

THE INFLUENCE OF MARKETING MIX ON CONSUMER PURCHASE PATTERNS USING THE APRIORI DATA MINING ALGORITHM

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ABSTRACT

The increasing volume of sales transaction data in retail and marketplace environments presents an opportunity to extract valuable insights for decision-making; however, such data are often underutilized. This study aims to analyze consumer purchasing patterns using the Apriori algorithm and to examine the influence of the marketing mix (product, price, place, and promotion) on purchasing decisions that shape these patterns. This research employs a quantitative approach by integrating data mining and statistical analysis. Transaction data are processed using the Apriori algorithm through RapidMiner to generate association rules and identify frequent itemsets. In addition, questionnaire data are analyzed using multiple linear regression to evaluate the effect of marketing mix variables on purchasing decisions. The results show that product, price, place, and promotion simultaneously have a significant effect on purchasing decisions. Partially, product ($t = 2.622$; $p = 0.011$), price ($t = 4.738$; $p = 0.000$), and place/distribution ($t = 2.239$; $p = 0.029$) have a significant positive effect, while promotion does not have a significant effect ($t = 1.486$; $p = 0.143$). The Apriori analysis reveals dominant purchasing patterns that can be translated into practical marketing strategies, such as product bundling and layout optimization. This study contributes by integrating association rule mining with marketing mix analysis to provide both predictive patterns and explanatory insights. However, the findings should be interpreted with caution due to data limitations, including a relatively small sample size ($n = 148$) and a short observation period of three months during peak season, which may limit generalizability. Despite these constraints, the results offer practical implications for optimizing marketing strategies and contribute theoretically to interdisciplinary research in data mining and consumer behavior.

Keywords : *Algorithm Apriori, Association Rules, Data Mining, Marketing Mix, Rapid Miner.*

1. Introduction

The increasing volume and need for data processing worldwide has led to rapid developments in data processing technology, driven by the ever-increasing demand for processed data (L. Chen & Zhu, 2022; Hassan et al., 2023; Silva et al., 2019). In the business aspect, especially in the field of sales, a businessman will collect various information to obtain maximum profits and minimize losses (Nath Sharma & Sadagopan, 2022). Market forecasting is both challenging and crucial for investors, traders, and researchers (Lin & Lobo Marques, 2024). Therefore, processing large amounts of data requires a system or method that can produce accurate information effectively and efficiently.

Two approaches that are increasingly being studied in parallel are the Apriori algorithm, a data mining technique based on association rules, and the marketing mix, traditionally known through the 4Ps framework—Product, Price, Place, and Promotion. The Apriori algorithm has been widely applied to uncover frequent itemsets and purchasing patterns in transactional data, enabling better decision-making in retail and e-commerce contexts (Naeem, 2023; Satria, 2023; Zhao, 2021). Meanwhile, the marketing mix remains a fundamental framework for understanding factors influencing consumer purchasing decisions and shaping business strategies (Alghanam, 2022; Lu, 2022). The integration of these two approaches provides a more comprehensive perspective by combining data-driven pattern discovery with strategic marketing analysis.

Although both share the same orientation, namely improving sales performance and customer satisfaction, studies that explicitly integrate the two approaches methodologically are still very limited.

Amelia et al. (2025) and Fernanda et al. (2023) demonstrated that the Apriori algorithm effectively generates valid association rules from transaction data, enabling the identification of frequent product combinations as a basis for sales strategy. Similarly, Iskandar et al. (2024) extended its application to product bundling strategies, linking computational analysis with marketing decisions, although without explicit integration of the marketing mix framework. On a broader scale, Maulana and Rohman (2025) applied Apriori to develop a product recommendation system in an agricultural e-marketplace, showing its adaptability across digital commerce contexts. Al Ghozali and Wibowo (2023) further highlighted their flexibility by applying association rule analysis to identify optimal policy mixes, providing a methodological basis relevant to marketing strategy formulation.

As consumer behavior becomes more complex, recent studies have begun connecting data mining with broader strategic analysis. Xiao et al. (2022) integrated association rules with mobile computing to analyze online consumer behavior, while Priya et al. (2024) showed that Apriori-based insights can inform pricing, bundling, and promotion decisions. Similarly, Patil et al., (2023) demonstrated that market basket analysis can reveal hidden purchasing patterns with direct managerial implications. However, these studies generally treat the marketing mix as an implicit outcome rather than an explicit analytical dimension, leaving a gap in the structured integration between association rule mining and the 4Ps framework.

On the side directly related to retail strategy, Hidayat et al., (2024) used association rule mining to determine retail sales strategies. This study employed the FP-Growth algorithm as an alternative to Apriori and generated five valid rules that can be used as a reference for business strategy. Meanwhile, Hasibuan & Fakhriza, (2024) applied the Apriori algorithm to predict the availability of beauty products based on consumer purchasing patterns—an approach that addresses the product dimension (product availability and variety) of the marketing mix, although without explicitly using the marketing mix framework.

All the articles reviewed show a consistent pattern the Apriori algorithm and association rule mining techniques have proven effective in exploring purchasing patterns, supporting bundling strategies, and providing data-driven recommendations. However, none of these studies explicitly use marketing mix elements (Product, Price, Place, Promotion) as categorization dimensions or analysis variables in the Apriori algorithm application.

The form of the marketing strategy implemented by Company X so far in terms of its products has the best and guaranteed good quality goods and the products offered are varied and complete according to what is needed and can compete with products from other manufacturers. Company X prioritizes quality, so prices are adjusted according to quality. If you order many paints, you will get a discount or discount. Furthermore, in terms of location/distribution channel, the Company X outlet itself is strategically located in the city center, very easy to reach by public transportation and this outlet is a direct distribution to consumers because branch outlets are still being planned. The outlet also feels comfortable and clean. In terms of promotion, Company X has carried out promotions with various forms of promotion through various social media and print media. As is the case now, social media is not left behind to make it a means of promotion to consumers directly through social media via Facebook and WhatsApp or offers made by sales. This is supported by marketing strategies that have been implemented effectively or not in increasing sales of each type of paint. So that it is necessary to analyze the Marketing Mix on the marketing strategy that has been carried out in determining the factors that influence consumer buying patterns on sales from consumer buying decisions.

