

Integration of a Salon Information System with the Apriori-Based Recommendation System and Reservation Optimization

Liliana Liliana^{1*}, Susana Limanto², Daniel Soesanto³, Kenny Reandy Kwando⁴, Gede Darma⁵

Abstract—Salons face challenges in reservation management, service time estimation, and leveraging transaction data for promotions. Existing studies typically develop information, reservation, and recommendation systems separately, while reservation systems often overlook service combinations, quantities, and the parallel execution of services. This study develops a Salon Information System (SIS) that integrates a bundling recommendation system based on the Apriori algorithm with a reservation system that estimates service duration using a brute-force method. The study's novelty lies in the direct integration of SIS transaction data into the recommendation system (eliminating the need for data re-entry), and the calculation of service times that account for both parallel and sequential service workflows. The system was developed based on case studies of three salons in Surabaya, with a requirements analysis involving 53 respondents. The recommendation system was tested using 64 transaction records, applying a minimum support of 20% and a minimum confidence of 80%. Evaluation was conducted through black-box testing, user validation using a 1–4 Likert scale, and a one-sample t-test. All system functions operated as expected. Average user ratings were 3.71 for administrative staff, 3.50 for therapists, and 3.82 for customers. Statistical test results yielded t-values of 5.83 and 14.94, exceeding the critical values at the 5% significance level. The recommendation system generated bundling rules with confidence levels of up to 100%. In practice, the system supports reservation management, uses transaction data to deliver more relevant promotions, and enables more accurate estimation of service capacity.

Index Terms—Integrated Information system, apriori algorithm, bundling recommendation, reservation optimization, salon management system.

Received: 27 March 2026; Revised: 10 July 2026; Accepted: 27 August 2026.

*Corresponding author

¹Liliana Liliana, Sistem Informasi, Universitas Surabaya, Surabaya, Indonesia (e-mail: lili@staff.ubaya.ac.id).

²Susana Limanto, Teknik Informatika, Universitas Surabaya, Surabaya, Indonesia (e-mail: susana@staff.ubaya.ac.id).

³Daniel Soesanto, Sistem Informasi, Universitas Surabaya, Surabaya, Indonesia (e-mail: daniel.soesanto@staff.ubaya.ac.id).

⁴Kenny Reandy Kwando, Teknik Informatika, Universitas Surabaya, Surabaya, Indonesia (e-mail: kenkwando08@gmail.com).

⁵Gede Darma, Department of Information Management, National Taiwan University of Science and Technology, Taipei City, Taiwan (e-mail: gededarma161@gmail.com).

I. INTRODUCTION

Physical appearance plays an important role in enhancing individuals' confidence in public settings [1], [2].

However, individuals may sometimes feel dissatisfied with their physical appearance. [3]. This dissatisfaction motivates people to invest significant time and money in perfecting their appearance. [3]. A salon is one place where people can enhance or maintain their appearance [4]. A salon usually offers various treatments, such as haircuts, coloring, keratin treatments, smoothing treatments, haircare, and makeup. Additionally, salons often sell various products to complement the treatments, such as serums and masks. This observation is supported by the findings of [5], which indicate that many individuals, particularly women, undergo beauty treatments and use various beauty products to maintain their appearance.

The salons studied also offer a variety of products and treatments to maintain and enhance a person's appearance. The average number of customers who visit the salon per day is between 15 and 18 on weekdays and between 30 and 40 on holidays. Meanwhile, the average number of therapists available in each salon is seven. A therapist will serve each customer according to their expertise. Most therapists have more than one area of expertise in providing treatment. A common challenge for these salons is that many customers arrive at nearly the same time, so some have to wait to be served, even though they have made a prior reservation. This issue arises because salons still rely on paper-based administrative processes, with customer reservations recorded sequentially in a physical book. This reservation method often results in several customers' reservations being missed, allowing the salon to accept other reservations simultaneously. Additionally, reservation recording has been carried out without accounting for treatment duration (salons set a fixed duration for all reservations, regardless of the number and types of treatments chosen), even though several treatments can be performed concurrently, making it difficult for the salon to accurately estimate customer service time. The increasingly fierce business competition compels every business actor to enhance their competitive advantage to survive [6].

Business actors can employ several strategies to increase competitive advantage, including innovating [7] and enhancing customer satisfaction [8]. One form of innovation is the use of integrated information technology to simplify and accelerate customer service. Meanwhile, customer satisfaction can be increased by improving service quality and promotions [9]. Improving the quality of customer service is necessary to maintain customer loyalty and emotional engagement [10]. Customers' emotional experiences often influence their desire to return and to recommend the brand to others.

Meanwhile, promotions are not only helpful in retaining existing customers but also in attracting new ones. New customers are typically individuals seeking new experiences at a specific salon. The salon chosen is usually obtained through recommendations from others or because one is interested in the promotions it offers. This condition makes promotions a key strategy for salons to attract new customers. One common type of promotion is bundling, in which multiple services and/or products are offered together as a single package at a lower price. [11]–[13]. Promotions will be more attractive when they align with what customers need. Previous surveys found that around 64% of 53 respondents were hesitant to purchase bundling promotions because they did not match their needs. To ensure the promotion aligns with customer needs, it is necessary to analyze customer transaction patterns using existing transaction history [14]. However, the large volume of transaction history data often makes it challenging to identify customer need patterns [11]–[19].

Numerous studies have used information technology to enhance the competitive advantage of certain salons. Reference [20] developed the back end of the information system for Irfan Salon using information technology. The purpose of the study was to integrate the processes of recording transaction data and managing product stock, thereby minimizing calculation errors in transaction and stock recording, facilitating report generation, and enabling more regular data storage.

Developing salon information systems solely from a back-end perspective makes the existing system non-interactive. Therefore, various studies have been conducted to develop salon information systems from two perspectives: the back end and the front end. Reference [4] developed a Geographic Information System (GIS) to facilitate easier access to salon locations and reservations for salon or barbershop customers by implementing Electronic Customer Relationship Management (E-CRM) [4]. The front end of this GIS includes transaction payment, a chat function for communication between customers and salons, customer ratings and reviews, and promotional information such as discounts. These features enable two-way communication, making the experience more interactive and engaging. Similar studies that also develop the front end of the salon information system include [13], [21]–[24], and [25]. Most researchers develop interactivity through online reservation features, either on websites or on mobile devices. The reservation feature is designed to reduce customer wait time, thereby increasing

customer satisfaction. The results of existing studies indicate that online reservations enable customers to make appointments without visiting the salon, streamline queue management, and support efficient time management within the salon.

