



Service Mining: A Service Intelligent System to Explore Valuable Services in Big Data Analysis and Mining Technology

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ABSTRACT

In recent years, rapid development of the Internet leads to overloaded service information. Therefore, finding services that correspond to their needs in the shortest time from substantial service information becomes a key challenge for consumers. Multiple platforms have emerged to assist customers in finding suitable services through systems. However, most of these platforms are product-oriented, mainly using product characteristics as filtering principles. Accordingly, the service intelligent system of this study identifies items strongly associated with valuable services based on the service value of customer preferences, and recommends them to the customer based on the service-dominant logic. This system applies the RFM approach and the apriori algorithm of association rules to design a service intelligent system. To verify the feasibility of the established service intelligent system, three experiments were conducted: screening core customers, analyzing preferred services of core customers, and generating a recommended valuable service set by adopting tourism data, which includes 62,575 valid customers with 72,244 valid travel records, from the Taiwan Tourism Bureau of the Ministry of Transportation and Communication. Hence, to assess the performance of this service intelligent system, a fourth experiment was designed to compare with the Apriori algorithm and analyze precision, recall, and fallout. The experiment results significantly reveal that valuable services are then recommended to the customers, enabling them and the enterprises to jointly create service value via the service intelligent system.

1. INTRODUCTION

Satisfying customer needs is a crucial element for most enterprises to achieve successful operation (Morisada et al., 2019). When providing products or services to customers, enterprises have to satisfy customer needs by maximizing product or service value, thereby enhancing customer loyalty and generating maximal profits for the enterprises (Liat et al., 2017; Iqbal et al., 2018). Information technology is a key element to enhance business advantages. Numerous enterprises apply various

information technologies to establish a satisfactory relationship with their customers and to know their customers more to design marketing strategies corresponding to customer attributes (Paul and Nazareth, 2010; Al-Khatib, 2023).

In recent years, rapid development of the Internet caused service information to grow fast in amount, exceeding customer limit to receive and sort information (Speier et al., 1999; Jackson and Farzaneh, 2012). Collecting various types of information requires considerable manpower and

time. Living in a competitive society, most customers focus on their jobs and do not have sufficient time to collect and sort various types of service information to find the type that corresponds to their needs (Paul and Nazareth, 2010). Therefore, customers encounter difficulties in finding the service information corresponding to their needs among numerous types of service information in a short time. Aiding customers to find the information service they need rapidly is a current trend (Zheng et al., 2013).

Multiple systems that provide the searching function have appeared online, enabling customers to find corresponding services rapidly (Pang, 2023). However, many search platforms remain product-oriented, using product characteristics as the basis for search, but overlooking the alternative to use the value generated by services as a main point of search. Numerous current studies have applied data mining to retrieve the product information customers need and their shopping rules (Carneiro et al., 2017; Hughes and Vafeas, 2018; He et al., 2023). Nevertheless, these studies have overlooked the importance of service and the significance of jointly creating service value with customers. In addition to satisfying the basic needs of customers, enterprises need to create service value that customers want with the customers jointly (Walsh et al., 2018). Most studies have focused on finding information that customers need and clarifying customer behavior through data analysis (Rong et al., 2012). However, previous studies have overlooked that the information found possessed value for the customers, and that the information had the potential to be forwarded to other customers (Lindhult et al., 2018; Morisada et al., 2019).

Furthermore, enterprises also wish to know whether the services they designed corresponded to customer needs and identify other services that customers need. By analyzing the conditions of service use, enterprises can find customers who have corresponding service needs, find potential customers, distinguishing their customer levels, and identifying the needs of most customers (Lindhult et al., 2018). Therefore, enterprises can focus their resources on strengthening marketing strategies to enhance competitiveness, so that they can survive in a competitive environment (Yuan and Yang, 2017). Enterprises need to distribute limited resources properly, develop services

customers need or distinguishing customer needs to develop marketing strategies that are effective to specific customer groups, thereby enhancing their competitiveness (Luca et al., 2015).

Customers can use mining rules to identify relevance from service information and retrieve service and service value that correspond to their needs (Moro et al., 2016; Qi et al., 2016; Carneiro et al., 2017). To our knowledge, most current studies have focused on a single industry, such as analyses on the consumption patterns in the retail industry and on online business-consumer consumptions, so few studies have provided a series of cross-field service experiences (Walsh et al., 2018). This study adopted a data mining technology to excavate customer behaviors of service use, identifying valuable services and providing them for the reference of customers, offering customers a series of service experiences. This study mainly investigated the following questions: 1) In an intensely competitive service environment, how can enterprises find potential customers and provide services with the highest value to enhance their competitiveness? 2) How can the service value generated from the process of customers using services be retained, transferred to and shared with other customers in need? To solve the aforementioned research questions, this study included the following objectives: 1) Establishing a service recommendation mechanism that is based on service value by considering the correlation between customers and the services they use. 2) Identifying the association among services to enhance the accuracy of services recommended, thereby providing services that satisfy customer needs.