The use of association rules in solving problems encountered at Company X uses the Apriori algorithm as a method for processing and determining the formation of rules. The Apriori algorithm is an algorithm that searches for items set frequencies using the Association Rule technique (Y. Chen, 2020). The Apriori algorithm uses previously known attribute frequency knowledge to process further information (Fang et al., 2022; Naeem, 2023). The Apriori Algorithm determines the possible candidates by paying attention to the minimum support and minimum confidence based on the percentage combination of an item in the database. However,

because traditional parallel association rule algorithms cannot meet the needs of large-scale datasets, and the Apriori algorithm can cause task execution failures due to memory overload when processing large-scale datasets, it is urgent to improve the Apriori algorithm to mine datasets more effectively (Dhinakaran, 2022; Wang & Gao, 2021; Zhao, 2021). This research will apply data mining to analyze consumer purchasing patterns. Apriori results translate into practical marketing mix tactics, including product, price, promotion, and place adjustments based on actual purchasing patterns. These recommendations simplify the application of findings in retail and marketplace operations.

2. Literature Review

Data Mining is an iterative and interactive process to find new patterns or models that are perfect, useful and understandable in a very large database (Shukla et al., 2017). Data Mining involves searching for desired patterns in large databases to help future decision makers. These patterns are recognized by certain tools that can provide useful and insightful data analysis that can then be studied more thoroughly, possibly using other decision support tools (Fang et al., 2022). Data mining is a process that employs one or more machine learning techniques to automatically analyze and extract knowledge. It is an iterative and interactive process for discovering new, meaningful, and understandable patterns or models within a large database (Sundari & Subaji, 2022).

Association rule mining is the process of extracting valuable knowledge that describes the relationships between data items from large amounts of data (Zhang & Zhang, 2023). ARM is a well-established technique in machine learning, specifically unsupervised learning, that aims to discover hidden and interpretable patterns in large datasets without relying on predefined class labels or target variables. Therefore, ARM-based approaches can enable clearer interpretations due to their inherent explainability (Aloisi et al., 2025). First, a set of strategies called steps to find frequently selected items and second is to define association mining rules. If this sub method takes place, the principle of using items can be extracted which can then become a positive association rule or a negative association rule. This method is used to find patterns that often appear in a set of transactions, where each transaction consists of several items or products. The advantages of the Apriori algorithm are the ability of the Apriori Algorithm which can handle large amounts of data and can simplify data because it uses a vertical tid-list data format that associates items with transactions that occur. Its detailed work of multiple iterations and database scans (Shukla et al., 2017).

Marketing strategy is a set of goals and objectives, policies and rules that provide direction to marketing efforts from time to time and at each level and location. Marketing strategy planning cannot be separated from the consumer side, because consumers have an important role, where consumers are a measuring tool in determining the success of a product or service. The role of marketing strategy cannot be separated from the marketing mix used by the company because the marketing mix is a set of marketing tools used to achieve the company's goals (Luo & Zhu, 2025; Malshe et al., 2025). The marketing mix is a combination of variables or activities that form the core of a marketing system. These variables include products, promotional activities, pricing structures, and distribution systems for goods and services. Companies use the marketing mix to achieve their marketing objectives, both for products and services, by targeting predetermined targets (Erdil & Özdemir, 2016).

The more sophisticated the computational techniques applied, the greater the gap between analytical findings and strategic marketing management needs. Studies such as Amelia et al. (2025), Fernanda et al. (2023), and Iskandar et al. (2024) consistently demonstrate the Apriori algorithm's ability to extract purchasing patterns from transaction data with high precision but stop right at the threshold between descriptive analytics and strategic recommendations. Amelia et al. (2025) use a measured support threshold of 20% and confidence of 65%, but the resulting association rules remain at the item level without mapping to any marketing mix dimensions. Fernanda et al. (2023) even unknowingly touch on the Place element of the marketing mix when recommending store shelf layout but never connect their findings to the concepts of product distribution and placement in the marketing literature. Iskandar et al. (2024) go further by suggesting a bundling strategy—essentially a product decision—but ignore the other three

elements, namely price, place, and promotion, which are equally crucial to the success of such a bundling strategy in the market. This pattern reflects a deeper epistemological tension: these studies are built on a foundation of computer science that prioritizes algorithm quality, rather than on a foundation of marketing management that prioritizes decision relevance. As a result, the resulting insights are tactical and fragmented, rather than providing holistic strategic guidance for business decision-makers.

A second group of studies including Maulana & Rohman (2025), Hasibuan & Fakhriza (2024), Hidayat et al. (2024), and Patil et al., (2023) show significant diversification of application contexts but simultaneously deepen the same gap. Maulana & Rohman (2025) successfully adapted Apriori for the agricultural e-marketplace ecosystem but neglected two of the most critical variables in agricultural product marketing: seasonal price fluctuations (Price) and limited geographic distribution reach (Place). Hasibuan & Fakhriza (2024) extended Apriori's functionality to predicting beauty product stocks but ignored the fact that spikes in demand due to promotional programs the Promotion dimension were the biggest confounding factor in the accuracy of these predictions. Hidayat et al. (2024) offered a stronger strategic orientation than other studies by generating five association rules that could directly serve as the basis for business policies. However, these five rules were presented in parallel without clear differentiation regarding which decision domains they should be acted upon. Patil et al., (2023) discusses the application of the Apriori algorithm to discover patterns of relationships between items through support and confidence analysis but still focuses on technical aspects without directly linking them to business strategy. When linked to the marketing mix, the results of Apriori analysis can actually be used to support decisions on product, pricing, distribution, and promotion aspects, such as bundling and cross-selling. Critically, this article is relevant as a foundation for data mining methodology but falls short in explaining its practical implementation for improving marketing performance. These four studies collectively demonstrate that expanding the domain of Apriori's application does not automatically enhance the managerial relevance of its results, as the fundamental problem lies not in the application context but in the absence of a structured interpretative framework. This absence of a marketing mix framework as a categorization system—rather than simply as a narrative implication—makes it difficult to integrate the findings into the actual marketing planning process.

