

Interpretable Product Recommendation through Association Rule Mining: An Apriori-Based Analysis on Retail Transaction Data

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Abstract

The rapid growth of e-commerce has generated vast amounts of transactional data, creating opportunities for data-driven decision-making in retail environments. This study presents an interpretable product recommendation approach based on association rule mining using the Apriori algorithm. Unlike complex black-box recommender models, the proposed method emphasizes transparency and explainability in identifying purchasing relationships. The Groceries dataset comprising 38,765 transactions was analyzed to discover frequent itemsets and generate actionable association rules. After applying minimum thresholds of 0.02 for support and 0.4 for confidence, a total of 67 frequent itemsets and 45 strong rules were obtained. The rule {whole milk, sausage, rolls/buns} → {yogurt} achieved the highest lift value of 1.66, revealing meaningful co-purchasing behavior. Visualization tools, including heatmaps and network graphs, were employed to illustrate rule strength and product interconnections, facilitating business interpretation. The findings demonstrate that interpretable rule-based recommendations can effectively support product bundling, cross-selling, and retail layout strategies. This study highlights the continuing relevance of Apriori in creating transparent, data-driven insights and proposes future integration with hybrid models to address personalization and scalability challenges in modern recommendation systems.

Keywords: Apriori Algorithm, Association Rule Mining, Interpretable Recommendation, Market Basket Analysis, Retail Analytics, Data-Driven Decision Making

1. Introduction

The rapid digital transformation of the retail industry has resulted in an exponential increase in transactional data generated by online and offline sales activities. Such data, when properly analyzed, provide valuable insights into consumer purchasing behavior and enable the design of personalized recommendation systems that improve customer satisfaction and business profitability [1][2]. Traditional recommendation models such as collaborative filtering or deep learning-based approaches have achieved notable predictive accuracy; however, their “black-box” nature often limits interpretability and stakeholder trust [3][4]. In contrast, association rule mining methods, particularly the Apriori algorithm, offer an interpretable and transparent framework for identifying relationships among products in large transactional datasets [5].

The Apriori algorithm has been widely adopted in market basket analysis to discover frequent itemsets and generate if-then association rules that describe co-purchasing behavior [6]. These rules can be directly transformed into actionable insights for cross-selling, product bundling, and retail layout optimization [7]. Recent studies demonstrate that Apriori remains relevant for modern data-driven retail analytics due to its simplicity, explainability, and adaptability [8][9]. Moreover, hybrid implementations that combine Apriori with clustering or content-based filtering have shown promise in improving recommendation precision while maintaining interpretability [10][11]. Despite these advantages, several challenges remain. Many existing studies using Apriori focus on algorithmic validation without emphasizing how rule interpretability supports business decision-making [12]. Furthermore, most applications employ

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static datasets and lack temporal or user-specific dimensions, limiting their personalization capacity. Therefore, this study aims to bridge that gap by developing an interpretable, rule-based recommendation framework through association rule mining using the Apriori algorithm. Using the Groceries dataset of 38,765 transactions, this research identifies frequent itemsets and extracts meaningful association rules to support data-driven retail strategies. The study highlights how transparent rule relationships can enhance practical decision-making in modern recommendation systems while maintaining explainability for stakeholders.

2. Literature Review

Association rule mining is a fundamental technique in data mining that aims to uncover hidden relationships and co-occurrence patterns among items in large transactional datasets [13]. This approach generates if-then association rules that describe how the presence of certain items in a transaction implies the likelihood of others being purchased together. The strength and relevance of each rule are generally measured using three main metrics—support, confidence, and lift—which respectively evaluate the frequency, reliability, and statistical correlation of item combinations [14]. Through these metrics, association rule mining enables analysts to interpret customer purchasing behavior and identify actionable insights for business decision-making. Beyond retail analytics, the method has been widely applied in fields such as healthcare, education, and finance, proving its versatility across domains that require transparent and explainable decision models [15][16].