2. LITERATURE REVIEW

2.1 Service-dominant logic

In the past, product provision was the mainstream on the market. Enterprises dominated the design, manufacture, and marketing of products, focusing on various functions and quality of products (Luca et al., 2015). However, the service-dominant logic centers on the perspective of service, involving a suggestion to transform from a manufacturing module to a service provision one (Vargo and Lusch, 2017). Service-dominant logic stresses that enterprises and customers should shift the focus from exchanging tangible products to exchanging intangible knowledge, skills, and services (Luca et

al., 2015; Hughes and Vafeas, 2018). In the service exchange process, intangible service can be transferred to customers through products (Vargo and Lusch, 2008; Vargo and Akaka, 2009). Therefore, to enhance competitiveness, enterprises should not only focus on the functions of the products, but also enhance the quality of intangible service transferred to customers (Vargo and Lusch, 2017). In this manner, enterprises can increase their survival competency in the market (Vargo and Akaka, 2009; Luca et al., 2015). To satisfy customer needs, enterprises must interact with customers. Consequently, service-dominant logic claimed that enterprises should consider the design and transfer of services from the perspective of consumers and encourage customer participation in these processes (Vargo and Lusch, 2008; Vargo and Lusch, 2017).

In the age of service economy, enterprises provide customized services to satisfy customer needs. Customer participation becomes increasingly crucial in the service transfer process (Sampson and Froehle, 2006). Therefore, the service value is jointly created by enterprises and customers, rendering the service a process of continual interaction between both parties (Vargo and Lusch, 2008; Vargo and Akaka, 2009). Through interaction, enterprises and customers share the information owned by each other, enhancing the level of information symmetry to prevent incorrect creation and production caused by false information. However, the quality and quantity of exchange are highly dependent on customers, because by participating in the process, consumers decide on the eventual level of service transfer and satisfaction (Ernst, 2002; Luca et al., 2015). The relationship is similar to that between a medical doctor and a patient: whether the doctor can make accurate diagnosis is highly dependent on the information provided by the patient. If the patient offers incomplete or inaccurate information, then the quality of medical service provided by the doctor is severely influenced. In addition, service-dominant logic claimed that services can be transmitted through products and organizations. These products and organizations play key roles, because unsatisfactory functions and quality of the products or inadequate professional abilities of the organizational staff tend to result in service failures, and further lead to decreased competitiveness of the enterprises (Vargo and

Lusch, 2008; Vargo and Akaka, 2009; Vargo and Lusch, 2017). Therefore, these mediating objects are essential in the service exchange processes.

As enterprises gradually came to value the service-dominant logic, they designed multiple communication channels to involve customers in the process of service design and production. During the interaction process of service, enterprises can identify the real needs of the customers, and further facilitate solving problems the customers encounter.

2.2 Recency, Frequency, and Monetary analysis

Recency, Frequency, and Monetary (RFM) analysis is a method of consumer analysis that enterprises adopt to analyze a great amount of data, thereby identifying target customers (Wong and Wei, 2018; Qi et al, 2023). The advantage of RFM analysis is using fewer variables as cluster attributes and reducing the complexity of the customer value analysis module to facilitate obtaining customer characteristics (Chiang, 2017). Schijns and Schroder (1996) considered that RFM analysis is a method of evaluating the long-term relationship between enterprises and customers. Through an RFM analysis, enterprises determine the service use conditions of the customers (e.g., the service that generates the greatest customer demand, and the service-use time of the customers), further analyzing the loyalty and contribution of customers (Walsh et al., 2018). In addition, RFM analysis can be applied to handle clusters effectively on the basis of customer value. Different service marketing strategies can be implemented to various customer clusters (e.g. enhancing purchase rate, increasing high-profit products, or transforming potential customers to long-term ones) to extend customer life cycle (Pai et al., 2025).

Hughes (1994) proposed to analyze massive data by using three variables, namely recency, frequency, and monetary values. Important customers and their purchase conditions can be identified through an RFM analysis (Bult and Wansbeek, 1995; McCarty and Hastak, 2007; Chen, 2009; Rungruang et al., 2024), which is defined as follows:

- (1) Recency (R) is defined as the temporal difference between the last purchase and the present time. This variable evaluates the possibility of next purchase by the customer.

The shorter the temporal space is, the higher repurchase willingness the customer exhibits.

- (2) Frequency (F) is defined as the consumption frequency of a customer in a specific period of time. The larger the value is, the more probably the consumer purchases again, and the higher loyalty the customer shows. F is also applied to present the interaction between customers and enterprises: higher interaction means higher possibility in purchasing.
- (3) Monetary (M) is defined as the total or average amount of money spent by a customer in a specific period of time. The larger the value is, the higher the expenditure is. This variable is used to evaluate the contribution and value of customers to enterprises.

(Total expenditure: $M = m_1 + m_2 + m_3 + \dots + m_n$;
average expenditure: $M = \frac{m_1 + m_2 + m_3 + \dots + m_n}{n}$, m = expenditure of single consumption, n = number of purchases)

There are lots of research focusing on customer topics by using an RFM analysis (Chiang, 2017; Walsh et al., 2018; Wong and Wei, 2018). Customer value analysis is used to identify customer characteristics; this method enables further analysis on abstract and useful knowledge of particular customers from mass data (Cheng & Chen, 2009; Qi et al., 2023). Companies analyze mass customer data to acquire customer value and loyalty and identify customer characteristics (Li et al., 2022). Such valuable and abstract knowledge concerning the customer is used to set the value of services provided for customers. The recency (R), frequency (F), monetary value (M) model is a crucial method of customer value analysis, and companies can apply value analysis to analyze customer data and identify target customers (Chiang, 2017; Walsh et al., 2018). The advantage of the RFM model is using few variables as cluster attributes to minimize the complexity of customer value analysis to obtain customer characteristics (Wong and Wei, 2018). Additionally, the RFM model is an analytical method extensively used in marketing to analyze customer values and identify potential customers that can serve as the basis for decision-making involving positioning and designing the next service.