Among the studies reviewed, Xiao et al. (2022) and Priya et al. (2024) come closest to truly integrating the Apriori algorithm and the marketing mix, yet they most clearly demonstrate the remaining gaps. Xiao et al. (2022) is the first study to explicitly mention product development, pricing, promotion, and market expansion as implications of the association patterns found, a significant conceptual leap in this literature. Priya et al. (2024) goes even further by simultaneously listing all four implications, essentially encompassing all elements of the 4Ps, making it the only study to simultaneously acknowledge the relevance of the marketing mix to Apriori. However, both Xiao et al. (2022) and Priya et al. (2024) position the marketing mix as merely a discourse on implications in the discussion section, not as an analytical dimension operationalized in the research design, data pipeline, or interpretation of results. Al Ghazali & Wibowo (2023) provide a different methodological bridge by using Apriori to analyze the fiscal 'policy mix,' demonstrating that the mix concept can be operationalized analytically—but its transferability to the marketing mix domain still requires explicit adaptations not provided by the research itself. Overall, this review concludes that It is clear that the most fundamental research gap is not in the technical algorithm or the breadth of application contexts, but rather in the absence of a research design that makes the 4P marketing mix framework a dimension of data categorization before the mining process, an analysis variable in the formation of association rules, and a structured recommendation classification system that can be directly translated into Product, Price, Place, and Promotion decisions. Research that fills this gap does not simply combine two existing approaches but creates a new analytical perspective that places the computational power of data mining in full service to the strategic needs of marketing management, a dual contribution that is both methodological and managerial.

From the critical synthesis above, three layers of research gaps can be precisely identified. The first gap is conceptual: no research from 2021–2025 explicitly integrates the 4Ps marketing mix framework as a categorization dimension or analysis variable in the association rule mining

process using the Apriori algorithm. This gap is the most fundamental because it concerns researchers' perspective (*weltanschauung*) on the relationship between data mining and marketing strategy—whether they are viewed as two separate domains or as two layers of a single, integrated analytical ecosystem. The second gap is methodological: there is no data preprocessing procedure that classifies transaction items based on marketing mix attributes before the Apriori algorithm is executed. This gap lies at the research design and data mining pipeline level. Research that fills this gap needs to propose new procedures for coding transaction data with the attributes Product (product category/type), Price (price class), Place (distribution channel), and Promotion (promotion status) so that the resulting association rules inherently have a strategic interpretation. The third gap is applicability: recommendations generated by previous studies cannot be directly translated into structured marketing management decisions. Research that fills this gap is expected to produce a recommendation framework differentiated according to the 4P dimensions—so that product managers, pricing managers, distribution managers, and promotion managers can each gain relevant and readily implementable insights from the same set of analyses, see Fig.1.

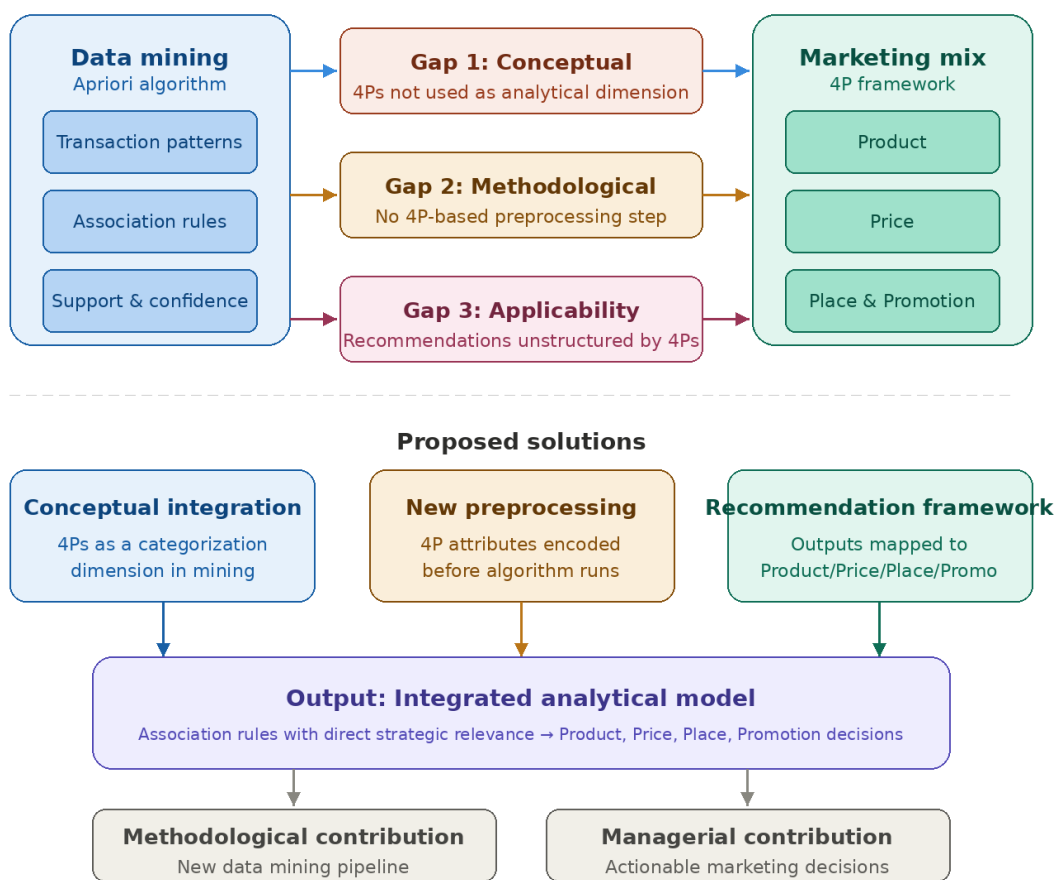


Figure 1. Conceptual framework of research gaps and proposed solutions

Figure 1 presents an overview of the conceptual framework of this study, which aims to address the identified gaps by proposing an integrated framework that combines association rule mining with the 4Ps of the marketing mix at the conceptual, methodological, and applicative levels. Specifically, this study introduces a preprocessing approach that embeds marketing mix attributes into transaction data prior to the execution of the Apriori algorithm, thus enabling the generation of association rules with immediate strategic relevance. Thus, the novelty of this study lies in transforming conventional pattern discovery into a marketing-oriented analytical model that bridges data mining output with actionable marketing decision-making.