The development of salon information systems has been carried out extensively, both from one perspective (front-end or back-end) and from two sides (front-end and back-end). Most research on the front end focuses solely on reservation systems, ratings, and reviews. The reservation system typically only records the appointment time and the list of selected treatments [22], [23], [25]. Sometimes, the number of treatments available for selection is limited, as seen in a study by [25], where the maximum number of treatments selected was 3. The estimated total treatment time is calculated by summing the durations of each selected treatment. However, some treatments can be done concurrently, such as a manicure, a pedicure, and a creambath. At the end of the creambath, a steaming process is performed to ensure the cream's nutrients are fully absorbed by the scalp, strengthening the hair. While waiting for the steaming process to finish, a therapist can perform a manicure or pedicure, reducing the total treatment time to less than the sum of the selected treatment durations. The time difference that arises and could have been allocated to another customer goes unused. Consequently, potential customers who wish to make a reservation at that time may be unable to do so, and may need to move to another salon. In addition, most of the reservation systems developed do not allow for selecting the preferred therapist because the system does not record the therapist's availability time slot.

Meanwhile, from the back-end perspective, previous research has primarily focused on data and inventory management, transaction recording, and report generation [12], [20]. The recorded data was only used to generate standard reports, such as sales and purchase summaries, reservation logs, and current stock. Sales data should be leveraged to gain deeper insights into customer needs, enabling salons to formulate effective business strategies and identify opportunities to attract new clients. Reference [19] conducted research to identify customer transaction patterns, specifically treatments that are frequently purchased together, by analyzing sales history using the Apriori Algorithm. The findings were then used to inform the creation of bundling promotions at the salon. The use of the Apriori Algorithm for bundling promotion creation was also explored by [11], [13], and [19] in other business fields.

The Apriori algorithm is a method for identifying associations among data sets that frequently co-occur, making it a valuable tool for decision-making [15]. Numerous studies have employed this algorithm to analyze data, especially retail sales data [10]–[13], [15], [16], [17], [26]–[30]. The analysis results are applied in various areas, including generating bundling promotions [11], [13], [19], inventory management [11]–[13], optimizing product layout in retail businesses [16], and income analysis [17]. In addition to the business sector, the Apriori algorithm is widely used to support decision-making in education [31], [32] and in the health sector, where

it diagnoses diseases based on patient lifestyle patterns [18], [33].

The Salon Information System (SIS) developed by [20] remains limited to the back end, specifically to data recording and reporting. Research [21]–[25] has equipped the SIS with a reservation system feature. However, existing reservation systems generally record only booking times and do not consider service duration. This limitation can lead to long queues and uncertainty about estimated service completion times, especially for customers who have already made reservations. In addition, stored historical data has not been fully utilized to analyze customer behavior and needs, thereby hindering the formulation of targeted business strategies. On the other hand, most studies analyzing customer shopping patterns use data that are not directly integrated with the main information system, necessitating re-entry or integration before analysis.

The purpose of this study is to develop an SIS integrated with a promo-bundling recommendation system and a reservation system. This research proposes two innovations. First, it integrates the SIS, the promo-bundling recommendation system, and the reservation system into a single system. Second, it optimizes the calculation of the estimated service duration by considering the number, types, and likelihood of concurrent treatments. Meanwhile, the main contributions of this research are:

- The bundling recommendation system was designed in an integrated manner with the SIS, allowing SIS data to be used directly within the bundling recommendation system without re-entry.
- The recommended bundling promotions are generated from an analysis of sales transaction data, ensuring they align with customers' general preferences and needs.
- The reservation system enables customers to select their preferred therapist, thereby enhancing customer satisfaction, particularly among existing customers.
- The estimation of service duration in the reservation system is computed using the brute-force method, considering the number, types, and possibility of treatments to be conducted concurrently, resulting in more accurate availability of time slots for customers.

The remainder of this paper is organized into three sections, with Section II describing the methodology and method employed. Section III explores the implementation of this method in recommending product bundling and calculating service duration estimates, offering analysis and discussion. Finally, Section IV summarizes the study's conclusions and outlines potential directions for future enhancements.

II. RESEARCH METHOD

This study adopts a case-based research approach within the salon business sector. Three salons in Surabaya were randomly selected as research subjects. The three salons were Metro Salon, located at Jalan Ubi VI No. 20, Wonokromo

District; Mila Salon, located at Jalan Rungkut Mejoyo Utara Block AF No. 41, Rungkut District; and Fank Generation Salon, located at Jalan Rungkut Mejoyo Utara IV Block AG No. 3, Rungkut District. The SIS will be developed using a combination of qualitative techniques, incorporating both the Waterfall and Agile approaches. The bundling recommendation system will be implemented using the Apriori algorithm, and the estimated service duration will be calculated using the brute-force method.

The Apriori algorithm is employed to implement the bundling recommendation system, and the brute-force method is used to optimize the reservation system. The reasons to implement Apriori algorithm were it is easy to understand and implement [13], [15], [18], [31], [32], [34], tends to be faster on small-scale datasets with simple transaction patterns [32], [35], requires less memory than the FP-Growth algorithm [13], [15], can perform parallel computing [32], and often used as a basis for the development of other association algorithms [33]. The brute-force method was chosen in this study because it is simple and reliable [36], [37]. Reliable means it explores all possibilities to achieve optimal output.

Figure 1 illustrates the development process of the SIS. The process begins by conducting interviews with salon staff and distributing questionnaires to salon customers at random. The interviews aimed to gather detailed information on existing workflows, including reservation procedures, transaction recording, inventory management, human resource management, review mechanisms, and promotional strategies. Meanwhile, the questionnaire was designed to collect information about customer experiences during salon transactions, including making reservations, purchasing products, receiving treatments, utilizing promotions, and providing reviews. The questionnaire was validated using expert judgment techniques, in this case by two supervisors. This technique was chosen instead of quantitative methods because the questionnaire used a nominal measurement scale and respondents were allowed to select more than one answer for a single question. A total of 53 respondents participated in the questionnaire.