Besides, Cheng and Chen (2009) input customer data into the RFM model to differentiate consumer

behaviors and analyze customer value. Subsequently, K-means clustering was applied to partition the customers, and rough set theory was employed to create meaningful rules. These rules enable companies to analyze their customer data, understand consumer behaviors, and establish marketing strategies suitable for these customers to improve purchase frequency or total spending or effectively retain customers and ultimately increase competitiveness. Hosseini et al. (2010) proposed a new framework, which added an additional parameter, "customer loyalty," to the RFM model. They then applied the Davies-Bouldin index to optimize the K-means clustering and expand the RFM model by partitioning customer loyalties by product. The aim was to increase customer loyalty and maximize profit to achieve a win-win relationship with customers.

Shim et al. (2012) proposed the customer-relationship management (CRM) strategy for small online stores. This strategy obtains an association rule and sequence pattern by analyzing transaction data of the store. They defined the R, F, and M of prominent customers; then, a model was established using mining techniques such as decision trees, neural networks, logistic regression, and bagging as basic classifiers to divide customers into prominent and nonprominent customers (Abbasimehr and Shabani, 2021). Finally, the association rule and sequence pattern were applied again to transaction data of prominent customers to identify rules and patterns applicable for CRM of online stores. Lo et al. (2008) conducted RFM customer value analysis using demographic information and transaction history from the database of an outdoor activity equipment store. Then, data mining was applied to customer partition to identify prominent customers and the purchase behavior characteristics of each customer group. The identification of highly valuable or potential customers and customization of marketing strategies to meet the requirements of different customer groups are ways to improve the competitiveness of a company. Thus, Miglautsch (2000) proposed the customer quintiles method, where customers are scored from 1 to 5 (5 being the highest) for the R, F, and M parameters based on their transaction history. The sum of their three scores is then compared with the mean score. Customers whose sum is higher than the mean score are considered prominent, whereas

those scoring lower than the mean score are considered potential customers. Chang and Tsai (2011) employed the RFM customer quintiles method to understand the loyalty and contribution level of a customer. High R meant a high repurchase rate; high F meant a high customer loyalty; and high M value meant a high customer contribution to the company.

By using RFM analysis, the value of individual customers can be evaluated objectively on the basis of quantization results. When customers exhibit high RFM value, they can be viewed as important ones (Cheng and Chen, 2009). Tsai and Chiu (2004) explained that the weight of these three variables varies according to industry types. Liu and Shih (2005) provided different RFM weight to different products, so that customers can be distinguished accurately. After the consumption conditions and repurchase possibility of customers are determined, recommendations of suitable products can be effectively made to target clients. Previous studies have focused on customer–enterprise interaction level. Few studies have analyzed customer–service associations. RFM analysis is suitable to analyze the interaction level between items. Therefore, this study adopted RFM analysis to analyze the correlations between customers and service value, as well as between service value and service to identify important customers who exhibit the highest loyalty and the services that generated the highest customer value (Pai et al., 2025). After association rules analysis was applied to the identified important services and customers, suitable services are recommended to the customers.

2.3 Apriori algorithms

Association rules are a data mining technology that is mainly used to analyze market transaction data or consumer purchase behaviors to excavate associations among consumption items (Agrawal et al., 1993). Association rules are defined as follows: Assuming that D is the transaction database, T is the set of total transaction data ($T = \{t_1, t_2, t_3, \dots, t_n\}$), then $T \in D$, and I represents all items in total transaction data ($I = \{i_1, i_2, i_3, \dots, i_m\}$). The expressions for association rules are: $X \rightarrow Y$, X and $Y \in I$, $X \cap Y = \emptyset$, where X and Y are items included in I , and that X and Y do not repeat. If this equation is established, then X and Y are highly related. The strength of association rules can be evaluated by

support (S) and confidence (C).

Support is defined as the transaction data ratio that simultaneously includes the transaction data of X and Y . Before association rules are applied, a minimum support level can be set as the threshold value.

$S = X \cap Y / T$ (X and Y are transaction items, whereas T is the total transaction data)

Confidence is defined in the data set of X , including the percentage of data set Y . If $X \rightarrow Y$ exhibits higher reliability (R), then when X appears, Y has a high probability to appear simultaneously.

$C = X \cup Y / X \cap T$ (X and Y are transaction items, T covers all transaction data)

Rules that are mined through association rules are established only when the S and R are larger than or equal to the minimal S and R . The threshold value of minimal S can be adjusted according to the number of high-frequency items generated in the mining process. When the number of frequent itemsets are too few, S needs to be decreased; conversely, S needs to be increased vice versa (Chen et al., 2009).

