basket Analysis is used to understand consumer purchasing patterns, while Association Rules with the Apriori Algorithm help identify relationships between different products. These methods reveal which items are frequently bought together, making bundling strategies more effective. The system will be designed with usability and ergonomic principles, ensuring it is user-friendly. The implications of this system include improved stock management, more accurate bundling, and better alignment with customer preferences, ultimately increasing satisfaction. Additionally, automation reduces errors and inconsistencies that occur with manual bundling. The expected outcome is a more efficient, effective, and comfortable system for food retailers, leading to higher sales, reduced losses, and greater overall customer satisfaction.

Keywords: Retailer, usable, Customer behavior, Market Basket Analysis, Association rules, Ergonomics

Introduction

Retail business is a sector that involves selling goods and services directly to consumers for personal use (Hameli, 2018). This is a final step in the supply chain system where products sold from various suppliers should reach the market immediately. So, retail entrepreneurs have the responsibility for delivering these products to the public through various channels either by physical media or digital media. Application of digital technology will affect the business process in retail to become more efficient (Roggeveen & Sethuraman, 2020) such that the conventional business process does not be effective anymore such as Data Inaccuracy, Inefficiency, Limited Data Access, Inventory Management Issues, Limited Reporting and Analysis, Customer Dissatisfaction, Increased Labor Costs (Pearlmutter et al., 2020). In response to these environments, many retailers are recognizing the need to embrace technology and automation for assisting to achieve a right target of the market (Roggeveen et al., 2016). Thus, consumer behavior is need to be understood and defined as an input in applying data mining methods (Roggeveen & Sethuraman, 2020). Consumer behavior analysis has been widely applied in the Food Retail Sector to find out the needs of consumers when shopping at outlets (Gridach, 2020). According to (Vidhya et al., 2019) that one of the effective analysis method is

How to cite: Fattah, B. R., & Soewardi, H. (2024). Development of Ergo-Bundling System for Food Retailer based on Data Mining. *Syntax Literate*. *(9)9*. http://dx.doi.org/10.36418/syntax-literate.v9i9
E-ISSN: 2548-1398

Association Rules and Market Basket Analysis (AR-MBA) as done by (Griva et al., 2018) that are an analysis on Food Retail's package recommendations for being purchased at certain hours. Moreover, Decision Support System (DSS) is required to be developed for helping a company to processing several information (Halim et al., 2019) and the most frequently approach used is the collaboration technique (Kutuzova & Melnik, 2018). This technique can analyze the similarity of products selected by consumers in previous transactions, they will choose almost the same product in the next transaction (Lessmann et al., 2021).

In line with understanding consumer habits, there are other issues that affect retail performance. Retailers face problems that affect many other retail sectors, the most food retailer's common problem is how to sell various food products in a given period of time because of product's shelf life (Lagorio & Pinto, 2021). If they fail to sell the various products, this will result in losses. In this case, a previous promotional strategy already implemented such as discount. Since losses often occur for many reasons, multiple technical solution actions are applied such as improvement sales system, forecasting, packaging or logistics to prevent the losses. Retailers need to be able to predict the stock levels of these products and plan a different, more effective sales strategy to meet consumer demand within the specified time (Schneider & Eriksson, 2020). One of the possible sales strategies is the bundling system, a combination of two or more products. Suppliers first set the prices of their products, and then the retailer decides whether to bundle two or more products (X. Guo et al., 2021).

Applying digital technology in the retail business is importnace, particularly to address challenges in conventional processes such as data inaccuracy, inefficient inventory management, and customer dissatisfaction. In this context, consumer behavior becomes a key element that must be understood as input in implementing data mining methods like Association Rules and Market Basket Analysis (AR-MBA), which have proven effective in analyzing product package recommendations in the food retail sector. However, one of the main problems faced by food retailers is how to sell food products with a limited shelf life. Failure to sell these products within a certain period will result in losses. Although promotional strategies like discounts have been implemented, losses still frequently occur for various reasons. Therefore, alternative sales strategies such as the bundling system, where multiple products are combined, are proposed as a solution.

While manual bundling is still often used, this method is considered ineffective. Thus, it is crucial to develop an automated bundling system that is more efficient and aligns with consumer preferences.