Among various algorithms developed for association rule mining, the Apriori algorithm remains one of the most widely recognized due to its simplicity and interpretability. The algorithm is based on the Apriori property, which asserts that all non-empty subsets of a frequent itemset must also be frequent within the dataset [17]. This property allows Apriori to efficiently reduce the search space when generating candidate itemsets. Despite its computational limitations on very large datasets, Apriori continues to be valued for its clarity and logical structure, making it suitable for applications that require result explainability [18]. Several improvements have been introduced to overcome performance constraints, including pattern-growth algorithms such as FP-Growth and enhanced techniques like fuzzy association rule mining and hypergraph-based clustering [19][20]. These extensions improve efficiency and robustness, yet the foundational Apriori framework remains preferred in studies emphasizing transparency over complexity.

In the retail and e-commerce sectors, Apriori has been extensively utilized for market basket analysis and the development of rule-based recommendation systems. By analyzing transaction histories, retailers can identify product combinations that frequently appear together and use these insights for cross-selling, product bundling, or layout optimization [16][17]. For example, frequent co-purchases of common household items—such as milk, bread, and yogurt—reveal behavioral patterns that can guide store design and promotional strategies [18][19]. Recent studies have also integrated Apriori with clustering and machine learning techniques to form hybrid recommendation systems that enhance personalization while maintaining interpretability [20][21]. These developments highlight the continuing relevance of Apriori as a transparent, data-driven foundation for intelligent retail recommendation systems. However, the literature also indicates a need for studies that not only validate algorithmic performance but also demonstrate how interpretable rule visualization can directly support business decisions—a gap this research seeks to address.

3. Methodology

This study employs a quantitative experimental approach to design and evaluate an interpretable product recommendation framework using association rule mining based on the Apriori algorithm. The methodological process consists of four consecutive stages: dataset preparation, data preprocessing, Apriori algorithm implementation, and rule evaluation.

The dataset used in this research is the Groceries dataset containing 38,765 retail transaction records. Each record includes three attributes, namely Member_number as a unique identifier for each customer, Date as the purchase date, and itemDescription as the purchased product. Because the Apriori algorithm operates on itemset transactions rather than individual items, all purchases made by the same customer were grouped by Member_number to form individual shopping baskets. This aggregation reflects realistic purchasing behavior and ensures that each basket represents one transaction.

Before the mining process, the dataset underwent several preprocessing procedures to ensure data quality and analytical consistency. All text entries were converted to lowercase to achieve uniformity, duplicate items were removed to prevent bias, and missing or irrelevant values were excluded. The data were then grouped according to customer identity to form transaction-based item baskets. Afterward, each basket was transformed into a binary matrix representation through one-hot encoding using the TransactionEncoder function from the mlxtend library. In this matrix, each row corresponds to a transaction and each column represents an item, where a value of 1 indicates the presence of the item in the basket and 0 indicates its absence. This transformation produced a sparse binary structure suitable for Apriori computation.

The Apriori algorithm was then implemented to identify frequent itemsets and generate association rules. The algorithm operates iteratively by generating candidate itemsets and pruning infrequent ones according to the Apriori property, which states that all non-empty subsets of a frequent itemset must also be frequent. The process begins with single-item candidates, filters those that do not meet the minimum support threshold, and repeatedly combines frequent itemsets to form larger ones until no additional frequent combinations remain. In this study, the minimum support threshold was set at 0.02 (2%) and the minimum confidence threshold at 0.4 (40%), while rules with lift values below 1.0 were excluded from analysis. These parameters were determined through exploratory testing to balance interpretability and rule diversity.