Agrawal et al (1993) proposed apriori algorithm, which is an important algorithm in association rules. Mainly based on using S , the algorithm systematically controls the generation of frequent itemsets (as shown in Figure 1). Two major steps are included:

(1) Generation of Candidate Itemsets:

Candidate itemsets are produced on the basis of frequent itemsets:

- To prevent from producing unnecessary candidate itemsets, if at least one child set of a candidate itemset is not a frequent itemset, then this candidate itemset does not need to be retained.
- Candidate itemsets have to include all frequent itemsets.
- No repeated candidate itemset should be produced. For example, the candidate itemset $\{a, b, c, d\}$ generates child itemsets such as $\{a, b, c\}$, $\{a\}$, $\{b\}$, $\{c\}$, and $\{a, c, d\}$. Redundant candidate itemsets causes meaningless calculation.

(2) Elimination of Candidate Itemsets:

On the basis of the set S , candidate itemsets that are smaller than S are eliminated, leaving the remaining candidate itemsets as frequent itemsets,

which then serve as the candidate itemsets for the next stage.

- (1) If $((S_i[1] = S_{i+1}[1]) \wedge (S_i[2] = S_{i+1}[2]) \wedge \dots \wedge (S_i[k-2] = S_{i+1}[k-2]) \wedge (S_i[k-1] = S_{i+1}[k-1]) \wedge (S_i[k-1] < S_{i+1}[k-1]))$
- (2) then $\{c = \{S_1[1], S_1[2], \dots, S_1[k-2], S_1[k-1]\}\}$
- (3) If $(c \in C_{k-1})$
- (4) then c join C_k
- (5) else delete c ;
- (6) Return C_k

Figure 1. The logic of apriori algorithm

The logical concept of apriori algorithm is easy to understand. Moreover, its calculation process comprises repetitive steps of generating candidate itemsets and eliminating those that are below the threshold value of S . This study involves using the

characteristics of apriori algorithm to identify valuable and highly associated services in customer service use history. Through RFM analysis, these services can be recommended to customers.

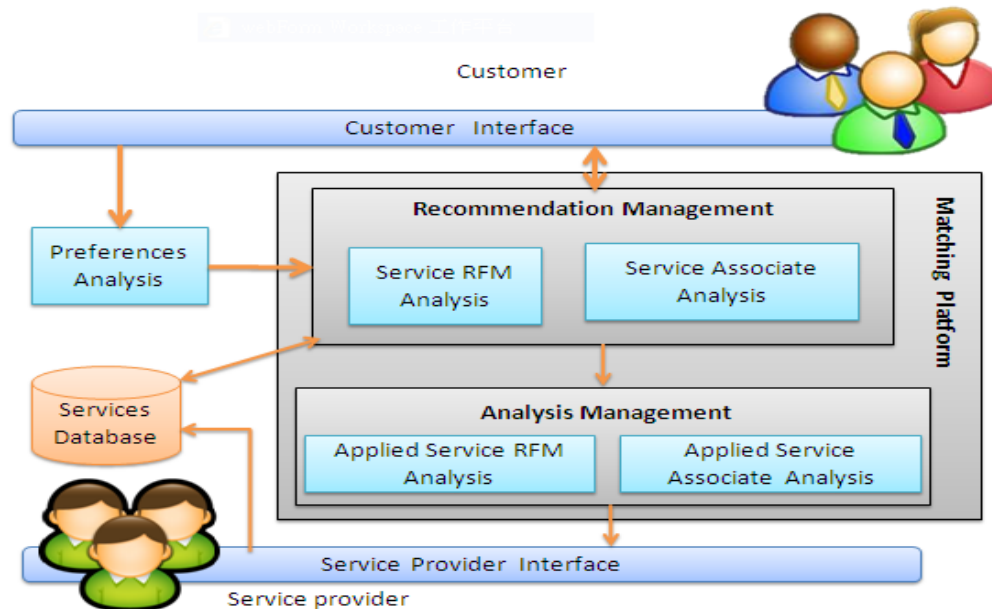


Figure 2. The systematic framework

3. METHODOLOGY

3.1 Research framework

This study investigates using an RFM module and association rules to identify the most valuable service, further recommending a series of related services to satisfy the comprehensive needs of the consumers. This study takes tourism situation as an example to design a service recommendation mechanism based on service value. Under customer preferences, tourism services that have service value and satisfy customer needs can be

recommended (Hameed et al., 2023). Figure 2 shows the systematic framework of the service recommendation mechanism, including the customer end and service provision end. At the customer end, customers can obtain service suggestions through the intelligent system, whereas at the enterprise end, enterprises can obtain useful information, such as the use conditions of services, from the analysis of the intelligent system.

First, customers select service preferences on a

customer interface. This piece of information is input into the RFM analysis module. Preference analysis of customer service and analysis of customer service are subsequently conducted to eliminate valueless services and generate a list of most valuable services. The list is output to the association rule analysis module to identify key association rules of services, service value, and customers. Therefore, this system recommends services to customers according to their service preferences. The customers can choose from the list, and the system records the service selected by the customers, further adjusting the association strength between service preference and service according to this record. Through this feedback mechanism, recommendation validity of this system to the customers can be enhanced.