Previous research provides a valuable foundation for developing an automated bundling system in retail. Several researchers, such as (Gridach, 2020; X. Guo et al., 2021; Sarker et al., 2019, 2019) have developed strategies based on Machine Learning concepts, focusing on re-procurement of inventory through Consumer Behavior Analysis and Data Mining. These studies demonstrate that understanding consumer behavior through data technology can improve inventory management and sales strategies. The research proved that provide concrete examples of applying technologies like Machine Learning, enabling automation and improving operational efficiency. Prior research validates Market Basket Analysis as a reliable method for identifying consumer purchasing patterns, which can be used to design more effective bundling strategies. Thus, the study aims to develop an automated bundling system using data mining techniques.

Research Methods

Data Mining and Machine Learning

CRISP-DM based on IBM which stands for Cross-Industry Standard Process for Data Mining, is a widely used methodology for guiding data mining projects. It consists of six main phases:

a) Business Understanding: This phase involves defining project goals, objectives, and success criteria from a business perspective.
b) Data Understanding: This phase focuses on data collection and exploration, identifying data sources, collecting relevant data, and understanding its structure, quality, and relationships.
c) Data Preparation: In this phase, data is cleaned, missing values are handled, variables are transformed, and data from multiple sources is integrated for analysis.
d) Modeling: This phase involves applying modeling techniques to the prepared data to build predictive or descriptive models, selecting algorithms, building and evaluating models, and tuning parameters.
e) Evaluation: Models are evaluated to assess their performance and determine how well they meet the project objectives, involving validation with testing data and performance comparison against requirements.

Usability Analysis

Usability is the level of usefulness of a system and indicates the level of interaction between the user and the system/computer device being accessed. The level of usability as per ISO 9241-11:1998 known as the capacity of goods for use by specific users to meet the objectives with the impact of assignment fulfillment by users, the efficiency of assignment fulfillment in time, and satisfaction or user response in terms of knowledge in a system being used. To get the relationship between usability and the system/software there was an Analysis called Human-Computer Interaction, the usability 5 criteria of Variables and Indicators to cover the scope of Human-Computer Interaction can be described as follows: Learnability, Efficiency, Memorability, Error and Satisfaction.

Survey

Data is collected through direct questioning methods, including written questionnaires, telephone interviews, face-to-face interviews and paper-based questionnaires or interviews. To enhance the efficiency of data collection, record the observations on a PC or online platform, computer tablet, or smartphone (Leedy & Ormrod, 2018). The survey of design system consists of collecting data of:

1) Market Basket Analisys: secondary data consist of transaction data of food retailer.
2) Usability: in this study, a practical application survey was applied using a checklist on an online platform to record data on the Usability Level of the Ergo-Bundling System using System Usability Scale (SUS) by John Brooke (1986) and Performance Testing by Jacob Neilson.

Design of Survey and Experiment

a) Subject: 5 Partisipant based on expert of their Knowledge of Business, Manufacture, Developer, and Designer.
b) Apparatus: Experiment of Performance Testing using ErgoBundling Application illustrated with Figure 1 and SUS Scale Questionnaire.

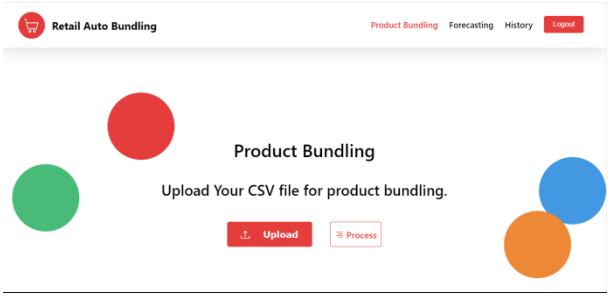

Figure 1. ErgoBundling Application

c) Procedures: Given to Participants with Presentation and Focus Group Discussion before Performance Testing and SUS Scale.
d) Scenario Performance Testing: Performance testing applied to measured Time-Based Efficiency. The scenario explained with Table 1 consist of 4 Task to be done by participants.