3. Research Methods

This study employs two complementary analytical methods: the Apriori algorithm and multiple linear regression. The selection of each method is grounded in the nature of the research objectives and the structure of the data employed. The Apriori algorithm was selected because it is structurally designed for transactional datasets in which each record consists of co-occurring items — precisely the data structure used in this study. Unlike clustering or supervised classification methods, Apriori operates without predefined class labels, making it suitable for exploration pattern discovery. Critically, it produces association rules that are inherently interpretable, a property essential when analytical outputs are intended to inform marketing management decisions rather than serve purely predictive functions. Alternative approaches such as decision trees or random forests, while predictively powerful, presuppose a labelled outcome variable and would constrain the discovery space to patterns already anticipated by the researcher.

Multiple linear regression was selected to quantify the influence of the 4P marketing mix dimensions on consumer purchase decisions. Since the dependent variable is measured on a continuous Likert-aggregated scale and the study involves multiple simultaneous predictors, multiple linear regression provides the most appropriate parametric framework for estimating the independent contribution of each 4P dimension while controlling for the others. Structural equation modeling, though capable of greater complexity, requires larger sample sizes and fully confirmed factor structures beyond this study's scope. Logistic regression was excluded as it is designed for categorical outcomes, and its application here would introduce unnecessary dichotomization of a continuous variable. Together, the two methods form a deliberate two-stage analytical architecture: Apriori operates at the pattern discovery layer, identifying co-occurring product attributes classified by the 4P framework, while multiple linear regression operates at the explanatory layer, statistically validating the influence of each 4P dimension on purchase decisions. This structure ensures the study moves beyond descriptive enumeration toward strategically actionable and statistically grounded conclusions.

The data was obtained from a survey of companies. In this study, the primary data used was obtained from questionnaires distributed to respondents and data records, such as sales transaction datasets. The dataset contains attributes such as code, stock name, member code, transaction number, status, date, and quantity. The independent variables in this study are indicators of the marketing mix (X) consisting of product (X1), price (X2), place/distribution (X3), and promotion (X4). The dependent variable referred to in this study is the sales level (Y). The population used as a source in this study is the average of all consumers, using the Slovin formula and a tolerance percentage of inaccuracy (precession) due to sampling errors that can still be tolerated, namely 0.1 or 10%. The number of respondents is 148 consumers and uses sales transaction data from January to March 2022. To strengthen the clarity and academic accuracy of research variables, operational definitions and indicators can be seen in Table 1.

Table 1 - Research variables and indicators

Variable	Operational Definition	Indicators
Product	Product refers to anything offered to consumers to satisfy their needs and wants, measured based on consumers' perceptions of the characteristics of the products provided by the company.	<ol style="list-style-type: none"> 1. Variety of products offered 2. Product quality 3. Clarity/type of products offered 4. Product availability
Price	Price is the amount of money that consumers must pay to obtain a product, measured based on consumers' perceptions of affordability and price suitability.	<ol style="list-style-type: none"> 1. Price affordability 2. Price suitability with quality 3. Price competitiveness 4. Discounts or price reductions
Place	Place refers to the location and distribution channels used by the company to make products available to consumers, measured based on accessibility and convenience.	<ol style="list-style-type: none"> 1. Strategic business location 2. Ease of transportation access 3. Distribution channel effectiveness 4. Environmental/store condition

Promotion	Promotion is a marketing communication activity conducted by the company to inform, influence, and persuade consumers to purchase products.	<ol style="list-style-type: none"> 1. Clarity of promotional information 2. Use of promotional media 3. Attractiveness of promotion 4. Promotion intensity
Purchase Decision	Purchase decisions are the process through which consumers determine their choice to buy a product, measured based on decision-making stages.	<ol style="list-style-type: none"> 1. Problem/need recognition 2. Information search 3. Evaluation of alternatives 4. Purchase decision

The simultaneous hypotheses of this study are:

- a. H₀ is accepted: if the calculated T < T table, it means that the marketing mix has a partial effect on the purchasing patterns of customers.
- b. H_a is not accepted: if the calculated T > T table, it means that the marketing mix has no partial effect on the purchasing patterns of customers.

The partial hypotheses of this study are:

- a. H₀₁: Product variables have no positive effect on purchasing decisions.
H_{a1}: Product variables have a positive effect on purchasing decisions.
- b. H₀₂: Price variables have no positive effect on purchasing decisions.
H_{a2}: Price variables have a positive effect on purchasing decisions.
- c. H₀₃: Place/distribution variables have no positive effect on purchasing decisions.
H_{a3}: Place/distribution variables have a positive effect on purchasing decisions.
- d. H₀₄: Promotion variables have no positive effect on purchasing decisions.
H_{a4}: Promotion variables have a positive effect on purchasing decisions.

Association Rules Mining is a procedure for discovering relationships between items in a predefined data set. Association Rules Mining searches for and discovers associations between items in a data set. With association rules data mining, the application aims to discover related information in the form of rules. Association Rules is a data mining technique that searches for association rules between combinations of items. When defining association rules, the measure of interest obtained from the results of certain computational data processing is considered.

