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Analysis of the Relationship between Product Popularity and Promotion Effectiveness in Beauty Clinics Using Decision Trees and Association Rules

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Abstract. With the growing need for personalized marketing in aesthetic clinics, understanding customer behavior is essential. This study aims to analyze the relationship between Decision Tree and Association Rule Mining to uncover patterns in service selection. Association Rule Mining identifies frequently co-occurring services, such as customers undergoing "Acne Clear 6 times" often opting for "VPL red marks 3 times" (Confidence = 58%) and those selecting "General Aesthetic Treatments" commonly using "Skin Supplement" (Lift = 17.46). Meanwhile, Decision Tree analysis segments customers based on service preferences, visit days, and demographics, revealing that Acne Treatments and Skin & Meso Rejuvenation are the most common, with Botox & Injectables peaking on Saturdays. The integration of both models confirms that Acne Treatment customers frequently choose Skin Repair or Laser Treatment, aligning with the Decision Tree's segmentation. This study demonstrates that combining Decision Tree and Association Rule Mining enhances service recommendations, allowing clinics to implement targeted promotions, such as Laser Treatment discounts for Acne Treatment customers. The findings highlight the value of Machine Learning techniques in refining customer segmentation, improving recommendations, and optimizing marketing strategies in aesthetic clinics.

Keywords: Decision Tree, Association Rule

1 Introduction

In today's highly competitive business environment, understanding customer behavior is essential for businesses to adapt and respond swiftly to market demands. This is particularly crucial for aesthetic clinics, which must tailor their services to meet customer needs effectively. Traditional marketing methods often fail to capture detailed customer preferences. This study utilizes Decision Tree analysis and Association Rule Mining to bridge this gap by providing insights into customer segmentation and service usage behavior. Decision Tree analysis helps classify customer groups based on demographics, purchasing habits, and service usage patterns to identify key factors influencing beauty treatment choices. Meanwhile, Association Rule Mining uncovers patterns in service combinations, identifying relationships between frequently co-selected services. A preliminary study in 2022 found significant correlations in service usage trends. For instance, 68% of customers who received acne treatment also opted for laser procedures. Additionally, 45% of customers who underwent skin rejuvenation treatments were likely to subscribe to additional care packages. By integrating these techniques, aesthetic clinics can move beyond generic marketing strategies and offer personalized promotions, enhancing customer engagement and satisfaction.

This study focuses on the potential of Decision Tree analysis and Association Rule Mining to optimize marketing strategies and service delivery in aesthetic clinics. By analyzing large-scale transaction data, the study aims to extract actionable insights that help clinics better understand customer trends and preferences. With Big Data playing an increasingly crucial role in business analytics, advanced Machine Learning techniques can identify hidden patterns influencing customer decisions. Data from 2022 indicates that the demand for specific beauty services has grown significantly, with 30% of facial treatment customers opting for additional skin rejuvenation services. Moreover, over 75% of customers who underwent laser procedures were likely to return for follow-up treatments within six months. These findings highlight the importance of analytical models in gaining deeper insights into customer behavior. The results of this study will support data-driven decision-making, allowing aesthetic clinics to enhance customer experience, improve targeted promotions, and elevate service quality. By leveraging these analytical models, businesses can strengthen customer loyalty, increase revenue, and maintain a competitive edge in the rapidly growing beauty and wellness industry.

2. Literature Review

2.1 Market Basket Analysis

Market Basket Analysis (MBA) and Association Rule Mining (ARM) have emerged as essential analytical methods in understanding consumer purchasing behaviors, particularly in competitive retail markets. Previous studies have emphasized the benefits of applying MBA in uncovering hidden patterns within transaction data, thereby enabling businesses to develop targeted promotions and improve product placements (Arora et al., 2022). One widely adopted technique for conducting MBA is the Apriori algorithm, known for efficiently identifying frequent itemsets and generating reliable association rules.

Arora et al. (2022) studied the application of MBA using the Apriori algorithm to analyze retail sales data over a 13-month period, comprising 541,911 transactions. The research aimed to uncover consumer buying patterns and product associations. The study highlighted strong associations such as customers purchasing "Red Retrospot Paper Napkins" frequently also selecting "London Tissues" (Confidence = 70%, Support = 25%, Lift = 1.5). Such associations are essential as they reveal purchasing trends and customer preferences, enabling stores to strategically arrange products and design effective promotional campaigns.