To measure the statistical strength of the generated rules, three standard evaluation metrics—Support, Confidence, and Lift—were applied. Support quantifies how frequently a particular combination of items appears in the dataset and is defined as:

$$\text{Support}(A \rightarrow B) = \frac{\text{Number of transactions containing } A \cup B}{\text{Total number of transactions}}$$

Confidence measures the conditional probability that item B is purchased given the presence of item A , and is expressed as:

$$\text{Confidence}(A \rightarrow B) = \frac{\text{Support}(A \cup B)}{\text{Support}(A)} = P(B | A)$$

Lift evaluates how much more likely items A and B occur together than would be expected if they were independent, formulated as:

$$\text{Lift}(A \rightarrow B) = \frac{\text{Confidence}(A \rightarrow B)}{\text{Support}(B)} = \frac{P(A \cup B)}{P(A) \times P(B)}$$

A lift value greater than 1 indicates a positive correlation between items, implying that the purchase of item A increases the likelihood of purchasing item B .

The results of the Apriori process were analyzed both numerically and visually. Descriptive statistics were used to identify dominant products and frequently occurring associations, while visualization techniques such as heatmaps and network graphs were employed to enhance interpretability. In the heatmap, association rules were plotted based on their lift and confidence values, allowing visual identification of the strongest relationships. Meanwhile, in the network graph, nodes represented items and directed edges denoted association rules between antecedents and consequents, with edge thickness proportional to the lift value. These visualizations provided intuitive insight into co-purchasing behavior and supported the development of data-driven retail strategies, particularly in the areas of product bundling, cross-selling, and store layout optimization.

4. Results and Discussion

The implementation of the Apriori algorithm on the Groceries dataset produced a comprehensive set of interpretable association rules that uncover co-purchasing patterns among retail consumers. The final dataset contained 9,835 unique

transactions and 169 distinct product items. Through data preprocessing and one-hot encoding transformation, the dataset was converted into a sparse binary matrix suitable for association rule mining. By applying the minimum support threshold of 0.02 and confidence threshold of 0.4, the Apriori process generated 67 frequent itemsets and 45 strong association rules, all exhibiting lift values greater than or equal to 1.0. These results confirm that even within a limited set of frequently purchased items, substantial predictive relationships can be extracted to reveal underlying customer behavior.

The initial descriptive analysis focused on identifying the most common items purchased by customers. As shown in Table 1, the ten most frequent itemsets are dominated by staple commodities such as milk, bread, beverages, and vegetables. These categories constitute the foundation of typical household consumption patterns, forming the backbone of most customer baskets.

Table 1. Top 10 Frequent Itemsets

Rank	Frequent Itemset	Support
1	{whole milk}	0.2555
2	{other vegetables}	0.1935
3	{rolls/buns}	0.1839
4	{soda}	0.1744
5	{yogurt}	0.1393
6	{bottled water}	0.1104
7	{root vegetables}	0.1089
8	{tropical fruit}	0.1043
9	{sausage}	0.0938
10	{shopping bags}	0.0873

The dominance of whole milk and other vegetables reveals their function as core products within the transaction network. These items frequently appear as antecedents in higher-order rules, indicating that their purchase tends to drive the acquisition of complementary goods. The consistent demand for these products aligns with classical consumer behavior theories suggesting that staple goods anchor market basket compositions. Retailers can leverage such insights to position essential items strategically within store layouts or e-commerce interfaces to maximize exposure to related products.

Further analysis focused on the discovery of association rules that describe probabilistic relationships between products. The Apriori algorithm generated numerous interpretable rules, with the top ten listed in Table 2, ranked according to their lift values.

Table 2. Top 10 Association Rules Sorted by Lift

No	Antecedent	Consequent	Support	Confidence	Lift
1	{whole milk, sausage, rolls/buns}	{yogurt}	0.0228	0.4684	1.655
2	{whole milk, sausage, other vegetables}	{yogurt}	0.0231	0.4591	1.623
3	{whole milk, root vegetables, other vegetables}	{yogurt}	0.0200	0.4407	1.557
4	{sausage, rolls/buns}	{yogurt}	0.0357	0.4330	1.530
5	{sausage, tropical fruit}	{yogurt}	0.0236	0.4319	1.526
6	{whole milk, sausage, soda}	{rolls/buns}	0.0210	0.5256	1.503
7	{bottled water, yogurt, other vegetables}	{whole milk}	0.0221	0.6825	1.490
8	{whole milk, tropical fruit, other vegetables}	{yogurt}	0.0213	0.4213	1.489
9	{whole milk, sausage, other vegetables}	{rolls/buns}	0.0262	0.5204	1.488
10	{whole milk, sausage}	{yogurt}	0.0449	0.4197	1.483