The collected data was analyzed to identify user needs. The findings serve as the foundation for system design. The SIS developed in this study comprises six processes: data management, sales, purchasing, reservations, attendance and payroll, and testimonials. In the reservation system, the system automatically calculates the estimated service duration to minimize customer waiting times.

This allows customers to schedule other activities outside of the salon appointment and allows the salon to accommodate additional customers. Therefore, accurate service time estimation is essential for optimizing service time. The estimated service duration is calculated using the brute-force method, considering whether services can be performed concurrently or sequentially. The brute-force method systematically explores all possible solutions to identify the

most optimal results.

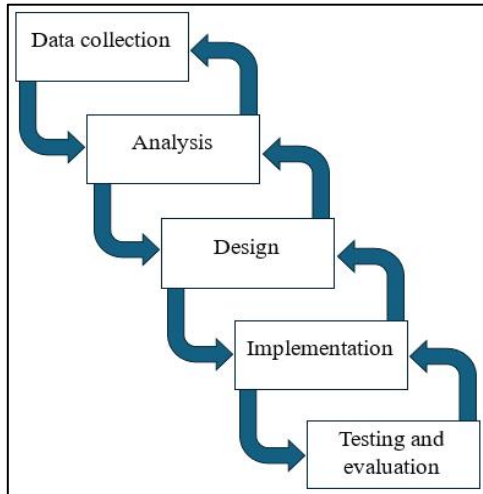


Fig. 1. Salon information system development stages.

Consequently, this method was chosen to ensure precise and reliable service time estimation. If there are multiple possible concurrent service combinations in a customer's order, the one with the shortest duration will be selected. The procedure for calculating estimated service times is presented in Pseudocode 1.

The time complexity of the array initialization process in Pseudocode 1, lines 1 and 2, respectively, is $O(1)$. If n is the number of services selected by the customer, then the process of separating services that can be performed in parallel from those that must be performed sequentially, as shown in lines 3 to 7, has time complexity $O(n)$. The initialization on line 8 has complexity $O(1)$. If S_q is the number of services selected by the customer that can only be performed sequentially, then the time complexity of calculating the duration of all sequential services is $O(S_q)$. In the worst case, all services ordered by the customer must be performed sequentially, so the complexity becomes $O(n)$. The next process is to generate all combinations of services that can be performed in parallel, as in line 11. If p represents the number of services that can be performed in parallel, then the time complexity of the command in line 11 is $O(2^p)$. In the worst case, if all services ordered by the customer can be performed simultaneously, the complexity of Pseudocode 1 is $O(2^n)$. Finally, the time complexity of computing the shortest duration across all parallel services, as shown in lines 12-14, is $O(p \cdot 2^p)$. Thus, the time complexity of Pseudocode 1 is $O(p \cdot 2^p)$.

The design results were implemented as an integrated application. The data design uses MySQL, and the implementation uses the Laravel framework. To evaluate the system's feasibility and functionality, two types of testing are conducted: verification and validation. Verification is performed using black-box testing, following several predefined scenarios. Each scenario represents a distinct process flow, enabling testing of various possibilities for both correct and incorrect cases. This testing aims to ensure that the given input produces the appropriate output.

Pseudocode 1. Estimated service duration calculation

```

Input:
  arrOrder: List of services ordered by the customer
  ds: Duration of individual service s

Output:
  totalDuration: Estimated total service duration

Variables:
  arrSeq: List of services that must be performed sequentially
  arrParallel: List of services that can be performed concurrently
  serviceSet: List of possible concurrent service combinations
  candidateSet: a list of parallelizable service combinations with the shortest service duration
  dss: The combination of services, ss, with the longest duration in serviceSet

Procedure:
1. initialize arrSeq = {}
2. initialize arrParallel = {}
3. for each service, s in arrOrder
4.   if s cannot be performed simultaneously with other services
5.     add s to arrSeq
6.   else
7.     add s to arrParallel
8. set totalDuration = 0
9. for each service, s in arrSeq
10.  totalDuration = totalDuration + ds
11. generate all possible combinations of service sets ( serviceSet ) from the Parallel area that satisfy the execution criteria.
12. candidateSet = { serviceSet with the shortest total duration }
13. for each serviceSet, ss in candidateSet
14.  totalDuration = totalDuration + dss
15. return totalDuration
  
```

Validation was conducted to ensure that the developed system met user requirements and to gather feedback for further improvement. The three user groups that represent validation are administrative staff, therapists, and salon customers. Two respondents represented the administrative staff group, two respondents represented the therapist group, and ten respondents represented the salon customer group. Validation was carried out through a demonstration of the SIS's features, followed by simulation sessions in which participants interacted directly with the system. In the final validation stage, respondents completed a questionnaire designed to evaluate the feasibility and supportability of the features provided and to gather feedback. The assessment used a Likert scale from 1 to 4, with 4 indicating a very positive response. The questionnaire was validated using expert judgment. This technique was chosen instead of the quantitative method because all respondents gave the same answers to several questions. The lack of variation in respondents' answers makes the quantitative method unsuitable. Therefore, the questionnaire was validated by two expert supervisors.

The bundling recommendation system was implemented using the Apriori algorithm. If d is the number of transactions, then the complexity of this algorithm is $O(d \cdot 2^d)$ [38]. The workflow of the Apriori algorithm is outlined as follows:

- Determine the minimum support and minimum confidence threshold.
- Calculate the support value of all 1-itemsets using (1). A set that contains only one item is called a 1-itemset.

$$\text{support}(X) = \frac{N(X)}{N} \quad (1)$$

where:

- $N(X)$ is the number of transactions containing item X .
- N is the number of transactions.