This paper reinforces the practical relevance of Market Basket Analysis and the Apriori algorithm in extracting meaningful insights from retail transaction data. By analyzing customer buying patterns, businesses can more accurately predict consumer needs and behaviors, thereby significantly enhancing their marketing strategies and overall sales performance. The integration of these analytical techniques allows retailers and service-oriented businesses, such as beauty clinics, to leverage consumer data effectively to maintain competitive advantages and improve business performance. [1]

2.2 Data Mining Framework Method

Kholod and Mokrenko (2022) present a structured data mining methodology consisting of 11 systematic steps specifically designed for Market Basket Analysis (MBA) using point-of-sale (POS) transaction data. This comprehensive approach begins by clearly defining business problems, transforming them into specific data mining goals. The second step involves selecting the relevant data, primarily POS transaction records from convenience stores. In the third step, the researchers conduct exploratory data analysis, utilizing visualization tools to understand data characteristics and preliminary relationships between products.

The fourth step establishes a model set, carefully selecting data representing diverse purchasing patterns. Step five addresses data quality issues, including managing missing values and incomplete data. In step six, data transformation is carried out to ensure suitability for association rule mining algorithms, typically involving converting sparse transaction data into analyzable formats.

The seventh step involves building the analytical model using rule-based algorithms, particularly the Apriori algorithm, defining specific thresholds for support, confidence, and lift metrics. Step eight emphasizes rigorous testing and validation of the generated association rules, ensuring their accuracy and reliability for practical implementation. Step nine covers the deployment of the validated model into business operations.

Step ten assesses results based on key business performance indicators, such as profitability and return on investment, highlighting the practical impact of the discovered insights. Finally, the eleventh step is iterative, recognizing the dynamic nature of data mining. As new insights and questions arise, the methodology encourages revisiting and refining analytical models continually. Kholod and Mokrenko's structured approach provides businesses a robust framework to extract actionable insights from transactional data, enhancing decision-making, strategic marketing, and overall operational efficiency. [8]

2.3 Relationship between Association Rule and Decision Tree

Previous studies have examined the application of Association Rule Mining and Decision Tree Analysis in predictive modeling. Ordonez & Zhao (2011) investigated their use in medical datasets and found that Decision Trees effectively classify patients based on key health attributes, while Association Rules identify co-occurring symptoms and frequently used treatments. Similarly, in the aesthetic clinic industry, these methods can be applied to classify customers based on demographic and behavioral attributes while identifying the most common service combinations. This study found that customers selecting "Acne Clear 6 times" frequently also opted for "VPL red marks 3 times", reflecting the co-occurrence patterns identified through Association Rules. [10]

Ayyagari (2019) proposed a hybrid approach that integrates Decision Tree Analysis and Association Rule Mining in object-relational databases to improve classification accuracy. The study demonstrated that combining both methods leads to better customer segmentation and enhanced personalization of services. This study similarly found that Decision Trees effectively group customers based on their service preferences, while Association Rules identify commonly paired service bundles, such as acne treatments and follow-up laser procedures. This supports the idea that businesses can leverage these techniques to develop precise marketing strategies and targeted promotions based on data-driven insights. [2]

Hamoud (2016) explored the role of Decision Trees and Association Rules in tumor diagnosis, demonstrating that Decision Trees efficiently classify patients based on structured data, while Association Rules uncover hidden relationships between symptoms and treatment options. This concept is applicable in aesthetic clinics, where Decision Trees categorize customers based on service history, while Association Rules identify services that are frequently purchased together. For example, this study found that customers who undergo facial treatments often subscribe to additional skincare packages, aligning with findings in medical research where treatment co-occurrence helps refine service recommendations. [4]

3. Data and Methodology

3.1 Data

The dataset used in this research comprises 3,358 transactional records from a beauty clinic, detailing customer purchases, products or services offered, pricing, applied discounts, and payment methods. Key data captured includes invoice numbers, transaction dates, product names, quantities sold, unit prices, total amounts paid, and discounts at both invoice and product levels. This dataset also records information about employee involvement and promotional offer expirations. Such comprehensive transactional data provides valuable insights into customer buying patterns, product popularity, and promotional impact. (Fig. 1).