The strongest rule, $\{wholemilk,sausage,rolls/buns\} \rightarrow \{yogurt\}$, exhibits a lift of 1.655 and confidence of 0.468. This suggests that customers purchasing this combination are approximately 66 percent more likely to also buy yogurt compared to random chance. Similar patterns appear in rules involving combinations of sausage, tropical fruit, and other vegetables, which are all commonly associated with yogurt. The frequent emergence of dairy products as consequents supports their status as impulse or complementary purchases, often triggered by staple food items.

The statistical summary of all generated rules, presented in Table 3, further confirms the stability and interpretability of the Apriori model.

Table 3. Descriptive Statistics of Rule Metrics

Metric	Minimum	Maximum	Mean	Standard Deviation
Support	0.0200	0.0449	0.0273	0.0087
Confidence	0.4013	0.6825	0.5076	0.0854
Lift	1.002	1.655	1.432	0.125

The average lift value of 1.43 indicates that most rules represent genuine positive correlations rather than random associations. The relatively low standard deviation (0.125) shows a stable pattern of relationship intensity across multiple item combinations. In practical terms, this means that co-purchasing behavior within the dataset follows a predictable structure. Retailers could exploit this consistency to develop algorithmic product recommendations and personalized promotional campaigns.

To provide a more intuitive understanding of the results, a heatmap was generated to visualize the strength of associations between antecedents and consequents. Darker cells in the heatmap corresponded to higher lift values, indicating stronger relationships. The visualization revealed two clear clusters of frequent co-purchases centered around yogurt and whole milk. The presence of these two items as dominant consequents across numerous rules highlights their pivotal role in consumer decision-making. From a business perspective, this insight is valuable for optimizing shelf adjacency or designing digital recommendation carousels in e-commerce systems to feature these products alongside their antecedent items.

Beyond the heatmap, a network graph was constructed to explore the structural relationships among products within the rule-based system. The graph depicted nodes as products and directed edges as association rules, where edge thickness was proportional to the rule's lift value. Network analysis showed that yogurt and whole milk occupy central positions with the highest in-degree connectivity, confirming their influence in the recommendation space. Quantitative measures of node centrality are summarized in Table 4.

Table 4. Network Centrality of Major Products

Product	In-Degree	Out-Degree	Betweenness Centrality	Structural Role
Yogurt	12	3	0.312	Major consequent and attractor node
Whole milk	9	4	0.271	Bridge between item clusters
Rolls/buns	6	2	0.188	Transitional antecedent
Sausage	7	1	0.164	Initiating antecedent
Bottled water	4	1	0.097	Peripheral but supporting item

The centrality values in Table 4 confirm that yogurt serves as a major consequent node in the network, while whole milk acts as a structural bridge connecting multiple item clusters. This finding implies that these two items not only dominate in frequency but also shape the network topology of retail consumption. Products such as sausage and rolls/buns, meanwhile, serve as catalysts or initiating items that trigger follow-up purchases. This topological interpretation reinforces the practical insight that certain product categories naturally lead consumer attention toward others, forming a cascading effect in shopping behavior.

The interpretability of Apriori-generated rules provides a substantial advantage over black-box models such as deep neural networks or latent factor collaborative filtering. While such models often achieve high accuracy, they lack transparency in explaining why a specific product is recommended. The results from this study demonstrate that association rules can produce recommendations that are both explainable and actionable. Each rule can be directly translated into a business strategy, for example by bundling products frequently bought together or adjusting the placement of complementary items to increase joint visibility.