The following are the steps in determining association rules:

1. High-frequency pattern analysis.
Analysis of the highest-frequency patterns using the Apriori algorithm is the stage of finding item combinations that meet the minimum requirement for an item's support value. This stage searches for item combinations that meet the minimum requirement for support values in the database. Support indicates the degree of dominance of an itemset over all transactions. This determines whether an itemset is worthy of confidence. After frequently occurring item combinations are identified, the next step is to search for associations.
2. Formation of Associative Rules
Formation of an association rule is the process of finding all the highest-frequency patterns. After all the highest-frequency patterns are found, association rules are then sought that meet the minimum requirement for confidence by calculating the confidence of the associative rule A→B. Example illustrates how an association rule is interpreted in the context of this study. Consider a rule of the form:
{Discounted Product, Mid-range Price} → {Repeat Purchase Decision} (support = 25%, confidence = 78%, lift = 1.94)
This rule is interpreted as follows. Among all consumer transactions in the dataset, 25% involve a combination of a discounted product and a mid-range price point alongside a repeat purchase decision — this is the support value, which reflects how frequently the pattern appears overall. Of all transactions that include a discounted product at a mid-range price,

78% are also associated with a positive repeat purchase decision — this is the confidence value, reflecting the conditional reliability of the rule. Finally, the lift value of 1.94 indicates that the co-occurrence of these elements is 1.94 times more likely than would be expected if the variables were statistically independent, confirming that the relationship is not coincidental.

Confidence is a measure that indicates the relationship between two items. The Apriori algorithm is a data retrieval algorithm using associative rules to determine the associative relationship of a combination of items. The Apriori algorithm, also known as association analysis, is known as a data mining technique that forms the basis for various other data mining techniques. The importance of an associative rule can be determined by two parameters: support and confidence. An association rule is said to be interesting if the support value is greater than the minimum support and the confidence value is greater than the minimum confidence.

The Apriori algorithm has the principle that "if an itemset appears frequently, then all subsets of that itemset also appear frequently." This principle refers to the nature of the support measure, which means that the support of an itemset never exceeds the support of its data subsets. Liang, (2024) uses a methodological approach to identify 'sentinel items' or key elements in association networks relevant to this research. This concept can be applied to identify which marketing mix elements (price, product, promotion, or place) most frequently appear as antecedents in association rules for consumer purchasing patterns.

4. Results and Discussions

Consumer purchasing patterns vary widely. These differences require producers to understand these differences when producing (Erdil & Özdemir, 2016). A product's alignment with consumer purchasing patterns will increase its market acceptance. This study examines how consumer perceptions of marketing mix elements (such as product quality and price) can be integrated into purchasing pattern analysis (Akgül, 2022). In the discussion, these findings support the argument that consumer psychological factors reflected in shopping behavior can be identified through association rules. Factors considered in this study include:

1. Age

A consumer's age can determine their purchasing patterns. The needs of each age group differ. For example, elementary school and college-aged children's clothing consumption patterns differ. Elementary school children prefer clothing with cartoon character motifs and bright colors, while college-aged children prefer clothing with more mature motifs, such as soft colors.

2. Gender

The purchasing patterns of male and female consumers differ. Women consume more products than men. This can be seen in the products available on the market, with more women's products than men's. For example, women's clothing has more styles than men's, so manufacturers must be astute in attracting consumers, especially women, by creating clothing innovations (women's clothing trends often change).

3. Occupation

A person's occupation also influences consumer purchasing patterns. Different occupations will lead to different consumption patterns. For example, farmers and office workers have different consumption patterns. Office workers buy clothes for the office (ties, shirts, etc.), while farmers buy everyday clothes for the fields (T-shirts, wide-leg pants, etc.).

4. Income

Different income levels have different impacts on consumer purchasing patterns. For example, when purchasing a bag, a woman with a high income will choose a very expensive and branded bag compared to a woman with a modest income.

5. Education

A consumer's education can also influence their purchasing patterns. Consumers with a high school education will be different from those with a master's degree. Consumers with higher education tend to be more selective in choosing products.

Marketing Mix is a collection of controlled tactical marketing tools that a company combines to produce the desired response in the target market. The marketing mix is one of factors influence the purchasing decisions of consumers (Astuti et al., 2015). The Marketing Mix consists of four elements: Product, Price, Place, and Promotion. The Marketing Mix must be tailored to the company's situation and conditions. Furthermore, the Marketing Mix is a combination of factors that the company can control to facilitate purchasing decisions. A company's marketing mix combines four strategies that meet the needs and preferences of a specific target market. Marketing success depends not only on each strategy but also on the combination of the four. This combination is used in developing the marketing mix.

Data processing shows an R-square of 0.675. This indicates that the percentage contribution of product function, price, place/distribution, and promotion (independent variables) to purchasing decisions (dependent variables) is 67.5%. This means that the variables used can explain 67.5% of the dependent variable, while the remaining 32.5% is influenced or explained by other variables not included in this study.

Table 2 - Results of simultaneous F test of marketing mix analysis on purchasing decisions

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	194.732	4	48.683	28.530	.000 ^b
	Residual	93.851	55	1.706		
	Total	288.583	59			
a. Dependent Variable: Purchase Decision (Y)						
b. Predictors: (Constant), Promotion (X4), Product (X1), Place/Distribution (X3), Price (X2)						

Based on Table 2, The F-test result ($F = 28.530$, $p < .001$) confirms that the four marketing mix dimensions (Product, Price, Place/Distribution, and Promotion) jointly and significantly predict consumer purchase decisions, indicating that the model is statistically robust and not attributable to chance. The regression accounts for a substantial portion of the variance in purchase decisions ($R^2 = 0.675$), meaning that approximately 67.5% of the variation in consumer buying behavior can be explained by the combined influence of the 4P marketing mix variables, a finding that underscores the practical relevance of an integrated marketing approach over isolated, single-variable interventions. From a strategic standpoint, these results provide empirical justification for businesses to allocate marketing resources across all four dimensions simultaneously rather than concentrating investment in a single element, as the collective explanatory power of the 4Ps suggests that consumer purchase decisions are shaped by a confluence of product quality, pricing strategy, distribution accessibility, and promotional effectiveness working in concert.

Manual data processing can only be performed on small amounts of data. Therefore, processing large amounts of data requires an application with the help of software commonly used to solve problems (Chuttar, 2022). The application is performed using Rapid Miner software. This aims to find frequent itemsets within a large data set. The application with Rapid Miner involves importing data from Excel and converting each attribute type to binomial. The dataset, the Apriori algorithm, parameters, and association rules are created into a worksheet, connected, and then run. The resulting association rule pattern for sales transaction data will emerge. Fa (2021) uses association rule mining to uncover hierarchical causal relationships between factors. This methodological approach is relevant to this research in explaining how marketing mix elements interrelate and influence consumer purchasing patterns. Using a dataset formed from data processing through the Knowledge Discovery in Database (KDD) stage, there are 20 transactions, each of which contains several products or items purchased by consumers. Therefore, the purchased items are given product codes to facilitate rule searches, as shown in table 3.