Table 1. Scenario Performance Testing

Task	Description
Task 1. Performing Login	Performing login into the system as the ErgoBundling user, then logging out and logging in again
Task 2. Selecting Bundling Menu and Uploading Bundling File and Reading Bundling Results	In the first step, the user finds the Bundling menu and uploads the bundling file
Task 3. Selecting Bundling Menu and Uploading Forecast File and Reading Forecast Results	The user finds the Bundling menu and uploads the forecast file then processes the file by selecting the "process" button.
Task 4. Reading History	The user can search for the date of the process that has been performed by finding the corresponding date, for example, January 23, 2024.

a. System Usability Scale Questionnaire
System Usability Scale (SUS) by Brooke for this study listed as 10 questions about Learnability, Memorability, Error and Satisfaction:
(SUS1). I think that I would like to use this system frequently
(SUS2). I found the system unnecessarily complex.
(SUS3). I thought the system was easy to use.
(SUS4). I think that I would need the support of a technical person to be able to use this system
(SUS5). I found the various functions in this system were well integrated.
(SUS6). I thought there was too much inconsistency in this system.
(SUS7). I would imagine that most people would learn to use this system very quickly.
(SUS8). I found the system very cumbersome to use.
(SUS9). I felt very confident using the system.
(SUS10). I needed to learn a lot of things before I could get going with this system.

Result and Discussion

Result of Design System

In this study, a Pareto diagram reveals that around 20% of the problems have a significant influence on the overall business processes. These issues include a lack of insight among human resources, reliance on manual labor for planning, inaccuracies in planning data for each branch, discrepancies between actual outcomes and forecasts, and limitations in data tracking and analysis. These challenges highlight the need for a more

efficient system to address productivity and profitability issues in food retail, supporting the conclusion that automation and data-driven approaches are essential.

Previous research has similarly identified the importance of automating retail processes to minimize human error and improve accuracy. Studies by (Korfiatis et al., 2019) and (Vidhya et al., 2019) have shown that integrating data mining and automated decision-making systems into retail operations can lead to better inventory management and more precise sales strategies. These findings align with the issues highlighted in this study, particularly regarding the dependence on human labor and inaccurate planning data.

In the *Data Understanding* phase, the first step is data selection, followed by data cleansing, where non-relevant items like cardboard are removed from the transaction data. This step is crucial to ensure the data used for analysis is accurate and meaningful, as supported by studies like (Nurmayanti et al., 2021), which emphasize the importance of data preprocessing for reliable analysis. Visualizing the data using bar graphs revealed that the most purchased item was Bottled Tamarind, with 3,771 units sold, accounting for 38% of transactions. Similarly, Arem-arem, Donuts, and Kroket were among the top-selling items, reflecting consumer preferences. This process mirrors findings in previous research, such as (Ha et al., 2011), where consumer behavior analysis was used to guide product bundling and stock management decisions, leading to more effective sales strategies. Thus, by addressing the 20% of key problems, and implementing automated systems supported by robust data analysis, this research aims to enhance productivity and profitability, building on the foundational work of earlier studies.

Result of Market Basket Analysis

From the association rules support count, it was found that rules occurring with a support level of 50% have a sufficient number of rules to be used as recommendations because they have a confidence level above 40%, which is higher than other support levels. The support value in the calculation results indicates that Item1 is purchased together with Item2 at a certain percentage rate of all transactions, while the confidence value signifies that the level of consumer confidence in buying Item1 together with Item2 is a certain percentage. By setting 40-50% minimum support and confidence values to ensure that the association rules generated only encompass significant and relevant purchase patterns. This helps avoid generating too many rules that may be useless or meaningless. Data Processing of association Rules is shown in Table 2 below:

Table 2. Association rules result of Ergo-Bundling System

No.	Premis	Conclusion	Confidence
1	Donat, Maffin	Arem_arem	0.4
2	Arem_arem, Maffin	Apem (conditional rules)	0.45
3	Arem_arem, KunirAsem_botol	Donat	0.45
4	Donat, KunirAsem_botol	Lemper (Conditional rules)	0.45
5	Misoa, Donat	Arem_arem	0.50

From those 2 itemset, a second data mining process was conducted to identify combination association rules that could be recommended to the company. To avoid rules containing the same items, conditional rules will be added to the system, namely for the wet bread product, which falls under the category of fast-expiring products that need to be sold immediately.

Compared to Rapid Miner Result of Association rules, the lift value shows that all of the rules have a relationship between Premise and Conclusion so the rules are good to be a bundling package food retailer.