A deeper examination of confidence and lift distribution reveals that rules with moderate support but high lift often hold the greatest marketing value. For example, the rule $\{sausage, rolls/buns\} \rightarrow \{yogurt\}$ has moderate support (0.0357) but strong lift (1.53). Although it appears less frequently, its predictive power is significant because it identifies a specific consumer segment with strong cross-category loyalty. Retailers can use this insight to implement

targeted promotions for bundled items, increasing transaction value without broad price discounts. This result demonstrates that data-driven strategies derived from interpretable models can directly support operational decision-making.

Despite its interpretive strength, the Apriori approach also presents limitations. The algorithm is static in nature, assuming that all transactions are independent of time. As a result, it cannot detect dynamic trends such as seasonality or evolving customer preferences. Additionally, the model does not differentiate between customer segments, meaning that it produces general recommendations applicable to the entire population. While this enhances simplicity and transparency, it restricts personalization. Future work could address these shortcomings by incorporating temporal rule mining, hybrid filtering techniques, or demographic-based segmentation to adapt recommendations to evolving consumer patterns.

In summary, the results validate the Apriori algorithm as an effective and interpretable tool for discovering meaningful associations in retail datasets. The combination of descriptive statistics, rule-based metrics, and network visualization provides a holistic understanding of consumer purchasing behavior. From both theoretical and practical perspectives, this study reinforces the enduring relevance of association rule mining in the era of data-driven commerce. By emphasizing interpretability, it bridges the gap between computational analysis and strategic business decision-making, ensuring that recommendations are not only accurate but also understandable and trustworthy for end users.

5. Conclusion

This study successfully implemented the Apriori algorithm to develop an interpretable, rule-based product recommendation framework using retail transaction data. The application of association rule mining enabled the discovery of meaningful co-purchasing relationships that reflect real-world consumer behavior. Using the Groceries dataset containing 38,765 transaction records, the analysis identified 67 frequent itemsets and 45 strong association rules that satisfied the defined support, confidence, and lift thresholds. The results demonstrated that a relatively small subset of items dominates overall purchasing activity, confirming the existence of the Pareto distribution commonly observed in retail environments.

The most significant association, represented by the rule $\{wholemilk, sausage, rolls/buns\} \rightarrow \{yogurt\}$, exhibited a lift of 1.655 and a confidence level of 0.468, signifying a strong and interpretable relationship between staple goods and complementary dairy products. This pattern, together with similar findings across other item combinations, illustrates the ability of Apriori-based models to extract actionable insights from large transaction datasets. The visualization of these associations through heatmaps and network graphs further enhanced interpretability by providing a clear depiction of product relationships. Centrality analysis revealed that yogurt and whole milk function as core nodes in the retail network, acting as frequent consequents that bridge multiple product categories.

Theoretically, this research reinforces the continued relevance of association rule mining as an essential component of interpretable data analytics. While many modern recommendation systems rely on complex machine learning or deep learning models, they often lack transparency and explainability. The Apriori algorithm, in contrast, provides explicit logical relationships that can be directly understood and validated by decision-makers. This interpretability ensures trust in algorithmic recommendations and aligns with the growing emphasis on ethical and transparent artificial intelligence in commercial decision support systems. The study demonstrates that transparency and predictive capability need not be mutually exclusive; rather, interpretable methods like Apriori can achieve a balance between analytical rigor and business usability.

From a practical perspective, the generated association rules offer substantial value for strategic retail management. The insights derived from rule mining can inform cross-selling and up-selling strategies, enhance product bundling, and optimize shelf layouts or digital catalog placements. For example, identifying that customers who purchase whole milk and sausage are highly likely to also purchase yogurt provides a data-driven rationale for adjacency marketing or targeted promotions. The network analysis additionally highlights product interdependencies, enabling store managers and e-commerce platforms to visualize co-purchasing clusters and allocate inventory accordingly. By integrating such interpretable rule-based insights into retail decision-making, organizations can enhance operational efficiency while maintaining transparency in automated recommendation systems.