Table 3 - Product list based on transaction data

<i>ItemSet</i>	Total	<i>ItemSet</i>	Total
ARIES Emulsion 663	3	BOYO Politur Vernis S600	2
ARIES Emulsion SW	1	BOYO Politur Vernis S611	3
ARIES GOLD Emulsion 402	4	JASMINE Emulsion 116	2
ARIES GOLD Emulsion 404	3	NO DROP 002	2
ARIES GOLD Emulsion SW	1	NO DROP 004	4
AVIAN Synthetic 192	1	NO DROP 007	4
AVIAN Synthetic 370	1	NO DROP 009	2
AVIAN Synthetic 465	2	NO DROP 010	3
AVIAN Synthetic 470	4	NO DROP 030	2
AVIAN Synthetic 630	2	NO DROP 031	3
AVIAN Synthetic SB	5	NO DROP Base B	2
AVIAN Synthetic SW	7	SUZUKA Lacquer 109	4
AVITEX Emulsion 771	1	WOOD-ECO Woodstain 103	2
AVITEX Emulsion SW	4	Grand Total	74

Data processing before using the Apriori algorithm was carried out through data selection, pre-cleaning, and data transformation. This was followed by a manual search for association rules using the Apriori algorithm using the initial 20 transactions. The search for association rules for all transactions was also carried out using Rapid Miner Studio 9.10 software. Data selection is important to ensure that the processed data meets the data requirements of the algorithm used. This ensures that data processing using the software does not result in errors, system failures, or inconsistent results. Based on the data selection results, the dataset consisted of the Item Name and Invoice Number attributes. Attribute selection was based on attributes that influence the association rule search process, as Market Basket Analysis (MBA) focuses solely on the types of items most frequently purchased together across all transactions (Qisman, 2021). In the testing phase, researchers conducted experiments on all transaction data with different minimum support and minimum confidence values, ranging from the highest minimum support value to the lowest minimum confidence value. The minimum support values used were 5%, 10%, and 20%, while the minimum confidence values were 30%, 40%, and 50%. The purpose of conducting tests with different minimum support and minimum confidence values was to compare each test result on sales transaction data. The following are the results of all tests performed.

This is based on Hikmawati, (2021), which offers a method for determining minimum support and confidence thresholds based on dataset characteristics. This is highly relevant in this study because determining the appropriate minimum support and confidence values affects the quality of association rules generated from retail transaction data. This method supports the validation of Apriori parameter selection used to identify purchasing patterns based on the marketing mix. Verma, (2020) implemented the MapReduce-Apriori framework for big data analytics in the retail industry. This research is highly relevant because it uses the Apriori algorithm in a similar retail context to this study. Verma's results can be used as a comparative reference in discussions about Apriori's effectiveness in identifying consumer purchasing patterns, particularly the relationship between marketing mix elements and transaction decisions.

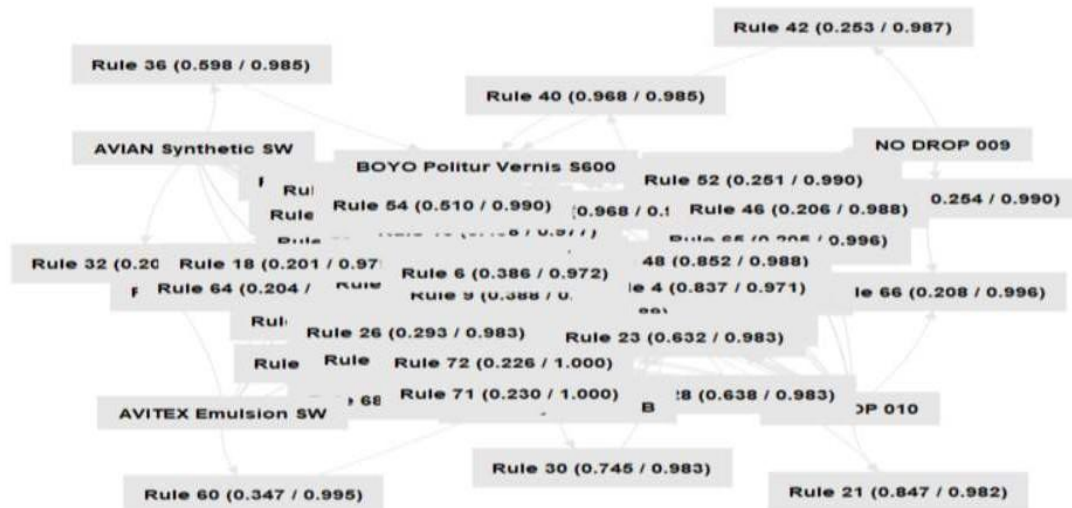


Figure 2. Graph association rules algorithm apriori results

Based on the test results fig.2, it was found that at support values of 5%, 10%, and 20%, no rules were generated when combined with a confidence value of 50%. For the combination of 5% support and 30% confidence, the number of rules generated was the highest of all the combined support and confidence values. From the graph above, it can also be concluded that the higher the combined support and confidence values, the fewer rules generated. The following are the test results for each combination of minimum support and minimum confidence values on 1,183 transaction data:

1. Results of the First Experiment

The first experiment used minimum support value of 5% and a minimum confidence value of 30%. Twenty-two association rules were formed in the second iteration.

2. Results of the Second Experiment

The second experiment minimum support value of 5% and a minimum confidence value of 40%. Eight association rules were formed in the second iteration.

3. Results of the Third Experiment

The third experiment used a minimum support value of 5% and a minimum confidence value of 50%. No association rules were formed in the second iteration.

4. Results of the Fourth Experiment

The fourth experiment used minimum support value of 10% and a minimum confidence value of 30%. Three association rules were formed in the second iteration.