Table 3. Association rules result of Rapid Miner

No.	Premis	Conclusion	Confidence	Lift
1	Donat, Maffin	Arem_arem	0.7799331103678929	2,4302E+15
2	Arem_arem, Maffin	Donat	0.855465884079237	2,2755E+16
3	Arem_arem, KunirAsem_botol	Donat	0.8868479059515062	2,3590E+16
4	Donat, Misoa	Arem_arem	0.7335109926715523	2,2856E+15
5	Arem_arem, Misoa	Donat	0.816160118606375	2,1710E+16

Table 3 explained about Association rules from Rapid Miner, Software of Data Analysis. Compared to rules that generated from Rapid Miner show that there are not significant differences in the results of the rules that occurred. The Minimum Confidence set at Level 0,8 and all of Lift value of the rules more than 1. A lift value more than 1 indicates that purchasing these items together has an independent relationship. In this way, lifts can provide insight into how strong the relationship between two items is and how relevant the association rules are in the context of Market Basket Analysis. So, the rules happened strong enough to represent the customer behavior of the retail.

This is supported by several previous studies that have stated the implementation of the Apriori Algorithm for data mining in enhancing business strategies provides faster analysis compared to other algorithms (Harshali, 2023). Additionally, another study (Fijriani et al., 2023) found that applying Market Basket Analysis using the Apriori algorithm in retail can help store owners understand and improve sales patterns. According pervious research (Sulianta et al., 2023), the results of data mining analysis using the Apriori Algorithm provide information to develop more effective business strategies, including inventory management, product promotions, and more accurate pricing decisions. Meanwhile (Kurniawan & Suwaryo, 2023) and (Qisman et al., 2021) concluded that the application of Apriori in retail can provide more effective sales recommendations to consumers. Therefore, the design of the Ergo-Bundling system, supported by the Apriori algorithm, can enhance productivity and business processes at Lestari Snack and Bakery.

Modeling Phase

1) Design Process

The Auto-Bundling System consists of 6 processes, including login, Menu Selection, Bundling Data Mining Process, Forecasting Data Mining Process, Storage Management, and Pricing Recommendation. There are two storage locations for the database, namely Localhost and Server. In the Auto-bundling system, the database is stored on Localhost and operated by the server. The Database server consists of both Database Frontend and Database Backend. All incoming data is automatically stored by the system into a specific path. For example, in process 5, Storage Management, when a user wants to review the bundling results from January 15, 2023, the user selects that date, and the server retrieves the bundling history data from the database backend for January 15, 2023, to be represented as the bundling results.

2) Result of Requirements analysis

Requirements analysis is a part of system analysis, which involves identifying the components needed for system design. There are four main steps: analyzing inputs, processes, outputs, and interfaces. The system requires Input data such as Registration Email, Username, Password, Sales ID, Time and Date, Item-set, Category Item-set, and Frequency/Quantity. Second, The Processes requires the system must Register new users with their name, email, username, and password. Allow users to log in with their username or email and password. Enable users to retrieve forgotten passwords via email. Let users select actions (prediction or bundling). Allow users to upload and re-upload sales data (CSV files) and Visualize predictions and bundling results through graphs or tables. Third, the system provides output of Sales Prediction Information for production decisions to optimize restocking and reduce losses, Bundling Package Information for promotional strategies to increase profit by selling products that need to be sold quickly. Last requires user interface by design the system includes interfaces for the Homepage, Registration, Login, Forgot Password, Upload Data Sales, Auto-Bundling Recommendations, and Forecasting Results.

Usability Analysis

1) Result of Efficiency

Effectiveness is measured based on the average success percentage of all respondents in the testing phase, with a total of 5 respondents from all specified user types. Data on the success rate of respondents, categorized by expertise such as Business Owners, Employees, Developers, and Designers, were collected using performance measurement techniques and calculated using the completion rate equation.

The Time to finish task called Time-Based Efficiency. In this study, Participants finished the task with 73% efficiency. P3 and P5 have 80% as the highest score to finished the task and the result show that Task 4 Search date history has the longest time to finished with 9,6 second per task. This is because there is no filter function applied on the page Search. Based on the result of Time-Based efficiency, The Ergo-Bundling System categorized as Quite effective. Application of the Data Mining Method is supported by several previous studies which state that system design using Data Mining can increase the productivity of a business (Braha, 2013; Y. Guo et al., 2020; Ngai et al., 2009).

2) Result of System Usability Scale Questionnaire

The selection of Usability test using SUS is based on statements from Sauro (2011) about SUS, explained that:

a) SUS is reliable. Users respond consistently to the scale items, and SUS has proven capable of detecting differences in smaller samples compared to other questionnaires.
b) SUS is valid. This means the tool measures what it is intended to measure.
c) SUS is not a diagnostic tool. It does not tell you what makes a system usable or not. It cannot diagnose specific elements that make the system usable.
d) SUS measures both the learnability and usability (5 elements) of a system.
e) SUS scores have a moderate correlation with performance testing of efficiency analysis.