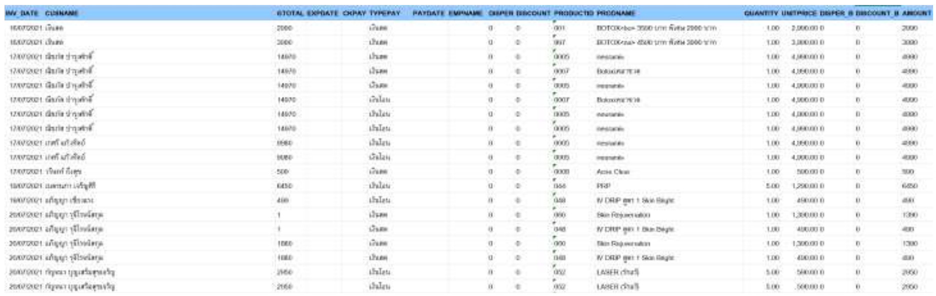

Fig. 1. Data Display

Data cleaning was an essential step conducted prior to analyzing the relationship between product popularity and promotion effectiveness. Initially, issues like incorrect formatting, inconsistent data types, and missing information were identified and systematically corrected. The cleaning primarily involved converting date columns into appropriate datetime formats and ensuring numerical consistency. Following this, data normalization was performed to standardize numerical attributes, facilitating effective comparison across transactions. This thorough preparation was critical for ensuring optimal performance and accuracy in subsequent analyses using Decision Trees and Association Rule Mining, enabling clear interpretation and actionable insights for targeted marketing strategies.

3.2. Atomicity of Product Records

During the data preparation process, the principle of atomicity was applied to break down product records containing multiple items into individual, clearly defined units. Originally, the dataset contained combined product entries such as "PRO BOTOX + MESOFAT + FILLER 1 cc.". These were separated into single-product records (e.g., "PRO BOTOX", "MESOFAT", "FILLER 1 cc.") to ensure clarity, improve data granularity, and facilitate precise analysis in subsequent modeling tasks. (Table 1).

Table 1. Atomicity Transformation of Combined Product Records

Before	After
PRO BOTOX + MESOFAT + FILLER 1 cc.	PRO BOTOX MESOFAT FILLER 1 cc.

3.3 Data Normalization and Entity Resolution

In the data preparation stage, Data Normalization and Entity Resolution were applied to resolve inconsistencies in product naming. Initially, multiple variations existed in the dataset, where different names were used to refer to the same product, causing redundancies and confusion during analysis. The normalization process began by standardizing product names into a consistent format, including textual adjustments such as removing unnecessary special characters and spaces, and ensuring uniform naming conventions. Subsequently, entity resolution was conducted to identify and consolidate different product names referring to the same entity into a single standardized name—for instance, combining variations like "BOTOX100," "botox-100 u.," and "Botox 100U" into the standardized "Botox (100 Units)." This process significantly improved data quality, reduced redundancy, and enhanced analytical accuracy and efficiency for subsequent analysis stages. (Table 2).

Table 2. Standardization of Product Names through Normalization and Entity Resolution.

Original Product Names	Normalized Standard Name
BOTOX100	Botox (100 Units)
botox-100 u.	Botox (100 Units)
Botox 100U	Botox (100 Units)

3.4. Data Preparation for Decision Tree and Association Rule

In the data preparation stage for the Decision Tree model, the data was initially examined to ensure that all attributes were of appropriate data types, and any discrepancies or incorrect data types were corrected accordingly. Irrelevant or redundant attributes were identified and systematically removed to simplify the dataset and enhance the efficiency of the subsequent analytical processes. Additionally, missing values were rigorously checked to guarantee the dataset's completeness and reliability, as completeness is essential for ensuring robust model performance. Subsequently, numeric attributes underwent normalization, scaling values into a consistent range of [0-1], facilitating equitable weighting and enhancing interpretability within the modeling process. Lastly, the Synthetic Minority Over-sampling Technique (SMOTE) was employed to address class imbalance by generating synthetic data points within minority classes, effectively improving the performance, accuracy, and overall reliability of the Decision Tree classification model. (Fig. 2).

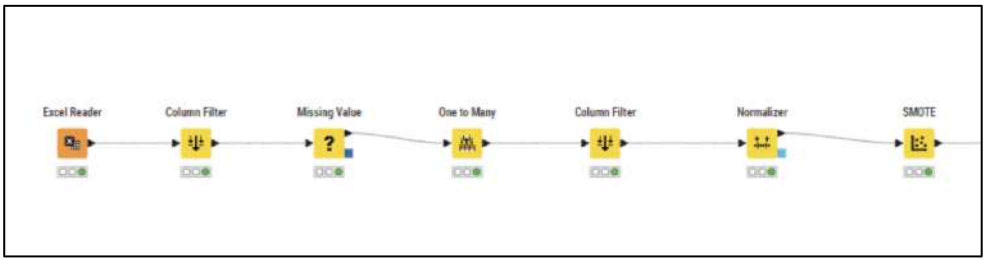

Fig. 2. Data Preparation.