In addition, enterprises input the services they wish to provide to this system, enabling customers to choose from the service experiences and value of each service. Through this system, enterprises can determine customer loyalty to services as well as the associations among customers, service value, and services, thereby providing a reference for enterprises in service design and strategy transfer. In this study, the correlation between service value and service experiences that customers prefer is first established through expert interviews. Subsequently, by using a questionnaire, the history of associations between services and customer service preference is collected, which then serves as a basis for the data of association rule calculation. A prototype system is developed in this study. Users are invited to use the system to verify the validity of this service recommendation mechanism. This systematic framework recommends valuable services that satisfy consumer needs on the basis of preference information entered by the customers. Furthermore, this system is expected to be suitable for enterprises of various fields. Therefore, the design of this system can be adjusted to various situations.

3.2 RFM analysis module

3.2.1 Preference analysis of customer service

In this step, customers first set their service preferences. Other customers who have the same preferences are then identified by this mechanism. The RFM value of these customers were further analyzed. The set of service preferences is $L_{like} =$

$\{l_1, l_2, l_3 \dots l_n\}$, $n > 0$, and l represents the preferred service. The set of customer service preferences is $T^p = \{t_1^p, t_2^p, t_3^p, \dots t_i^p\}$, $i > 0$, and t_i^p refers to the choice of service preferences entered by the customers. C is the set of all customer lists, expressed as $C = \{c_1, c_2 \dots c_m\}$, $m > 0$.

RFM module of service preferences includes analysis of several steps. After the service preference choice l_1 is input by customers c_1 .

(1) This mechanism lists customers who selected service preference l_1

$C_{(c_1, l_1)} = \{c_1, c_2 \dots c_j\}$, $0 < j < m$, and $C_{(c_1, l_1)} \in C$.

(2) After a customer list $C_{(c_1, l_1)}$ is determined, this mechanism identifies all records of selection related to service preference l_1 from each customer in the list $C_{(c_1, l_1)}$. For example, the record of all selections by customers c_1 that are related to service preference l_1 is $T^p_{(c_1, l_1)}$.

The service preference record of customer c_1 on l_1 is $T^p_{(c_1, l_1)} = \{t_1^p, t_2^p, t_3^p, \dots t_j^p\}$, $j > 0$, and $j < i$.

(3) Calculating the RFM values of customers to their service preferences.

- $R_{c_j} = \text{Now} - c_j t_{i \text{ time}}^p$

Now refers to the present time, whereas $c_j t_{i \text{ time}}^p$ refers to the latest time that customer c_j selected this service.

- $F_{c_j} = \sum_{k=1}^n c_j t_k^p$, $m = 1 \dots n$ ($m < k < n$)

F_{c_j} refers to the total number of times customer c_j selects this service preference. The total number of times is obtained from adding all times from the first selection $t_{k=1}^p$ to the last selection $t_{k=n}^p$.

- $M_{c_j} = \sum_{m=1}^n c_j T^s M_{SUM}$ ($m1 \dots n$)

T^s refers to the set of the service use history of all customers.

The RFM values of all customers who selected this service preference are:

$$R_c = \{R_{c_1}, R_{c_2}, R_{c_3}, \dots R_{c_j}\}$$

$$F_c = \{F_{c_1}, F_{c_2}, F_{c_3}, \dots F_{c_j}\};$$

$$M_c = \{M_{c_1}, M_{c_2}, M_{c_3}, \dots M_{c_j}\}$$

(4) R_c , F_c , and M_c are subsequently added and their average values are respectively $\overline{R_c}$, $\overline{F_c}$ and $\overline{M_c}$.

(5) A list of customers whose R_{c_i} , F_{c_i} , and M_{c_i} values are larger than $\overline{R_c}$, $\overline{F_c}$ and $\overline{M_c}$ is obtained. This list of important guests in history serves as the basis for the RFM module analysis on customer service.

3.2.2 Customer service analysis

After the list of important customers in history regarding a specific service preference is obtained, the service use history of these customers is identified. The RFM values of these services are subsequently calculated to filter the most valuable services. S is defined as the set of all services: $S = \{s_1, s_2, s_3 \dots s_n\}$, $n > 0$. T^S is the set of all entries of service use history. One entry of service use history is expressed as T_i^S , and $T_i^S \in T^S$ is a set consisted of several services. Among all entries of service use history of a customer, the i entry of service use history record is: $T_i^S = \{(s_1, t_1, m_1), (s_2, t_2, m_2), \dots, (s_n, t_n, m_n)\}$, where (s_j, t_j, m_j) means that Service s_j is used in Time s_j , and the value of this service is m_j , $1 \ll j \ll n$. When several services are used in the same time slot, they are arranged in alphabetical order by their names.

After the use history of key services is identified, the RFM values of these services are separately calculated.

- (1) $R_{s_j} = \text{today} - s_j t_{i \text{ time}}^S$, representing the difference between the current time and $t_{i \text{ time}}^S$, the last time Service s_j was selected. The value serves as the R value of this service regarding this service preference.
- (2) $F_{s_j} = \sum_{m=1}^n s_j t_k^S$, where $m = 1$, and $m < k < n$. F_{s_j} represents the total frequency of Service s_j used in this service preference; in other words, the F value of Service s_j regarding this service preference.
- (3) $M_{s_j} = \sum_{m=1}^n s_j M_{SUM}$, where $m \geq 1$, and $m < k < n$. M_{s_j} refers to the total value of Service s_j , which is the M value of this service.