Usability test started with respondents rate each statement on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree). The SUS score is calculated based on the responses to these questions to evaluate the overall usability of the system. The score is calculated using the following formula:

*SUS SCORE = ((R1 - 1) + (5 - R2) + (R3 - 1) + (5 - R4) + (R5 - 1) + (5 - R6) + (R7 - 1) + (5 - R8) + (R9 - 1) + (5 - R10)) * 2.5 .....(Equation 1)*

Based on the percentile score results of the SUS with score 74, the Ergo-Bundling system categorized as "Good" rating with an "Acceptable" Usability Level, which means that the usability test results are acceptable in representing the system as "Good" in Learnability, Memorability, Error, Efficiency, and Satisfaction.

Conclusion

This research paper discusses the challenges faced by retail entrepreneurs in selling various food products within a specific period of time and proposes an automated bundling system to overcome the problem. The system uses data mining techniques, specifically market basket analysis, to understand consumer behavior and identify patterns in purchasing products. The result of Market Basket Analysis shows the recommendation product consists of package with min Confidence level 40%, Package 1 Maffin, Donat, Arem_arem with price IDR9,000. Package 2 Arem_arem, Tamarin Juice, Lemper with price IDR 10,000. Package 3 Arem_arem, Maffin and Apemwith price IDR 8,500. Package 4 Misoa, Donut, Apem with price IDR 8,000. And Package 5 Donut, Tamarin Juice, Arem-arem with price IDR 10,500. The study also incorporates usability and ergonomics concepts to design a user-friendly and efficient bundling system. The results show that the automated system is “Quite effective” in predicting stock levels, generating bundling recommendations, and improving Efficiency, Therefore, results of SUS explain that Ergo-Bundling system is “Good” and Acceptable to represent the usability of elements Learnability, Memorability, Error and Satisfaction. This research provides valuable insights for retail businesses in optimizing product sales strategies and management.

BIBLIOGRAPHY

Braha, D. (2013). *Data mining for design and manufacturing: methods and applications*. 3. Springer Science & Business Media.

Fijriani, M., Hayati, U., Dwilestari, G., Rizki Rinaldi, A., & Faturrohman, F. (2023). Implementasi Market Basket Analysis Pada Toko Retail Menggunakan Algoritma Apriori. *Kopertip : Jurnal Ilmiah Manajemen Informatika Dan Komputer*, *7*(1). https://doi.org/10.32485/kopertip.v7i1.252

Gridach, M. (2020). Hybrid deep neural networks for recommender systems. *Neurocomputing*, *413*. https://doi.org/10.1016/j.neucom.2020.06.025

Griva, A., Bardaki, C., Pramatari, K., & Papakiriakopoulos, D. (2018). Retail business analytics: Customer visit segmentation using market basket data. *Expert Systems with Applications*, *100*, 1–16.

Guo, X., Zheng, S., Yu, Y., & Zhang, F. (2021). Optimal bundling strategy for a retail platform under agency selling. *Production and Operations Management*, *30*(7), 2273–2284.

Guo, Y., Wang, N., Xu, Z.-Y., & Wu, K. (2020). The internet of things-based decision support system for information processing in intelligent manufacturing using data mining technology. *Mechanical Systems and Signal Processing*, *142*, 106630.

Ha, J., Kambe, M., & Pe, J. (2011). Data Mining: Concepts and Techniques. In *Data Mining: Concepts and Techniques*. https://doi.org/10.1016/C2009-0-61819-5

Halim, S., Octavia, T., & Alianto, C. (2019). Designing facility layout of an amusement arcade using market basket analysis. *Procedia Computer Science*, *161*. https://doi.org/10.1016/j.procs.2019.11.165

Hameli, MSc. K. (2018). A Literature Review of Retailing Sector and Business Retailing Types. *ILIRIA International Review*, *8*(1). https://doi.org/10.21113/iir.v8i1.386

Harshali, P. (2023). Enhancing Retail Strategies through Apriori, ECLAT& FP Growth Algorithms in Market Basket Analysis. *International Journal on Recent and Innovation Trends in Computing and Communication*, 11(9), 3831–3838. https://doi.org/10.17762/ijritcc.v11i9.9637

Korfiatis, N., Stamolampros, P., Kourouthanassis, P., & Sagiadinos, V. (2019). Measuring service quality from unstructured data: A topic modeling application on airline passengers' online reviews. *Expert Systems with Applications*, *116*. https://doi.org/10.1016/j.eswa.2018.09.037