Table 3. Column Selected Include and Exclude.

Column	Status	Description	Support for Decision Tree
INV_NO	Excluded	Invoice number	ID only, no predictive value
INV_DATE	Excluded	Invoice date	Needs preprocessing; use Month/Day instead
CUS_CODE	Excluded	Customer code	Unique ID, not behavior-related
PRODUCTID	Excluded	Product/service ID	Uninformative unless mapped; use category instead
QUANTITY	Excluded	Purchase quantity	Redundant with GTOTAL
UNITPRICE	Excluded	Price per unit	GTOTAL already reflects value
DISCOUNT	Excluded	Discount given	Often zero or minor impact
PRODUCTNAME	Excluded	Service/product name	Too specific; high cardinality
GTOTAL	Included	Total paid	Shows spending behavior
TYPEPAY	Included	Payment method	Target variable (e.g., Cash, Transfer)
Product Category	Included	Type of service	Key feature for customer interest
GENDER	Included	Customer gender	Useful for behavior segmentation
Month	Included	Purchase month	Reveals seasonal trends
Day	Included	Day of the month	May indicate payday behavior
Day_Name	Included	Day of the week	Captures weekday vs weekend patterns

In preparing data specifically for Association Rule Mining, the raw dataset was first thoroughly reviewed for correctness, consistency, and suitability for this particular analytical method. Unnecessary attributes and irrelevant columns were systematically identified and filtered out, resulting in a streamlined and relevant dataset optimized for the association analysis. Furthermore, products were meticulously re-categorized based on domain expertise and empirical insights gained through direct observations within the clinic environment, ensuring that product categorization accurately reflected real-world customer behaviors and practices. After establishing these meaningful product categories, categorical variables were encoded through appropriate encoding techniques, transforming textual or categorical attributes into numerical or binary representations suitable for transactional analysis (0, 1). Finally, before performing the Association Rule analysis, comprehensive validation procedures were implemented to verify the integrity and accuracy of the encoded transactional dataset, ensuring the reliability and validity of the subsequent analytical outcomes.

3.5 Product Type Categorization for Association Rule Modeling

To develop an Association Rule model for analyzing customer purchasing behavior in aesthetic clinics, this study grouped all products in the dataset into broader product types rather than using individual product names. The purpose of this categorization was to reduce data complexity, enhance interpretability of the model outcomes, and better reflect how customers perceive services in real-world contexts—where they typically recognize services by category rather than specific product names. Using product types instead of individual items also helps eliminate non-actionable rules that may arise from items with different names but similar purposes. Furthermore, it allows the model to identify strategic-level relationships between service categories, which makes the resulting insights more actionable in designing promotions, service packages, and targeted marketing strategies aligned with customer needs.

The product categorization was carried out through a manual classification process. The researcher conducted on-site field visits to actual aesthetic clinics to observe the services offered and understand how products are grouped in practice. Interviews with clinic staff were also conducted to gain insights into how product types are defined from an operational standpoint. Based on the information gathered, products were grouped into categories such as Skin Treatments, Filler & Botox, Laser Services, Cosmeceuticals, and Body Contouring, among others. (Table 4).

- **Reduces redundant rule patterns**: By grouping similar products into unified categories, this approach simplifies the dataset and results in clearer, more interpretable association rules.
- **Improves rule accuracy**: It better reflects actual purchasing behavior, as customers often recognize services by category rather than by specific product names. For example, "laser services are often purchased together with skin treatment packages."
- **Supports promotional design**: Association rules derived from product-type level insights can be more easily applied to the development of promotions or service packages that align with real customer behavior

Table 4. Product Type for Association Rule

Group	Product Type	Number of Products
1	Acne Treatment	718
2	Muscle Relaxation and Contouring	477
3	Skin Injection	476
4	Laser Treatment	404
5	Vitamin Therapy	257
6	Facial Fat Reduction	152
7	Promonth Muscle Relaxation and Contouring	133
8	Skin Repair	130
9	Skin Supplement	112
10	Vitamin Therapy (Long term)	93