- c. Delete 1-itemsets that do not meet the minimum support threshold. L_1 denotes the set of 1-itemsets that meet the minimum support threshold.
- d. Use $\{L_1\}$ to compute the support for all 2-itemsets. The support for an itemset consisting of two items, X and Y , is calculated using (2) [39]. $N(X \cup Y)$ is the number of transactions containing items X and Y . After that, find all L_2 . Repeat this step until no more k -itemsets can be found.

$$\text{support}(X, Y) = \frac{N(X \cup Y)}{N} \quad (2)$$

- e. For each k -itemset, L_k , generate all nonempty subsets of L_k .
- f. For each nonempty subset s of L_k , form a rule in the form: $s \rightarrow \{L_k - s\}$
- g. Delete rules that do not meet the minimum confidence threshold. The confidence value of each rule is calculated using (3) [39].

$$\text{confidence}(X \rightarrow Y) = \frac{\text{support}(X, Y)}{\text{support}(X)} \quad (3)$$

- h. The recommended bundle promotions are selected from n association rules with the highest confidence value.

To evaluate the performance of the bundling recommendation system, daily sales transaction data from October 25, 2023, to January 22, 2024, was used. Daily sales transaction data is stored in multiple files to reduce redundancy. Before generating recommendations, the data is first filtered according to the user-specified date, then merged, and relevant attributes are extracted to support the recommendation process. The relevant attributes include the invoice number and the ID of the purchased service or product. After this preprocessing step, the final dataset consists of 64 records. Implementing SIS in salons requires significant time, including training human resources to run the SIS effectively. During the trial, SIS was not fully implemented because the human resources needed to run it were not yet available, resulting in limited data collection.

The testing used a minimum support threshold of 20% and a minimum confidence threshold of 80%, ensuring that only frequently co-occurring and highly reliable itemsets were considered in generating recommendations. The benchmarks used to determine the threshold values are [30], [40], [41].

III. RESULT AND DISCUSSION

The SIS is developed from two perspectives: the front end and the back end. The scope of this system is broader than that

of the research reported in [20], which focused solely on the back end. The back-end users are administrative staff and therapists. Administrative staff manage all aspects of salon operations, while therapists deliver treatments to customers. Back-end features include data management, attendance, payroll, and commission calculation, purchasing, sales, and reservations management. Data management encompasses verifying incoming data, as well as adding, deleting, and modifying data to meet business process requirements. Attendance tracking and commission calculations help owners better manage their workforce; scheduling can be balanced to the salon's needs, and payroll can be administered more equitably by accounting for each employee's specific role and workload. Sales and reservation management facilitate the handling of customer transactions, aiming to boost customer satisfaction and foster loyalty, while also serving as a source of information for management decision-making. On the front-end, customers can access information about products, services, and promotions.

Additionally, customers can make reservations or view their reservation history. Products offered to consumers can be tailored based on transaction history, just as product bundles can be customized to match consumer habits. Reservation history is highly valuable to customers, as it allows them to view details such as the date of their last service and the staff member who assisted them—information that can serve as a reference when scheduling future appointments.

The reservation page of the SIS front end is shown in Fig. 2. When making a reservation, customers can specify their desired schedule, the treatments and products they select, and their preferred therapist for each treatment. The option to select a preferred therapist may be important in service-based businesses because the service provider can influence customer retention; in such businesses, the individual providing the service is a key factor in attracting and retaining clients. Customers, particularly those visiting salons, typically prefer to see the same therapist every time, or at least one who shares similar characteristics with the therapist who usually serves them. If the reservation request can be accommodated, the system displays an estimated treatment duration. This estimate considers whether treatments can be performed concurrently. As shown in Fig. 2, for example, a customer selects a pedicure, a manicure, and a haircut, each lasting 30 minutes. The pedicure and manicure can be performed simultaneously by two different therapists because the customer does not choose the therapist. Therefore, the total estimated service duration is reduced to 60 minutes, rather than 90 minutes. One of the key advantages of this study over previous research is the ability to produce more accurate estimates of treatment duration. To the best of the authors' knowledge, previous studies have primarily relied on fixed treatment durations. Having a more accurate estimate of the treatment duration allows customers to plan their other

activities more effectively.

Fig. 2. Reservation page of the front-end of the SIS.

Verification results indicated that all features within the SIS were functioning properly and producing expected output. These results indicate that the system can support the operational processes of a salon business. Although the verification of the estimated service duration calculations yielded correct results, in practice it was unable to eliminate the waiting time for customers who had already made reservations.

Further analysis revealed several contributing factors to this issue, which were:

- Some customers who had made reservations arrived late.
- Some customers requested additional treatments besides those initially booked. During service sessions, therapists often promote ongoing salon services and special offers. In some cases, customers are attracted to these promotions and opt for additional services.
- In practice, actual service times may exceed those recorded in the database due to therapist inexperience or differing customer expectations. For example, a less experienced therapist may take longer to apply nail polish carefully, and customers may request corrections if the results are unsatisfactory, further extending the service time.
- Some salons continued to serve customers without reservations, even when their service times overlapped with scheduled appointments. This action is taken to maintain good relationships with customers, as salons strive not to turn away customers who have already walked in.
- There were transition times between services and the time to prepare materials and equipment for the next service. The tools used can vary depending on the type of service. For example, a customer may order a haircut and a hair dye treatment. would require different sets of tools: scissors, combs, and clips for the haircut, and dye, bowls, gloves, and brushes for coloring. This requires additional time to switch and prepare the equipment.

These factors collectively disrupt the SIS's scheduling accuracy and operational efficiency. Addressing this requires strong commitment and operational discipline from salon management and staff. Additionally, further research is needed

to determine the duration of preparation and transition times between services, as these intervals can vary considerably depending on the type and complexity of the service provided.

Validation was carried out in collaboration with two salons: Fank Generation Salon and Metro Salon. Fig. 3 presents the distribution of respondents who participated in the validation process. Most of the customer respondents were female, accounting for approximately 70% of the total sample. 80% of customer respondents were between 17 and 21 years old, while the remaining 20% were between 22 and 30 years old. This gender distribution aligns with [5], which found that women engage in personal grooming activities more frequently than men.