According to the aforementioned steps, the RFM values of Service s_j are calculated as follows:

$$R_S = \{R_{s_1}, R_{s_2}, R_{s_3}, \dots, R_{s_j}\}$$

$$F_S = \{F_{s_1}, F_{s_2}, F_{s_3}, \dots, F_{s_j}\}$$

$$M_S = \{M_{s_1}, M_{s_2}, M_{s_3}, \dots, M_{s_j}\}$$

3.3 Analysis module of association rules

First, D is defined as the transaction database, T as the transaction data, S as the set of all services, and min_sup as the minimal value of support. $S_{k \text{ min_sup}}$ refers to the frequent itemset produced after the apriori algorithm is conducted. C_k refers to candidate itemsets, where c represents a candidate item. The calculation process of the apriori algorithm is shown in Figure 1. In the beginning, S

is defined as all services: $S = \{s_1, s_2, s_3, \dots, s_n\}$. The method of `count_every_service_1th` is then adopted to calculate the use frequency of all services to produce candidate (1-) itemset S_1 . Subsequently, the `check_min_sup` method is used to eliminate items in the candidate (1-) itemset S_1 that are smaller than the support value. The frequent (1-) itemset $S_{1 \text{ min_sup}}$ is therefore produced. On the basis of Frequent itemset $S_{(k-1) \text{ min_sup}}$, Candidate itemset C_k is generated by using Join. To produce Frequent itemset $S_{k \text{ min_sup}}$, items in the Candidate itemset C_k that exhibit a lower activity frequency than the minimal Support value min_sup are deleted. This step is executed repeatedly until no candidate itemset can be generated from $S_{k \text{ min_sup}}$. $S_{k \text{ min_sup}}$ is subsequently returned. The two candidate itemsets are sequenced and compared. If both are established, then these candidate itemsets fully correspond to the conditions for combination. Therefore, the two candidate itemsets can be combined to form another candidate itemset. In addition, if all child sets that include Candidate items c of $(k-1)$ are frequent $(k-1)$ itemsets, then Candidate item c is selected to join Candidate itemset C_k . Candidate item c is deleted vice versa. Eventually, the result is returned to Candidate itemset C_k .

4. EXPERIMENTS

The present study established a service intelligent system based on a list of prominent customers and most valuable services according to an RFM analysis module. Then, an analysis module of association rules was applied to identify services associated with these most valuable services to recommend them to the customers. This study adopted tourism data from the Taiwan Tourism Bureau of the Ministry of Transportation and Communication as research data. The data included travel time, travel expenses, preferences, and services adopted; 75,228 customers and 92,127 travel records were collected. To avoid incomplete or incorrect data affecting research results, preprocessing measures such as filtering, standardization, and conversion were employed, obtaining 62,575 valid customers with 72,244 valid travel records. Additionally, the tourism transaction code, customer code, travel date, tourism service preferences, travel expenses, and tourism service history of each customer were

obtained. To verify the feasibility of the established service intelligent system, three experiments were conducted: screening core customers, analyzing preferred services of core customers, and generating a recommended valuable service set. In this way, the experiments verified whether the recommended services met the requirements of the customer. Additionally, to assess the performance of this service intelligent system, a fourth experiment was designed to compare with the Apriori algorithm and analyze precision, recall, and fallout.

4.1 Experiment 1: Screening core customers

4.1.1 Experimental objectives

The main objective of Experiment 1 was to analyze the service preferences of customers. Then, the RFM analysis module for customer preferences was applied to analyze customers' course of usage of this service, which was then applied to identify prominent customers. This study analyzed all the services used by customers and identified prominent and representative customers to reduce the number of customers for analysis. Therefore, Experiment 2 had to analyze only the course of service usage of these prominent customers to identify valuable services.

4.1.2 Experimental procedure

This experiment analyzed the travel records of customers to understand their preferences for tourism services, travel time, and travel expenses and to define the core customer group. This study identified six tourism service preferences and denoted them as P101, P102, P103, P104, P105, and P106.

- (1) When a customer input a certain service preference, the system identified all the usage records of this service preference.
- (2) The latest travel dates of each customer using this preferred service were obtained to calculate the R, F, and M values of each customer.
- (3) The customer quintiles method (Miglautsch, 2000) was employed to standardize the R, F, and M values for each of the six preferences.
- (4) Customers with high R, F, and M values in each Table 3. RFM standardization results of customers (P101)

of the six service preferences were then identified.

4.1.3 Experimental results

Table 1 presents the standardization rules for the RFM value of service preference P101. A raw R value between 68 and 80 was standardized to 1, a raw R value between 56 and 67 was 2, a raw R value between 44 and 55 was 4, a raw R value between 32 and 43 was 4, and a raw R value between 20 and 31 was 5. A raw F value of 1 was standardized to 1, a raw F value of 2 was 2, and so on. A raw M value between 1 and 9 was standardized to 1, a raw M value between 10 and 18 was 2, and so on. Because the course of each customer was different, RFM standardization rules for each service preference were different. Table 2 presents the RFM standardization rules for service preference P103. Table 3 presents the RFM standardization results of each customer in service preference P101. For example, the raw R value of customer C9269 was 51, which was standardized to 3; the raw F value of this customer was 1, which was standardized to 1; and finally, the raw M value of this customer was 3, which was standardized to 1.