5. Results of the Fifth Experiment

The fifth experiment used a minimum support value of 10% and a minimum confidence value of 40%. Three association rules were formed in the second iteration.

6. Results of the Sixth Experiment

The sixth experiment, with a minimum support value of 10% and a minimum confidence value of 50%, resulted in no association rules being formed in the second iteration.

7. Results of the Seventh Experiment

The seventh experiment, with a combination of a minimum support value of 20% and a minimum confidence value of 50%, produced no rules at all (0 rules). This is because the results of previous tests, both with a minimum confidence value of 30% and a minimum confidence value of 40%, only produced a confidence value with a maximum limit of 0.44, or approximately 44%. This value is less than 50%, which does not meet the requirements set at the beginning of the test.

Of the seven experiments conducted, the first experiment with a minimum support value of 5% and a minimum confidence value of 30% is the rule combination that researchers can recommend for determining the most frequently purchased products by consumers. Based on the association rules obtained, 15 product types were identified, with support values ranging from 0.5% to 15%. The support value obtained was small, at <20%, and the confidence value obtained was <50%. This was due to the variety of products sold. The types of products sold reached 428, resulting in a low support calculation. The processed transaction data was from January to March 2022, with a total of 1,183 transactions, which affected the confidence obtained. From the obtained rule data, it can be seen which products are frequently purchased together by each consumer. This can facilitate the store in making other business decisions, such as recommending promotional packages and which products to restock simultaneously.

The results of the partial t-test on the independent variables are described as follows:

1. Partial t-test hypothesis on the independent variable product (X1) on purchasing decisions (Y)
The results of the product hypothesis test show a calculated t-value of 2.622, or positive, with a significance level of 0.011. Therefore, the calculated t-value is greater than the t-table ($2.622 > 2.00404$) and the significance level is less than 0.05 ($0.011 < 0.05$), which means that the hypothesis in this study rejects H01 and accepts Ha1. Therefore, it can be concluded that "product partially has a positive and significant influence on purchasing decisions."

2. Partial t-test hypothesis on the independent variable price (X2) on purchasing decisions (Y)
The results of the product hypothesis test show a calculated t-value of 4.738, or positive, with a significance level of 0.000. Therefore, the calculated t-test is greater than the t-test ($4.738 > 2.00404$), and the significance level is less than 0.000 ($0.000 < 0.05$), meaning that the hypothesis in this study rejects H02 and accepts Ha2. Therefore, it can be said that "price partially has a positive and significant influence on sales decisions."

3. Partial t-test hypothesis on the independent variable, place/distribution (X3), on purchasing decisions (Y).

The results of the product hypothesis test show a calculated t-test of 2.239, or positive, with a significance level of 0.029. Therefore, the calculated t-test is greater than the t-test ($2.239 > 2.00404$), and the significance level is less than 0.029 ($0.029 < 0.05$), meaning that the hypothesis in this study rejects H03 and accepts Ha3. Therefore, it can be said that "place/distribution partially has a positive and significant influence on sales decisions."

4. Partial t-test hypothesis for the independent variable promotion (X4) on purchasing decisions (Y)

The product hypothesis test results show a calculated t-value of 1.486, or positive, with a significance level of 0.143. Therefore, the calculated t-value is greater than the t-table ($1.486 < 2.00404$) and the significance level is less than 0.143 ($0.143 > 0.05$), which means that the hypothesis in this study accepts H04 and rejects Ha4. Therefore, it can be concluded that "promotion partially has no positive and significant influence on sales decisions."

The Influence of the Product Variable (X1) on Consumer Purchasing Patterns

The results of this study indicate that the product influences consumer buying interest. Based on the partial regression analysis of X1 for product, the calculated t-value was 2.622, greater than the t-table value of 2.00404. This means that H01 is rejected, and the significance value is $0.011 < 0.05$. This indicates that the product variable has a positive influence on purchasing decisions, influencing consumer purchasing patterns. In this study, the product variable was measured using four sub-variables: product variety, guaranteed product quality, product object, and product availability. The results of this study align with the results of the distributed questionnaire. Table 4.7 shows that most of respondents agreed with the sub-variables with an average of 4.11 for all types of products offered, stock availability, and product quality. These results align with those of Alghanam (2022) developed a data mining model to predict consumer purchasing behavior in an e-commerce context. This research is relevant as a comparison because both analyze consumer purchasing behavior using data mining techniques.

Discussions can link these findings to research focused on brick-and-mortar retail, where the marketing mix (particularly product placement and price) has a different influence on purchasing patterns compared to e-commerce. Especially with products that have strong brand power, this is in accordance with Beichert et al., (2024) which also examined the impact of brands on influencing purchase intentions.

The Influence of the Price Variable (X2) on Consumer Purchasing Patterns

The results of the study indicate that price has the most dominant influence on consumer buying interest. Based on the partial regression analysis of X2, the calculated t-value was 4.738, greater than the t-table value of 2.00404. This means that H02 is rejected, and the significance value is $0.000 < 0.05$. This indicates that the price variable has a very positive effect on purchasing decisions, influencing consumer purchasing patterns. In this study, the price variable was measured using four sub-variables: price discounts, affordable prices, standard pricing, and payment periods. The results of this study align with the results of the distributed questionnaire. Table 4.8 shows that respondents agreed with the sub-variables with an average of 3.63, agreeing that the paint price offered is affordable and competitive, the price is commensurate with the product's quality and benefits, the payment period, and the discount. This finding aligns with Wu, (2020) study, which states that frequent itemset mining can handle uncertainty in transaction data. The relevance to this research lies in how continuous marketing mix elements such as price and promotion can be categorized before being processed with Apriori. This finding strengthens the discussion on data preprocessing in consumer purchasing pattern research. Lu, (2022) analyzed shifts in consumer shopping behavior on e-commerce platforms. This research is relevant as a comparison in discussions of consumer purchasing patterns, particularly how price in marketing mix elements influence purchasing decisions. Lu's findings support the argument that the marketing mix significantly influences retail consumer purchasing patterns.