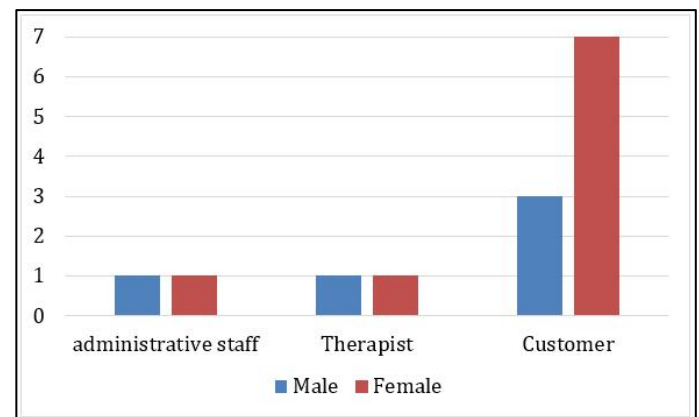


Fig. 3. Respondents' profile.

Table 1 summarizes the evaluation results from administrative staff and therapist respondents regarding the perceived feasibility and supportability of each feature in the SIS back end. Meanwhile, Table 2 presents customer respondents' assessments of the feasibility and supportability of each front-end feature. Both tables indicate highly positive responses across all respondent groups. The average scores given by administrative staff, therapists, and customers were 3.71, 3.5, and 3.82, respectively, based on a 4-point scale.

Table 1.
Assessment Results from Administrative Staff and Therapist Respondents

Features	Percentage of Respondents Who Gave Rating (%)			
	1	2	3	4
Administrative Staff				
Reservation management			50	50
Sales			50	50
Purchase				100
Internal product usage tracking			50	50
Bundling recommendations			50	50
Employee attendance				100
Payroll				100
Therapists				
List of upcoming reservations			50	50
Salary and commission			50	50
Average score of administrative staff respondents	3.71			
Average score of therapists' respondents	3.50			

To statistically evaluate the respondents' assessments, one-sample t-tests were conducted -assuming normally distributed

data. The one-sample t-test was selected because the population variance was unknown and the administrative staff and therapist dataset comprised only 18 observations. The alternative hypothesis stated that the population mean was greater than 3, indicating a positive assessment of the SIS. Using a 5% significance level, the test statistic for the Admin and Therapist group was 5.83, exceeding the critical value of 1.74. Similarly, the Customer group yielded a test statistic of 14.94, also exceeding its critical value of 1.68. Details of the test can be found in Tables 3 and 4.

Table 2.
Assessment Results from Customer Respondents

Features	Percentage of Respondents Who Gave Rating (%)			
	1	2	3	4
Reservation			10	90
Selection of therapists during the Reservation			50	50
Reservation History			20	80
Salon Information (products, services, and promotions)			10	90
Overall				100
Average score	3.82			

As shown in Table 3, the mean assessment score provided by administrative staff and therapists was significantly higher than the reference value of 3 ($M=3.667$, $SD=0.485$, $t(17)=5.831$, $p<0.001$). Therefore, the null hypothesis is rejected. This finding indicates that administrative staff and therapists generally evaluated the SIS positively. For Table 4, the one-sample t-test showed that the mean customer assessment was significantly higher than the reference value of 3 ($M=3.82$, $SD=0.388$, $t(49)=14.941$, $p<0.001$). Therefore, the null hypothesis was rejected, indicating that customers generally provided a positive assessment. Compared with Table 3, customer assessments were higher and showed less variability than those of administrative staff and therapists: the customer mean is 3.82 compared to administrative staff/therapists at 3.667, while the customer SD of 0.388 is smaller than the administrative staff/therapists' SD of 0.485. In both cases, the null hypothesis was rejected in favor of the alternative hypothesis. Overall, these results provide statistical evidence that users perceived the SIS as supportive of salon business operations and helpful in facilitating customer access to information and reservation services. However, the successful implementation and sustainability of the system depend on salon management's commitment and integrity to ensure the smooth execution of business processes.

The integration between the SIS and the product bundling recommendation system is implemented by embedding the recommendation system as a feature in the SIS back end. Sales transaction data retrieved from the SIS serves as input for the recommendation process, thereby enhancing data consistency across systems, eliminating manual data re-entry, and reducing the time required to prepare input data. This differs from most existing studies, which develop product

bundling recommendation systems separately from the SIS. The integration of both systems is a key strength of this research, as it automates data flow and eliminates the need for re-entry during the recommendation process.

Table 3.
t-Test for Assessment of Administrative Staff and Therapists

Null hypothesis	$\mu \leq 3$
Alternative hypothesis	$\mu > 3$
Significance level	0.05
Sample size	18
Degree of freedom	17
Sample mean	3.667
Sample standard deviation	0.485
t-test statistic	5.831
Upper critical value	1.740
p-value	1.00229E-05

Figure 4 presents the interface of the recommendation page. Users can specify the sales-data period used to generate recommendations, enabling more relevant and up-to-date results. As shown in Fig. 4, based on transaction data from October 25, 2023, to January 22, 2024, at least 20% of customers who had (1) pedicures and natural makeup or (2) pedicures and relaxation massages also had manicure services. The first rule had 25% support and 89% confidence, while the second rule had 20% support and 100% confidence. This information reveals that efforts to improve appearance are not limited to the face, but also extend to the feet and hands, as well as the relaxation of tension and fatigue. The inclusion of toenail and fingernail care in all recommendations implies that these services were particularly in demand during that period. Customer behavior and treatment preferences during that period can be used to create targeted promotions that align with customer needs, thereby increasing sales or attracting new customers.

Table 4.
t-Test for Customer Assessment

Null hypothesis	$\mu \leq 3$
Alternative hypothesis	$\mu > 3$
Significance level	0.05
Sample size	50
Degree of freedom	49
Sample mean	3.82
Sample standard deviation	0.388
t-test statistic	14.941
Upper critical value	1.677
p-value	3.5401E-20

The frequencies of service occurrences across all transactions from October 25, 2023, to January 22, 2024, are presented in Table 5. As shown in Table 5, Manicure was the most frequently selected service, appearing in approximately 50% of the transactions. Facials are also highly popular on an individual basis; however, despite this strong standalone appeal, they are relatively rarely combined with other services. This pattern suggests that facial treatments may be more suitable as standalone services than as components of bundled

packages.