Group	Product Type	Number of Products
11	Facial Lifting and Tightening (Device-Based)	76
12	Laser Treatment (Long term)	65
13	Hair Removal Treatment	49
14	Skin Supplement (Long term)	49
15	Acne Treatment (Long term)	46
16	Uncategorized	43
17	Promonth Laser Treatment	41
18	Skin Injection (Long term)	37
19	Promonth Skin Injection	29
20	Promonth Acne Treatment	17
21	Facial Contouring and Lifting	17
22	Promonth Facial Lifting and Tightening (Device-Based)	16
23	Promonth Facial Fat Reduction	16
24	Advanced Skin Rejuvenation	16
25	Hair Removal Treatment (Long term)	15
26	Promonth Laser Treatment (Long term)	13
27	Dermal Fillers and Facial Contouring	12
28	Promonth Skin Supplement	12
29	Promonth Dermal Fillers and Facial Contouring	12
30	Promonth Skin Injection (Long term)	6
31	Promonth Advanced Skin Rejuvenation	4
32	Promonth Vitamin Therapy	3
33	Advanced Skin Rejuvenation (Long term)	2
34	Promonth Skin Supplement (Long term)	1
35	Chemical skin treatment	1
36	Promonth Hair Removal Treatment (Long term)	1

3.6 Decision Tree

Decision Tree modeling is a supervised learning technique that is widely used for classification tasks in data mining. It provides an interpretable flowchart-like structure in which internal nodes represent decisions based on input features, and leaf nodes correspond to class outcomes. In this study, the Classification and Regression Tree (CART) algorithm was utilized to analyze aesthetic clinic service usage and customer behavior based on features such as total spending (GTOTAL), product category, gender, and day of the week. The tree construction follows a top-down, greedy approach that recursively splits the dataset to maximize homogeneity within resulting subsets. The splitting criterion in the CART algorithm is based on the Gini Index, which measures the impurity of a node. The Gini Index GGG of a node is defined as:

$$G = 1 - \sum_{i=1}^{n} p_i^2 \quad (1)$$

Where p_i is the proportion of observations belonging to class iii, and nnn is the number of classes. A node with a Gini Index of 0 indicates perfect purity, meaning all samples belong to a single class. The algorithm selects the feature and threshold that result in the greatest reduction in weighted Gini impurity between the parent and its child nodes. Before constructing the Decision Tree, data preprocessing was conducted to ensure model efficiency and reliability. Categorical variables were encoded appropriately, and numerical attributes were normalized to a standard scale. In addition, class imbalance was addressed using the Synthetic Minority Over-sampling Technique (SMOTE), which generates synthetic instances in the minority class to improve learning performance. Once trained, the Decision Tree provided interpretable segmentation rules that highlight relationships between spending behavior, service category selection, and demographic patterns. These insights are valuable for developing targeted marketing strategies in aesthetic clinics. These insights are valuable for developing targeted marketing strategies in aesthetic clinics, before being visualized in the form of a Decision Tree model diagram as shown in the Fig. 3.

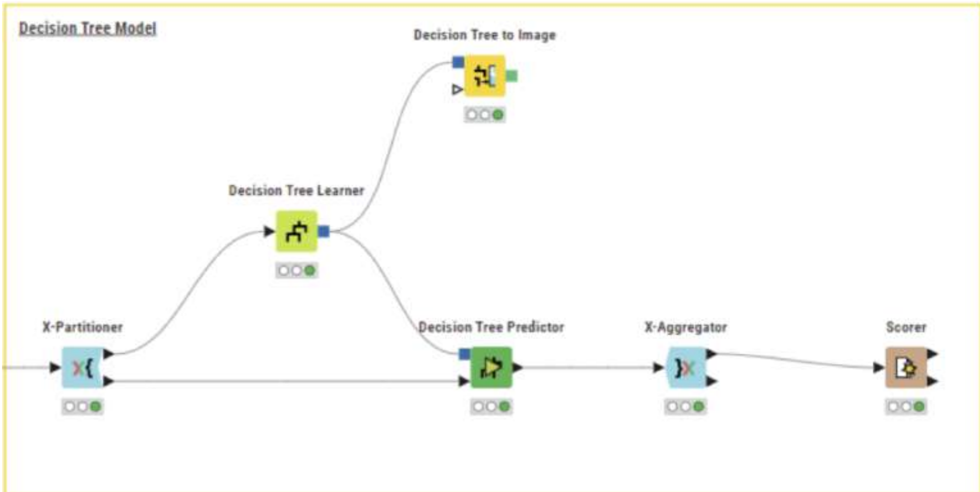

Fig. 3. Decision Tree Model in KNIME Program.