The Influence of Place/Distribution Variables (X3) on Consumer Purchasing Patterns

The results of the study indicate that place/distribution influences consumer buying interest. Based on the partial regression analysis of X3, the calculated t-value was 2.239, greater than the t-table value of 2.00404. This means that H03 is rejected, and the significance value is $0.029 < 0.05$. This indicates that the place/distribution variable has a very positive effect on purchasing decisions, influencing consumer purchasing patterns. In this study, the place/distribution variable was measured using four sub-variables: strategic location, transportation facilities, direct distribution channels, and store environment conditions. The results of this study align with the results of the distributed questionnaire, which showed that an average of 4.11 agrees with the strategic location of the product, easy public transportation, timely order delivery, and comfortable store conditions. The distribution channel implemented was direct to consumers purchasing at the outlet without intermediaries. This is in line with research Saguansap et al., (2025) findings that location also plays a crucial role in rental decisions, especially in urban areas. This was done to maintain customer satisfaction in terms of timely delivery of various paint product variations. In addition to distribution channels, this includes the location and condition of the outlet or store. The location is quite strategic, in the city center and easily accessible by public transportation.

The Influence of the Variable Promotion (X4) on Consumer Purchasing Patterns

The results of the study indicate that promotions influence consumer buying interest. Based on the partial regression analysis of X4, the calculated t-value was 1.486, greater than the t-table value of 2.00404. This indicates that Ha4 is accepted, and the significance value is $0.143 < 0.05$. This indicates that the promotion variable does not influence consumer purchasing patterns on purchasing decisions. In this study, the promotion variable was measured using four sub-variables: personal selling in providing detailed information, promotional media, promotional presentation, and combination. The results of this study align with the results of the distributed questionnaire. Respondents agreed with the sub-variable average of 2.94, while they disagreed with the product promotion provided through social media or print advertising, sales employees who can promote the product effectively, advertising that is effective and efficient, and alternative

promotional combinations. Based on the test, the marketing mix analysis of the implemented marketing strategy showed that the promotion variable had no effect. This is supported by Sun (2020) which states that marketing mix factors such as price can be weighed differently when analyzing purchasing patterns, resulting in more accurate and meaningful rules. This means that not all variables have the same weight. Current promotions are limited to Facebook and WhatsApp, with few banners, infrequent participation in specific events, and a lack of detailed information provided to consumers by sales staff. These factors contributed to the decline in customers and sales. Determining the products in brochures is done based on the products that are most frequently purchased together, the products that are promoted are the least popular products of the type that are most frequently purchased together with the most frequently purchased products. So, from the association's results, a proposal was obtained for 22 product combination packages that can be promoted by adding promotions or discounts given, see in table 4.

Table 4 - Proposed promotion package combinations

No	Package Combination	Conf %	No	Package Combination	Conf %
1	AVIAN Synthetic 192 AVIAN Synthetic SW	0,48	12	BOYO Politur Vernis S 600 AVIAN Synthetic SW	0,38
2	AVIAN Synthetic 194 AVITEX Emulsion SW	0,45	13	NO DROP 009 AVITEX Emulsion SW	0,37
3	BOYO Politur Vernis S AVIAN Synthetic SW	0,44	14	NO DROP 010 AVITEX Emulsion SW	0,37
4	AVIAN Synthetic SB AVIAN Synthetic SW	0,44	15	BOYO Politur Vernis S 600 AVITEX Emulsion SW	0,37
5	AVIAN Synthetic 194 AVIAN Synthetic SW	0,44	16	AVIAN Synthetic SW AVITEX Emulsion SW	0,37
6	AVITEX Emulsion SW AVIAN Synthetic SW	0,41	17	BOYO Politur Vernis S610 AVIAN Synthetic SW	0,36
7	ARIES GOLD Emulsion SW AVITEX Emulsion SW	0,41	18	NO DROP 004 AVIAN Synthetic SW	0,36
8	NO DROP 002 AVIAN Synthetic SW	0,41	19	NO DROP 009 AVIAN Synthetic SW	0,35
9	BOYO Politur Vernis S601 AVIAN Synthetic SW	0,4	20	NO DROP 004 AVITEX Emulsion SW	0,34
10	ARIES GOLD Emulsion SW AVIAN Synthetic SW	0,39	21	AVIAN Synthetic SB AVITEX Emulsion SW	0,32
11	BOYO Politur Vernis S607 AVIAN Synthetic SW	0,39	22	BOYO Politur Vernis S607 NO DROP 009	0,3

5. Conclusion

This study demonstrates that the integration of association rule mining, particularly the Apriori algorithm, with marketing mix analysis provides a more comprehensive approach to understanding consumer purchasing behavior. Unlike previous studies that primarily focus on transactional pattern discovery, this research contributes by linking data-driven insights with strategic marketing elements, thereby offering a more holistic decision-support framework. This integration represents the main novelty of the study, as it bridges the gap between data mining techniques and managerial marketing strategies. From a theoretical perspective, the findings enrich the literature on data mining applications in retail by extending the use of association rules beyond pattern identification toward strategic interpretation within the marketing mix context. This study highlights how purchasing patterns can be translated into actionable marketing variables such as product bundling, pricing strategies, and promotional planning, thus strengthening the conceptual linkage between analytics and marketing theory. Practically, the results provide valuable insights for business practitioners, particularly in retail and e-commerce sectors. The identified association rules can be utilized to optimize product placement, develop effective bundling strategies, and improve inventory planning. By aligning data mining outputs

with marketing mix decisions, companies can enhance their competitiveness and responsiveness to consumer behavior patterns.

However, this study is not without limitations. The analysis is based on a relatively limited dataset, both in terms of transaction volume and observation period, which may affect the generalizability of the findings. Additionally, the use of a single algorithm (Apriori) may not fully capture more complex or dynamic relationships compared to other advanced methods such as FP-Growth or machine learning-based approaches. Methodological constraints, including fixed support and confidence thresholds, may also influence the resulting rules.

Future research is therefore recommended to expand the dataset scope, incorporate multi-period or real-time data, and compare multiple data mining algorithms to improve robustness and accuracy. Furthermore, integrating additional analytical approaches, such as customer segmentation or predictive modeling, could provide deeper insights and strengthen the strategic implications of the findings.

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