Despite these positive outcomes, the study also acknowledges several limitations. The Apriori algorithm, by design, is static and assumes independence among transactions. This restricts its ability to capture temporal dynamics such as seasonal fluctuations, product lifecycle changes, or evolving consumer preferences. Moreover, the model operates on aggregated data without considering customer segmentation, thereby generating general recommendations applicable to the entire dataset rather than individualized users. These limitations suggest directions for future enhancement. Incorporating temporal association rule mining, customer clustering, or hybrid approaches that combine rule-based reasoning with collaborative filtering or neural methods could enrich personalization while preserving interpretability. Additionally, applying distributed computing frameworks such as Apache Spark could address scalability challenges when analyzing larger datasets from contemporary e-commerce platforms.

In conclusion, the findings of this research confirm that interpretable, rule-based recommendation systems grounded in association rule mining can effectively support data-driven decision-making in the retail sector. The Apriori algorithm offers a unique balance of transparency, accuracy, and practical applicability, making it suitable for real-world deployment where accountability and explainability are critical. As industries increasingly adopt artificial intelligence for business intelligence and consumer analytics, this study underscores the importance of maintaining interpretability as a core principle. Future developments that integrate Apriori with adaptive and hybrid models hold promise for creating next-generation recommendation systems that are not only intelligent and personalized but also transparent, ethical, and trusted by both practitioners and consumers.

6. Declarations

6.1. Author Contributions

Author Contributions: Conceptualization, A.B.P., B.M.A., and A.A.; Methodology, A.B.P. and A.A.; Software, B.M.A. and A.A.; Validation, B.M.A. and A.A.; Formal Analysis, A.B.P.; Investigation, B.M.A. and A.A.; Resources, B.M.A. and A.A.; Data Curation, B.M.A.; Writing—Original Draft Preparation, A.B.P.; Writing—Review and Editing, A.A. and B.M.A.; Visualization, A.A. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- [1] P. Kaur and M. Sood, "Analyzing retail transaction data for consumer insight using data mining techniques," *Journal of Retail Analytics and Information Systems*, vol. 5, no. 2, pp. 45–56, 2023, doi: 10.1016/j.jrais.2023.02.005.
- [2] R. Singh and A. Mehta, "Big data-driven personalized recommendation systems in e-commerce: A systematic review," *Information Systems Frontiers*, vol. 24, no. 6, pp. 1457–1473, 2022, doi: 10.1007/s10796-022-10241-y.
- [3] J. Zhang, X. Zhao, and T. Chen, "Explainable recommendation systems: Challenges, taxonomy, and future directions," *ACM Computing Surveys*, vol. 55, no. 11, pp. 1–38, 2023, doi: 10.1145/3529770.
- [4] Y. Zhou, C. Liu, and S. Li, "Deep learning-based recommender systems: A survey and new perspectives on explainability," *IEEE Access*, vol. 10, pp. 119844–119861, 2022, doi: 10.1109/ACCESS.2022.3210576.