3.7 Association Rule

The Apriori algorithm was employed to examine customer service usage behavior in beauty clinics, with the objective of discovering service combinations that are frequently selected together. These patterns can reveal behavioral insights useful for designing promotional strategies and creating effective service bundles. Two key evaluation metrics were applied: Support, which measures the proportion of transactions containing a specific combination of services, and Confidence, which represents the conditional probability that service B is purchased when service A has already been selected.

$$Support = \frac{Number\ of\ Transaction}{Total\ Transaction} \times 100\% \tag{2}$$

$$Confidence = \frac{Number\ of\ Transaction\ Containing\ A\ and\ B}{Total\ Transaction\ A} \times 100\% \tag{3}$$

In this study, the minimum support threshold was set at 0.2% and the minimum confidence threshold at 15%, following the recommendations of Han, et al. [] This approach allows the identification of rare but strategically valuable patterns, particularly in niche markets such as aesthetic clinics, where certain services may have low transaction frequencies yet hold significant marketing potential. The resulting association rules, such as "customers receiving Acne Clear 6 times are also likely to purchase VPL Red Mark Laser 3 times," offer practical guidance for targeted marketing, personalized promotions, and optimized service combinations aligned with actual customer behavior. [5]

4. Result

4.1 Decision Tree Result

The CART-based Decision Tree model, trained on selected features such as total spending (GTOTAL), service category, gender, payment method, day of week, and purchase month, achieved an overall accuracy of 71.2%, indicating substantial agreement between predicted and actual classes. The best classification performance was observed in the *Botox & Injectables* category (Recall = 0.78, F-measure = 0.776), while *Collagen & Mask Treatments* showed the lowest performance (F-measure = 0.502) due to overlapping characteristics and low representation.

Table 5. The model's classification results

Service Category	Recall	Precision	F-measure	Specificity	Accuracy
Laser Treatments	0.624	0.632	0.628	0.913	-
Hygiene Treatments	0.587	0.583	0.585	0.993	-
Skin & Meso Rejuvenation	0.727	0.741	0.734	0.882	-
Acne Treatments	0.739	0.754	0.746	0.931	-
Collagen & Mask Treatments	0.564	0.452	0.502	0.97	-
Botox & Injectables	0.78	0.771	0.776	0.938	-
Overall	-	-	-	-	0.712

The tree structure identified *GTOTAL* as the primary splitting criterion. Customers with GTOTAL ≤ 0.0742 were associated mainly with *Skin & Meso Rejuvenation* and *Acne Treatments*, while high-spending customers (GTOTAL > 0.0742) showed a strong preference for *Botox & Injectables*. Additional splits, such as GTOTAL ≤ 0.0123 and visits on Saturdays, refined the segmentation, revealing distinct clusters like low-cost preference groups and weekend-driven demand for aesthetic services. These findings provide interpretable rules that can guide targeted promotions and service bundling strategies.

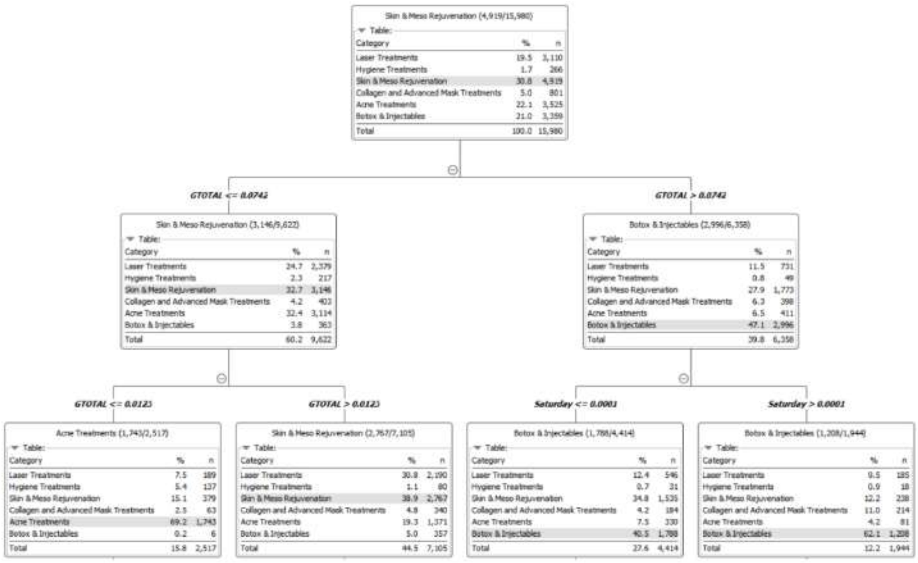

Fig. 4. Decision Tree Structure

4.2 Association Rule Result

Using the Apriori algorithm, 24 association rules were extracted from beauty clinic service transactions after excluding services with a frequency below 0.2%. The model parameters were set to a minimum support of 0.2%, a minimum confidence of 15%, and evaluated using Lift.