Table 1. The standardization rules for the RFM value (P101)

Score	R value	F value	M value
1	68~80	1	1~9
2	56~67	2	10~18
3	44~55	3	19~27
4	32~43	4	28~36
5	20~31	5	37~45

Table 2. The standardization rules for the RFM value (P103)

Score	R value	F value	M value
1	68~79	1	1~6
2	56~67	2	7~11
3	45~55	3	12~16
4	32~44	4	17~21
5	20~31	5	22~25

Service preference	Customer ID	R value	F value	M value
P101	C9269	3	1	1
P101	C21368	5	2	2
P101	C8427	5	1	1
P101	C10617	4	1	1
P101	C2629	4	1	1
P101	C14362	3	1	1
P101	C19828	3	1	1
P101	C1797	5	1	1
P101	C15657	5	1	1
P101	C10184	4	2	2
P101	C21467	4	1	1

Table 4. The ratios of prominent customers

Service preference	Numbers customers	of Numbers prominent customers	of Ratio of Prominent customers
P101	49,370	9,906	20.06%
P102	4,340	860	19.82%
P103	3,663	635	17.34%
P104	184	9	4.89%
P105	780	110	14.10%
P106	4,238	873	20.60%

According to Table 4, 49,370 customers used service P101. Among these, 9,906 (20.06%) prominent customers were identified. A total of 4,340 customers used service preference P102. Among these, 860 were identified as prominent customers (19.82%). A total of 3,663 customers used service preference P103, and 635 (17.34%) of these were identified as prominent customers. A total of 184 customers used service preference P104, and nine (4.89%) were prominent customers. A total of 780 customers used service preference P105, and 110 (14.10%) were identified as prominent customers. A total of 4,238 customers used service preference P106. Of these, 873 (20.60%) were identified as prominent customers. In summary, out of the 62,575 customers, this experiment identified the core customers distributed among the six service preferences and applied RFM analysis to identify prominent customers effectively.

4.2 Experiment 2: Analyzing preferred services of core customers

4.2.1 Experimental objectives

Experiment 2 analyzed the services used by prominent customers using the RFM analysis module for customer preferences to identify valuable services. Results of this analysis were then used as source data for Experiment 3.

4.2.2 Experimental procedure

After screening, standardization, and conversion of tourism data, the service preferences of prominent customers were analyzed. Particularly, travel date, services used, and the preference level of a service were analyzed.

- (1) For each service preference, the most recent use was used to calculate the R value of each service.
- (2) The F value, mean usage frequency, was calculated for each of the six service

preferences.

- (3) The M value of each service preference was calculated by collecting the preference level of each customer for each use.
- (4) The customer quintiles method (Miglautsch, 2000) was employed to standardize the R, F, and M values of each service.
- (5) Services with high R, F, and M values were identified for the six service preferences.

4.2.3 Experimental results

According to Table 5, when a prominent customer chose service preference P101, 45 services were used. Of these, 27 valuable services were identified (60%). The RFM values of these services were higher than the mean value, which was 13. When a prominent customer chose service preference P102, 45 services were used; 12 (26.67%) of these were valuable services with RFM values higher than the mean value of 9. When a prominent customer chose service preference P103, 44

services were used; 13 (29.55%) valuable services with RFM values higher than the mean value of 10 were identified. When a prominent customer chose service preference P104, 33 services were used; three (9.09%) valuable services whose RFM values were higher than the mean value of 11 were identified. When a prominent customer chose service preference P105, 42 services were used; 13 (30.95%) valuable services with RFM values higher than the mean value of 9 were identified. Finally, when a prominent customer chose service preference P106, 39 services were used; eight (20.51%) valuable services whose RFM values were higher than the mean value of 9 were identified. This experiment analyzed the course of service usage of customers through RFM model analysis. Additionally, service values engendered during use were quantified to identify valuable services effectively.

Service preference	The mean value of RFM	Numbers of used services	Numbers of valuable services	Ratio of services	valuable
P101	13	45	27	60%	
P102	9	45	12	26.67%	
P103	10	44	13	29.55%	
P104	11	33	3	9.09%	
P105	9	42	13	30.95%	
P106	9	39	8	20.51%	
					P106 (1) S101, S102 (2) S101, S104 (3) S101, S208

4.3 Experiment 3: Generating a recommended valuable service set

4.3.1 Experimental objectives

The main objective of Experiment 3 was to analyze and identify services that were strongly associated with the valuable services using the RFM analysis module for customer preferences. This analysis resulted in the identification of highly valuable services that could be recommended to customers. Table 6. The recommendation set of valuable services

Service preference	The recommendation list of Valuable services
P101	(1) S101, S102, S501
P102	(1) S101, S102, S104
P103	(1) S101, S102, S103 (2) S101, S102, S104
P104	(1) S101, S102
P105	(1) S101, S102, S104

4.3.2 Experimental procedure

- (1) Valuable services identified in Experiment 2 were put into the frequent candidate itemset.
- (2) Levels of support and confidence were then calculated for each service in the frequent candidate itemset to identify a candidate item.
- (3) Subsequently, join and delete functions from the association rules were employed for hashing to generate a new candidate itemset. The support and confidence of each of these items were then calculated to identify adequate candidate items.
- (4) Finally, a candidate itemset was considered fit for recommendation when its candidate items were unable to generate a new candidate itemset and the support and confidence of

these items exceeded the threshold.