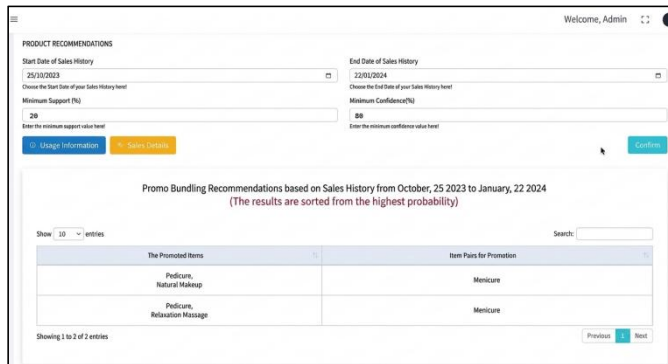


Fig. 4. Interface of the recommendation page.

Table 5.
Service Support Value

Services	Support
Men's cutting	0.078125
Washing (hair loss)	0.078125
Creambath	0.156250
Manicure	0.500000
Pedicure	0.375000
Coloring	0.031250
Natural makeup	0.375000
Relaxation massages	0.281250
Curls	0.062500
Facial	0.468750
Women's cutting	0.078125
Manicure, Pedicures	0.343750
Manicure, Natural makeup	0.328125
Manicure, Relaxation massages	0.265625
Manicure, Facial	0.140625
Pedicures, Natural makeup	0.281250
Pedicures, Relaxation massages	0.203125
Pedicures, Facial	0.078125
Natural makeup, Relaxation massages	0.140625
Natural makeup, Facial	0.093750
Relaxation massages, Facial	0.046875
Pedicures, Manicure, Natural makeup	0.250000
Manicure, Pedicures, Relaxation massages	0.203125
Manicure, Natural makeup, Relaxation massages	0.140625
Pedicures, Natural makeup, Relaxation massages	0.109375
Pedicures, Manicure, Natural makeup, Relaxation massages	0.109375

Other findings indicate that manicure, pedicure, and natural makeup services are often purchased together. The service combinations most frequently purchased together are:

- Manicure + Pedicure (0.34375, approximately 22 transactions)
- Manicure + Natural makeup (0.328125, approximately 21 transactions)
- Pedicure + Natural makeup (0.28125, approximately 18 transactions)
- Manicure + Relaxation massages (0.265625, approximately 17 transactions)
- Pedicure + Relaxation massages (0.203125, approximately 13 transactions)

For the association rule Pedicure $\rightarrow$ Manicure, the

confidence value was 0.9167, indicating that approximately 91.7% of customers who selected a pedicure also selected a manicure. Furthermore, the lift value calculated using formula (4) [42] is 1.83, indicating that the Pedicure–Manicure relationship is not merely due to the general popularity of manicures; customers who get a pedicure are approximately 1.83 times more likely to get a manicure than the general customer base.

$$Lift(A \rightarrow B) = Confidence(A \rightarrow B) / Support(B) \quad (4)$$

For the three-service combination of pedicure, manicure, and natural makeup, the support value was 0.25, indicating that 25% of all transactions included all three services. The association rules generated by the Apriori algorithm exhibited higher confidence values than those for service combinations selected solely by frequency of occurrence. This shows that the recommendations generated by the Apriori algorithm have a stronger basis for implementation than those based on popularity. The Apriori and brute-force algorithms produced the expected results for the relatively small datasets examined in this study. However, these algorithms are highly inefficient when used on large datasets. This is because both algorithms evaluate all possible combinations. This computational limitation presents significant opportunities to develop faster, more efficient algorithms.

IV. CONCLUSION

This study contributes an integrated approach that combines a Salon Information System (SIS), an association-rule-based bundling recommendation system, and reservation scheduling optimization within a single platform. This integration enables the direct use of operational transaction data to generate recommendations without re-entry, while also expanding reservation mechanisms to account for services that can be performed either in parallel or sequentially. Thus, the study demonstrates that salon operational data can be leveraged not only to support administrative processes but also to inform decisions about promotions and service capacity management.

In practical terms, this system can assist salon managers in formulating bundling promotions based on customer transaction patterns, allocating therapists and service slots more strategically, and providing customers with more informative service time estimates. Such information can be used to enhance service capacity utilization and support daily operational planning.

This study has several limitations. The recommendation system was evaluated using a relatively small dataset of 64 transactions, and the study was conducted at a limited number of salons; therefore, the generalizability of the results requires further validation. The accuracy of service-duration estimates is also influenced by operational factors such as customer lateness, service additions, preparation and transition times, and variations in actual service duration. Furthermore, this study did not conduct a comparative evaluation of Apriori against other recommendation algorithms, so the relative performance of Apriori could not be determined.

Future research should use larger, more diverse datasets and compare Apriori with other approaches, such as FP-Growth, collaborative filtering, and hybrid methods. Future system development could also focus on real-time personalized recommendations based on individual customer histories and preferences. Regarding reservations, predictive scheduling models could be developed by leveraging historical data on therapist performance, actual service durations, customer lateness, and transition times to generate real-time service duration estimates and dynamically adjust schedules based on salon operational conditions.