Number of association rules: 24

|	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhangs_metric	jaccard	certainty	kulczynski
12	Hair Removal Treatment (Long term)	Skin Supplement (Long term)	0.005969	0.019101	0.0028	0.47	24.43	1.000000	0.002672	1.839186	0.964829	0.125000	0.456281	0.306250
18	Skin Supplement, Acne Treatment	General Aesthetic Treatments	0.014723	0.013928	0.0036	0.24	17.46	1.000000	0.003376	1.303024	0.956830	0.142857	0.232555	0.250193
21	General Aesthetic Treatments	Skin Supplement, Acne Treatment	0.013928	0.014723	0.0036	0.26	17.46	1.000000	0.003376	1.326334	0.956058	0.142857	0.246042	0.250193
11	General Aesthetic Treatments	Skin Supplement	0.013928	0.043772	0.0048	0.34	7.83	1.000000	0.004166	1.455129	0.884652	0.090226	0.312776	0.225974
20	Acne Treatment, General Aesthetic Treatments	Skin Supplement	0.011142	0.043772	0.0036	0.32	7.34	1.000000	0.003094	1.409178	0.873552	0.069767	0.290366	0.201623
1	General Aesthetic Treatments	Acne Treatment	0.013928	0.251492	0.0111	0.80	3.18	1.000000	0.007639	3.742539	0.695319	0.043818	0.732802	0.422157
7	Acne Treatment (Long term)	Skin Repair	0.017907	0.051333	0.0028	0.16	3.03	1.000000	0.001866	1.123421	0.682218	0.041916	0.109862	0.104910
19	Skin Supplement, General Aesthetic Treatments	Acne Treatment	0.004775	0.251492	0.0036	0.75	2.98	1.000000	0.002388	2.994031	0.667866	0.014173	0.666002	0.382120
8	Facial Contouring and Lifting	Muscle Relaxation and Contouring	0.006367	0.168325	0.0032	0.50	2.97	1.000000	0.002112	1.663351	0.667601	0.018561	0.398804	0.259456
13	Promonth Acne Treatment	Laser Treatment	0.006765	0.153203	0.0024	0.35	2.30	1.000000	0.001351	1.308686	0.569778	0.015152	0.235875	0.184263
9	Facial Fat Reduction	Muscle Relaxation and Contouring	0.058048	0.168325	0.0191	0.33	1.95	1.000000	0.009321	1.239026	0.518114	0.092131	0.192915	0.221121
14	Skin Supplement (Long term)	Laser Treatment	0.019101	0.153203	0.0052	0.27	1.77	1.000000	0.002247	1.161321	0.442784	0.030952	0.138912	0.152300
15	Promonth Skin Injection	Skin Injection	0.011540	0.173898	0.0028	0.24	1.39	1.000000	0.000779	1.088056	0.282839	0.015251	0.081689	0.128699
6	Skin Supplement	Acne Treatment	0.043772	0.251492	0.0147	0.34	1.34	1.000000	0.003715	1.127888	0.263871	0.052482	0.113387	0.197454
22	Skin Injection, Acne Treatment	Laser Treatment	0.021488	0.153203	0.0040	0.19	1.21	1.000000	0.000687	1.039250	0.176495	0.023310	0.037768	0.105580
23	Skin Injection, Laser Treatment	Acne Treatment	0.013132	0.251492	0.0040	0.30	1.20	1.000000	0.000677	1.073946	0.172339	0.015267	0.068854	0.159427
10	Facial Lifting and Tightening (Device-Based)	Muscle Relaxation and Contouring	0.030243	0.168325	0.0060	0.20	1.17	1.000000	0.000878	1.036186	0.151744	0.030983	0.034922	0.118415
0	Acne Treatment (Long term)	Acne Treatment	0.017907	0.251492	0.0052	0.29	1.15	1.000000	0.000670	1.052589	0.131810	0.019578	0.049962	0.154729
3	Acne Treatment	Laser Treatment	0.251492	0.153203	[illegible]	0.17	1.11	1.000000	0.004049	1.020382	0.127050	0.117582	0.019013	0.223613
4	Laser Treatment	Acne Treatment	0.153203	0.251492	[illegible]	0.28	1.11	1.000000	0.004049	1.036602	0.112303	0.117582	0.035330	0.223613

Fig. 5. Evaluate Association Rule Result

The highest Lift value (24.43) was found in the rule Hair Removal Treatment (Long term) - Skin Supplement (Long term), indicating that customers who receive long-term hair removal services are over 24 times more likely to also purchase long-term skin supplements compared to random chance. Other notable rules include Skin Supplement, General Aesthetic Treatments - Acne Treatment (Confidence = 0.75, Lift = 2.98) and General Aesthetic Treatments - Acne Treatment (Confidence = 0.80, Lift = 3.18), highlighting strong behavioral links between general *skin* care and acne-related treatments. These insights can be leveraged to design effective marketing strategies, bundled service packages, and cross-selling campaigns.