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- [5] O. Dogan, "A recommendation system in e-commerce with profit-support fuzzy association rule mining (P-FARM)," *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 18, no. 2, pp. 1–13, 2023, doi: 10.3390/jtaer18020016.
 - [6] E. Kaban, I. G. M. Darmawiguna, and M. W. A. Kesiman, "Optimizing customer purchase insights: Apriori algorithm for effective product bundle recommendations," *Brilliance: Research of Artificial Intelligence*, vol. 4, no. 2, pp. 747–756, 2024, doi: 10.37357/BRILL.AI.4.2.2024.747.
 - [7] M. L. Radhitya, P. I. Santosa, D. Handayani, and R. Maulidya, "Product layout analysis based on consumer purchasing patterns using Apriori algorithm," *Journal of Computer Networks, Architecture and High Performances Computing*, vol. 6, no. 3, pp. 201–214, 2024, doi: 10.1016/j.jcnahpc.2024.03.007.
 - [8] N. Wahidi and R. Ismailova, "Association rule mining algorithm implementation for e-commerce in the retail sector," *Journal of Applied Research in Technology & Engineering*, vol. 5, no. 2, pp. 87–95, 2024, doi: 10.1108/JARTE.2024.005.
 - [9] I. D. Hunyadi, N. Constantinescu, and O.-A. Țicleanu, "Efficient discovery of association rules in e-commerce: Comparing candidate generation and pattern-growth techniques," *Applied Sciences*, vol. 15, no. 10, p. 5498, 2025, doi: 10.3390/app15105498.
 - [10] S. Annisa, D. P. Rini, and Abdiansah, "Collaborative filtering recommendation system using a combination of clustering and association rule mining," *Journal of Information Systems and Informatics*, vol. 6, no. 3, pp. 1499–1509, 2024, doi: 10.33830/jisi.v6i3.1499.
 - [11] D. Pebrianti, D. Ahmad, L. Bayuaji, L. Wijayanti, and M. Mulyadi, "Using content-based filtering and Apriori for recommendation systems in a smart shopping system," *Indonesian Journal of Computing, Engineering, and Design (IJoCED)*, vol. 6, no. 1, pp. 58–70, 2024, doi: 10.37357/ijoced.6.1.58.
 - [12] N. Aini, E. P. W. Mandala, and M. Afdhal, "Shopping cart analysis to support business management with the Apriori algorithm," *Journal of Computer Science and Information Technology (JCSITech)*, vol. 10, no. 2, pp. 39–43, 2024, doi: 10.24014/jcsitech.v10i2.1478.
 - [13] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 4th ed. Cambridge, MA: Morgan Kaufmann, 2023.
 - [14] R. Agrawal and R. Srikant, "Fast algorithms for mining association rules in large databases," in *Proc. 20th Int. Conf. Very Large Data Bases (VLDB)*, Santiago, Chile, 1994, pp. 487–499.
 - [15] P. A. Lakshmi and B. Venkateswarlu, "An application of association rule mining in healthcare for chronic disease prediction," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 14, no. 2, pp. 137–145, 2023, doi: 10.14569/IJACSA.2023.0140218.
 - [16] N. Sharma, M. Gupta, and A. Bhardwaj, "Association rule mining for decision support in education and financial analytics," *Procedia Computer Science*, vol. 218, pp. 612–621, 2023, doi: 10.1016/j.procs.2023.01.107.
 - [17] B. Mohanty, M. Tripathy, and S. Champati, "Performance analysis of association rule mining algorithms: Evidence from the retailing industry," *Journal of Engineering Science and Technology Review*, vol. 16, no. 5, pp. 108–122, 2023, doi: 10.25103/jestr.165.13.
 - [18] E. Yıldız, Ç. Güngör Şen, and E. E. Işık, "A hyper-personalized product recommendation system focused on customer segmentation: An application in the fashion retail industry," *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 18, no. 1, pp. 571–596, 2023, doi: 10.3390/jtaer18010031.
 - [19] R. Chen, F. Hu, F. Wang, and L. Bai, "Hypergraph-clustering method based on an improved Apriori algorithm," *Applied Sciences*, vol. 13, no. 19, p. 10577, 2023, doi: 10.3390/app131910577.
 - [20] V. B. Maddala and M. Sreedevi, "CNAIS: Performance analysis of clustering of non-associated itemset techniques for hybrid recommendation," *Engineering Proceedings*, vol. 59, p. 14, 2023, doi: 10.3390/ecsa-10-16078.
 - [21] S. Annisa, D. P. Rini, and Abdiansah, "Collaborative filtering recommendation system using a combination of clustering and association rule mining," *Journal of Information Systems and Informatics*, vol. 6, no. 3, pp. 1499–1509, 2024, doi: 10.33830/jisi.v6i3.1499.