Kurniawan, A., & Suwaryo, N. (2023). Analysis of the Apriori Algorithm for Enhancing Retail Product Staple Sales Recommendations. *International Journal Software Engineering and Computer Science (IJSECS)*, *3*(3). https://doi.org/10.35870/ijsecs.v3i3.1877

Kutuzova, T., & Melnik, M. (2018). Market basket analysis of heterogeneous data sources for recommendation system improvement. *Procedia Computer Science*, *136*. https://doi.org/10.1016/j.procs.2018.08.263

Lagorio, A., & Pinto, R. (2021). Food and grocery retail logistics issues: A systematic literature review. *Research in Transportation Economics*, *87*. https://doi.org/10.1016/j.retrec.2020.100841

Leedy, P. D., & Ormrod, J. E. (2018). Practical research. Planning and design. Planning and design (11th ed.). *Journal of Applied Learning & Teaching*, *1*(2).

Lessmann, S., Haupt, J., Coussement, K., & De Bock, K. W. (2021). Targeting customers for profit: An ensemble learning framework to support marketing decision-making. *Information Sciences*, *557*. https://doi.org/10.1016/j.ins.2019.05.027

Ngai, E. W. T., Xiu, L., & Chau, D. C. K. (2009). Application of data mining techniques in customer relationship management: A literature review and classification. *Expert Systems with Applications*, *36*(2), 2592–2602.

Nurmayanti, W. P., Sastriana, H. M., Rahim, A., Gazali, M., Hirzi, R. H., Ramdani, Z., & Malthuf, M. (2021). Market Basket Analysis with Apriori Algorithm and Frequent Pattern Growth (Fp-Growth) on Outdoor Product Sales Data. *International Journal of Educational Research & Social Sciences*, *2*(1). https://doi.org/10.51601/ijersc.v2i1.45

Pearlmutter, D., Theochari, D., Nehls, T., Pinho, P., Piro, P., Korolova, A., Papaefthimiou, S., Mateo, M. C. G., Calheiros, C., Zluwa, I., Pitha, U., Schosseler, P., Florentin, Y., Ouannou, S., Gal, E., Aicher, A., Arnold, K., Igondová, E., & Pucher, B. (2020). Enhancing the circular economy with nature-based solutions in the built urban environment: Green building materials, systems and sites. *Blue-Green Systems*, *2*(1). https://doi.org/10.2166/bgs.2019.928

Qisman, M., Rosadi, R., & Abdullah, A. S. (2021). Market basket analysis using apriori algorithm to find consumer patterns in buying goods through transaction data (case study of Mizan computer retail stores). *Journal of Physics: Conference Series*, *1722*(1). https://doi.org/10.1088/1742-6596/1722/1/012020

Roggeveen, A. L., Nordfält, J., & Grewal, D. (2016). Do Digital Displays Enhance Sales? Role of Retail Format and Message Content. *Journal of Retailing*, *92*(1). https://doi.org/10.1016/j.jretai.2015.08.001

Roggeveen, A. L., & Sethuraman, R. (2020). Customer-Interfacing Retail Technologies in 2020 & Beyond: An Integrative Framework and Research Directions. In *Journal of Retailing* (Vol. 96, Issue 3). https://doi.org/10.1016/j.jretai.2020.08.001

Sarker, I. H., Kayes, A. S. M., & Watters, P. (2019). Effectiveness analysis of machine learning classification models for predicting personalized context-aware smartphone usage. *Journal of Big Data*, *6*(1), 1–28.

Schneider, F., & Eriksson, M. (2020). Food waste (and loss) at the retail level. In *Routledge Handbook of Food Waste*. https://doi.org/10.4324/9780429462795-10

Sulianta, F., Madsu, Y. M., Syukriyah, Y., & Fahrezi, M. M. (2023). Konsumen Sebagai Co-Creation untuk Menentukan Strategi Bisnis Menggunakan Algoritma Apriori pada Industri Retail Skala Internasional. *Jurnal Sistem Dan Teknologi Informasi (JustIN)*, *11*(3). https://doi.org/10.26418/justin.v11i3.67377

Vidhya, R. V., Tushar, S., & Swapnil, W. (2019). A Review on Online Super-market Models And Customer Interpretations. *Journal of Emerging Technologies and Innovative Research*.