4.3 Strategic Promotion Results from Integrated Models

Insights from the integrated Decision Tree and Association Rule models informed three targeted promotional strategies for beauty clinics. The Decision Tree segmented customers by spending level, visit timing, and service preference, while Association Rule Mining revealed frequent service pairings for bundling opportunities. The Glow & Clear Journey campaign targets low spenders using acne and skincare services, identified by GTOTAL ≤ 0.0123 and weekday visits, with the rule Skin Supplement - Acne Treatment (Lift = 2.98, Confidence = 0.75) supporting a progressive care package from skincare to acne treatment and supplements. The Precision Botox Elite campaign focuses on high spenders (GTOTAL > 0.0742) who favor Botox & Injectables, mainly on weekends, with no significant co-usage with other services, suggesting an exclusive premium offering rather than a bundled package. The Weekday Acne Boost strategy appeals to students and professionals with frequent weekday acne treatments, supported by the rule Acne - Skin Supplement (Lift > 1.3), enabling weekday promotions with cross-service rewards to increase retention and upselling. This integrated approach demonstrates how combining Decision Tree's customer segmentation with Association Rule's service pairing discovery enables highly contextual, behavior-aligned promotions, enhancing both ROI and customer satisfaction.

Table 6. The model's classification results

Promotion Name	Target Segment	DT Insight	AR Insight	Strategic Focus
Glow & Clear Journey	Low spenders using acne/skincare services	GTOTAL < 0.0123, Acne popular on weekdays	Skin Supplement → Acne Treatment (Lift = 2.98, Conf. = 0.75)	Progressive path: Skin-Acne→ Supplement
Precision Botox Elite	High spenders with single-service focus	GTOTAL> 0.0742, Botox users on weekends	Botox not strongly co-used with other services	Exclusive offer for standalone premium service
Weekday Acne Boost	Students and working professionals	Acne usage on Mon-Fri, frequent visits by GTOTAL low	Acne → Skin Supplement co-use (Lift > 1.3)	Frequency-based discount with cross-sell incentive

5. Discussion

This study combined Decision Tree classification and Association Rule Mining to analyze customer behavior in beauty clinics, enabling precise segmentation and targeted marketing strategies. The Decision Tree revealed spending-based patterns: low spenders (GTOTAL ≤ 0.0123) predominantly chose Acne Treatments, while high spenders (GTOTAL > 0.0742), especially on weekends, preferred Botox & Injectables as standalone services. The model achieved 71.2% accuracy with a Cohen's Kappa of 0.625, confirming its reliability in identifying strategically important customer segments.

Association Rule analysis identified meaningful service pairings, particularly Skin Supplement, General Aesthetic Treatments - Acne Treatment (Confidence = 0.75, Lift = 2.98), indicating a sequential transition from general skincare to acne-specific treatments. This insight supports the creation of multi-phase service packages to increase long-term customer engagement. Botox & Injectables, despite their popularity among high spenders, did not appear in strong associations, suggesting they are best positioned as exclusive, premium offerings.

The integration of both models informed three tailored promotions—Glow & Clear Journey, Precision Botox Elite, and Weekday Acne Boost - each aligned with distinct behavioral segments. While the approach demonstrates strong potential and aligns with prior research, applying it to other clinics requires well-structured, standardized transactional data to ensure accuracy and consistency, including atomic service records, standardized product naming, and consistent service categorization.

6. Conclusion

This study examined the relationship between product popularity and promotion effectiveness in beauty clinics using Decision Tree and Association Rule Mining techniques. The Decision Tree analysis revealed that low-spending customers predominantly chose acne treatments, while high-spending customers preferred premium standalone services such as Botox & Injectables. Association Rule analysis identified meaningful service pairings, particularly the transition from general skincare to acne treatments. Integrating insights from both models led to the development of three targeted promotions—*Glow & Clear Journey*, *Precision Botox Elite*, and *Weekday Acne Boost*—each designed to match the behaviors and needs of specific customer segments. The findings demonstrate that combining customer segmentation with service relationship analysis can create behaviorally aligned and practically applicable marketing strategies in the beauty clinic sector, improving marketing return on investment (ROI), enhancing competitive advantage, and fostering long-term customer satisfaction.

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