REFERENCES

- [1] R. Aggarwal, R. Ranjan, and R. Chandola, "Effect of body image on self esteem: A systematic literature review and future implication," *Eur. Chem. Bull.*, vol. 12, no. 4, pp. 6087–6095, 2023, doi: doi: 10.48047/ecb/2023.12.si4.5412023.09/05/2023.
- [2] S. Rathee, "Appearance in relation to the activities performed by adolescents," *Int. J. Sci. Eng. Sci.*, vol. 7, no. 8, pp. 42–49, 2023, [Online]. Available: <https://ijses.com/wp-content/uploads/2023/08/63-IJSES-V7N8.pdf>
- [3] A. Looman, M. Id, C. S. A. Silva, and M. A. C. Varella, "The contrasting effects of body image and self-esteem in the makeup usage," *PLoS One*, pp. 1–11, 2022, doi: 10.1371/journal.pone.0265197.
- [4] I. K. Dharma, K. Putra, I. N. Piarsa, and I. M. Sukarsa, "Geographic information system for booking beauty salon and barber shop with an android-based ECRM approach," *Sci. J. Informatics*, vol. 7, no. 1, pp. 52–65, 2020, doi: doi: 10.15294/sji.v7i1.22675.
- [5] T. Thamrin, S. Steffy, T. Linda, and L. Sembiring, "Investigating the online shopping pattern for beauty brands most liked by Indonesian women," *Front. Bus. Econ.*, vol. 1, no. April, pp. 24–34, 2022, doi: doi: 10.56225/finbe.v1i1.82.
- [6] D. Patrisia, M. R. Linda, and Abror, "Creation of competitive advantage in improving the business performance of banking companies," *J. Siasat Bisnis*, vol. 26, no. 2, pp. 121–137, 2022, doi: 10.20885/jsb.vol26.iss2.art1.
- [7] I. Farida and D. Setiawan, "Business strategies and competitive advantage: The role of performance and innovation," *J. Open Innov. Technol. Mark. Complexity*, vol. 8, no. 3, pp. 1–16, 2022, doi: <https://doi.org/10.3390/joitmc8030163>.
- [8] V. Kyurova and B. Koyundzhyska-davidkova, "Study of customer loyalty in small and medium-sized enterprises in the field of trade in Bulgaria," in *SHS Web of Conferences*, 2021. doi: 10.1051/shsconf/20219207036.
- [9] F. Anggraini and A. Budiarti, "Pengaruh harga, promosi, dan kualitas pelayanan terhadap loyalitas pelanggan dimediasi kepuasan pelanggan pada konsumen gojek," *J. Pendidikan Ekon.*, vol. 08, pp. 86–94, 2020, doi: doi: 10.26740/jupe.v8n3.p86-94.
- [10] S. Rahayu and K. Kunci, "Pengaruh kualitas pelayanan, harga dan promosi terhadap loyalitas pelanggan melalui kepuasan pelanggan," *J. Ekon. Ekon. Syariah*, vol. 5, no. 2, pp. 2192–2207, 2022, doi: 10.36778/jesya.v5i2.808.
- [11] H. B. Sabila and A. A. Algorithm, "Implementation of apriori algorithm for data mining on sales transaction data," *Int. J. Electr. Energy Power Syst. Eng.*, vol. 6, no. 3, pp. 189–193, 2023, doi: doi: 10.31258/ijeepse.6.3.189-193.
- [12] F. Putrawansyah, "Application of the apriori algorithm to purchase patterns," *Indones. J. Comput. Sci.*, vol. 12, no. 1, pp. 553–561, 2023, doi: 10.33022/ijcs.v12i2.3105.
- [13] S. Limanto, D. Absari, and E. A. Thamrin, "Integration of bundling product recommendation system and stock management in fast fashion retail business," in *Conference: 2024 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA)*, 2024. doi: 10.1109/ICICYTA64807.2024.10913200.
- [14] R. R. Ramadina, T. H. Pudjiantoro, and I. Santikarama, "Sistem customer relationship management (CRM) menggunakan metode asosiasi algoritma apriori untuk menentukan rekomendasi produk," *J. ICT Inf. Commun. Technol.*, vol. 19, no. 1, pp. 50–59, 2020, doi: 10.36054/jict-ikmi.v19i1.143.
- [15] H. Xie, "Research and case analysis of apriori algorithm based on mining frequent item-sets," *Open J. Soc. Sci.*, vol. 9, pp. 458–468, 2021, doi: 10.4236/jss.2021.94034.
- [16] A. Anggrawan and C. Satria, "Menentukan akurasi tata letak barang dengan menggunakan algoritma apriori dan algoritma fp-growth determination of item layout accuracy using apriori algorithm and FP-growth algorithm," *Matrik J. Manajemen, Tek. Inform. dan Rekayasa Komput.*, vol. 21, no. 1, pp. 125–138, 2021, doi: 10.30812/matrik.v21i1.1260.
- [17] I. A. Ashari, A. Wirasto, and D. N. Triwibowo, "Implementasi market basket analysis dengan algoritma apriori untuk analisis pendapatan usaha retail implementation of market basket analysis with apriori algorithm for retail business income analysis," *Matrik J. Manajemen, Tek. Inform. dan Rekayasa Komput.*, vol. 21, no. 3, pp. 701–709, 2022, doi: 10.30812/matrik.v21i3.1439.
- [18] K. Gulzar *et al.*, "An efficient healthcare data mining approach using apriori algorithm: A case study of eye disorders in young adults," *information*, vol. 14, no. 203, pp. 1–14, 2023, doi: <https://doi.org/10.3390/info14040203>.
- [19] H. Herlawati *et al.*, "Penentuan pola frekuensi jenis perawatan kecantikan berbasis web menggunakan algoritma Apriori (Studi kasus: Peterson Salon Bekasi)," *Journal of Students' Research in Computer Science*, vol. 3, no. 2, pp. 241–254, Nov. 2022, doi: 10.31599/jsrsc.v3i2.1381.
- [20] J. N. Wijareni, F. T. S. Butarbutar, and I. Agus, "Sistem informasi pelayanan barang dan jasa berbasis desktop pada salon irfan," in *Seminar Nasional Riset dan Teknologi (SEMNAS RISTEK)*, 2022, pp. 184–188. doi: doi: 10.30998/semnasristek.v6i1.5673.
- [21] B. J. M. Putra, A. Purwatama, and P. O. D. A. Purnamasari, "Pengembangan aplikasi reservasi salon keshoo berbasis web," *J. Electr. Electron. Mech. Inform. Soc. Appl. Sci.*, vol. 2, no. 2, pp. 24–30, 2023, [Online]. Available: <https://eemisas.aknpacitan.ac.id/index.php/eemisas/article/download/42/22>
- [22] P. Monalisa, D. Marlina, and F. Rastic, "Sistem informasi reservasi jasa treatment pada latasia salon," in *Seminar Nasional Riset dan Inovasi Teknologi (SEMNAS RISTEK)*, 2023, pp. 397–403. [Online]. Available: <https://proceeding.unindra.ac.id/index.php/semnasristek/article/view/6355/1768>
- [23] V. F. Qolbi, L. Sugiarto, and H. Turmudi, "Perancangan sistem informasi pemesanan salon kecantikan pada aura salon berbasis website," *J. Penelit. Sist. Inf.*, vol. 1, no. 3, pp. 258–268, 2023, doi: 10.54066/jpsi.v1i3.792
- [24] J. S. Lubis, Irvan, and D. Irwan, "Rancang bangun sistem informasi booking tempat pada salon lely guna memudahkan konsumen Berbasis web," *J. Softw. Eng. Comput. Sci. Inf. Technol.*, vol. 4, no. 1, pp. 308–313, 2023, doi: 10.54066/jpsi.v1i3.792
- [25] I. S. Mahendra, Wasino, and T. Handhayani, "Perancangan dan implementasi sistem pemesanan online jadwal waktu untuk layanan barber," *J. Ilm. Tek. Inform. dan Sist. Inf.*, vol. 12, no. 3, pp. 1613–1626, 2023, [Online]. Available: <https://ojs.stmik-banjarbaru.ac.id/index.php/jutisi/article/view/1649/0>
- [26] M. R. Alboalebrah and S. Al-augby, "Unveiling the causes of fatal road accidents in Iraq: An association rule mining approach using the apriori algorithm," *J. Cyber Secur. Risk Audit*, vol. 2025, no. 2, pp. 1–11, 2025, [Online]. Available: <https://thetap.blob.core.windows.net/jcsra/articles/published/1577439617166.pdf>
- [27] D. R and K. R, "Mining consumer behavior patterns in e-commerce using apriori algorithm and sequential pattern analysis," in *2025 International Conference on Automation and Computation (AUTOCOM)*, 2025. doi: 10.1109/AUTOCOM64127.2025.10956521.
- [28] T. Stylianou and A. Pantelidou, "A machine learning approach to consumer behavior in supermarket analytics," *Decis. Anal. J.*, vol. 16, no. June, pp. 1–19, 2025, doi: 10.1016/j.dajour.2025.100600.
- [29] S. Zhou, "Research on online shopping recommendation algorithm

- based on apriori algorithm with association rules,” in *2024 International Conference on Intelligent Education and Computer Technology (IECT 2024), June 2830, 2024, Guilin, China*, Association for Computing Machinery, 2024, pp. 322–328. doi: 10.1145/3687311.3687370.
- [30] A. S. Wibowo and D. S. Donoriyanto, “Implementation of data mining to analyze consumer purchasing patterns using the apriori algorithm,” *Indones. J. Comput. Sci.*, vol. 14, no. 1, pp. 913–923, 2025, doi: <https://doi.org/10.33022/ijcs.v14i1.4652>.
- [31] F. M. Amin, E. F. Rusydiyah, and A. N. Azizah, “Personalized Library Book Recommendations Using K-Means Clustering and Association Rules,” *J. Scientometr. Res.*, vol. 14, no. 1, pp. 32–45, 2025, doi: 10.5530/jscre.20251005.
- [32] Y. Li and H. Zhang, “Big data technology for teaching quality monitoring and improvement in higher education - joint K-means clustering algorithm and apriori algorithm,” *Syst. Soft Comput.*, vol. 6, no. April, pp. 1–12, 2024, doi: 10.1016/j.sasc.2024.200125.
- [33] N. Piran, M. Farhadian, and A. R. Soltanian, “Diabetic foot ulcers risk prediction in patients with type 2 diabetes using classifier based on associations rule mining,” *Sci. Rep.*, vol. 14, no. 635, pp. 1–12, 2024, doi: 10.1038/s41598-023-47576-w.
- [34] S. Xu, “An Apriori Algorithm to Improve Teaching Effectiveness,” *Int. J. Performability Eng.*, vol. 16, no. 5, pp. 792–799, 2020, doi: 10.23940/ijpe.20.05.p13.792799.
- [35] S. R. Karimah and E. D. Udayanti, “Comparison of apriori and FP-growth algorithms in market basket analysis for online book sales,” *J. Appl. Informatics Comput.*, vol. 10, no. 1, pp. 566–574, 2026.
- [36] A. F. Akadji, A. G. F. S. H. Lihawa, M. Eka, K. A. Sasmito, H. Prasetyo, and A. S. D. Auliyani, “Comparative analysis of structural-based reduction and brute force algorithms for determining metric dimensions in tree graphs,” *J. Digit. Technol. Comput. Sci.*, vol. 3, no. 2, pp. 90–99, 2026, doi: <https://doi.org/10.66053/dtcs.v3i2.696>.
- [37] R. D. Shukla, C. Singh, A. Singh, H. Singh, and A. Kaur, “Dual-method evaluation for cost-effective renewable-integrated EV charging scheduling,” in *2025 International Conference on Electrical and Electronics Engineering, ICE3 2025*, 2025. doi: 10.1109/ICE367573.2025.11448897.
- [38] D. Wicaksono, M. I. Jambak, and D. Matthew, “The comparison of apriori algorithm with preprocessing and FP-growth algorithm for finding frequent data pattern in association rule,” in *Advances in Intelligent Systems Research*, 2020, pp. 315–319.
- [39] P. Tan, M. Steinbach, and V. Kumar, *Introduction to Data Mining*. Pearson Addison-Wesley, 2006. [Online]. Available: <https://pzs.dstu.dp.ua/DataMining/assoc/bibl/IntroductiontoDataMining.pdf>
- [40] N. Purwati, Y. Pedliyansah, H. Kurniawan, S. Karnila, and R. Herwanto, “Komparasi metode apriori dan fp-growth data mining untuk mengetahui pola penjualan,” *J. Inform. J. Pengemb. IT*, vol. 8, no. 2, pp. 155–161, 2023, doi: 10.30591/jpit.v8i2.4876.
- [41] H. Chen, M. Yang, and X. Tang, “Association rule mining of aircraft event causes based on the apriori algorithm,” *Sci. Rep.*, pp. 1–18, 2024, doi: 10.1038/s41598-024-64360-6.
- [42] IBM, “Lift in an association rule,” IBM Documentation Help. [Online]. Available: https://www.ibm.com/docs/en/db2/11.1.0?topic=SSEPGG_11.1.0%2Fco m.ibm.im.model.doc%2Fco_lift_in_an_association_rule.htm