4.3.3 Experimental results

Table 6 presents the recommendation set of highly associated services. For instance, if a customer prefers service P101, the system would recommend services S101, S102, and S501.

4.4 Experiment 4: Performance evaluation

4.4.1 Experimental objectives

This experiment evaluated the performance of the intelligent system established in this study and the effectiveness of the Apriori algorithm using conventional association rules through precision, recall, and fallout. Precision indicates the ability of the system to offer the correct services. Precision = $\frac{P}{R}$, where P is the number of recommended services employed by the customer and R is the number of recommended services. Recall represents the ratio of recommended services to those actually used by

the customer. Recall = $\frac{P}{A}$, where P is the number of recommended services employed by the customer and A is the total number of services used. However, as the number of service recommendations increased, the precision decreased, and recall rate increased. Therefore, the fallout value was employed to reduce this disparity by integrating the precision and recall rates to provide an evaluation with the highest accuracy.

$$\text{Fallout} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

4.4.2 Experimental procedure

- (1) The precision, recall, and fallout of the intelligent system established in this study were calculated.
- (2) The precision, recall, and fallout of the Apriori algorithm of the conventional association rules were calculated.

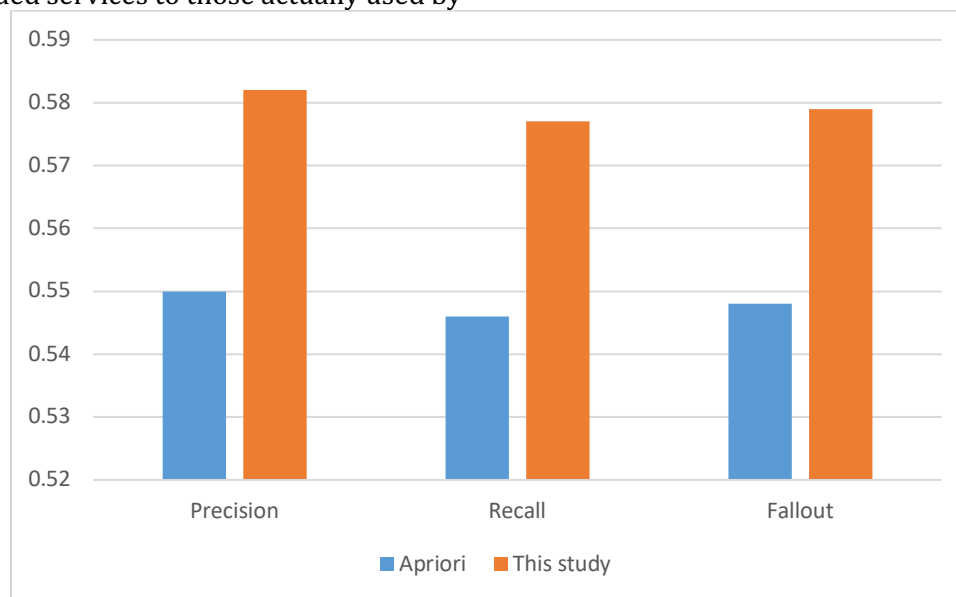


Figure 3. The comparison of the proposed intelligent system and the Apriori approach

4.4.3 Experiment results

According to Figure 3, the precision, recall, and fallout of the intelligent system established in this study were 0.582, 0.577, and 0.579, respectively, whereas those of the Apriori algorithm using the conventional association rules were 0.550, 0.546, and 0.548. That is, the intelligent system proposed in this study was more effective than the Apriori algorithm using the conventional association rules. In other words, the service recommendations proposed by this system contained a higher ratio of valuable services than the recommendation items proposed using only the Apriori algorithm with the

conventional association rules. Therefore, the intelligent system established in this study could assist customers in efficiently finding desirable and valuable services.

5 DISCUSSION

Because of the intangibility and perishability of services, companies providing services are unable to document and quantify service value. However, the present study employed the RFM model to analyze tourism data of customers; prominent customers were identified, and the value of customer-preferred services was quantified to

make effective recommendations for suitable customers. Additionally, this study revealed that service values differed for each service preference. For example, the R value of service preference P101 was between 31 and 36 and thus standardized to 1, which means that customers took longer to choose this service. However, the R value of service preference P102, which was between 30 and 39, was standardized to 4, which means this service was frequently chosen (Table 5). The service values of these two service preferences were remarkably different. Additionally, the association between services varied under different service preferences (Table 6).

Service value varies with the conditions of use of different customers. The intelligent system established by this study analyzes time, frequency, and value of usage rather than using a single factor for analysis. Therefore, valuable customer groups and services could be accurately analyzed. For example, a newly available service contributed more to R value than an older service, but the newer service did not necessarily fulfill the other requirements of the customers. Moreover, a service that was often chosen weighed more on the F value than one chosen less frequently. However, if the time when a service was frequently chosen was 10 years ago, its F value, albeit high, was invalid. To avoid such data distortion, this study analyzed three factors simultaneously to enhance the accuracy of its intelligent system.

Common intelligent systems are usually limited to a single type of service. Therefore, finding an adequate service is costly because researchers must collect useful information for each type of service that interests customers before compiling and analyzing relevant information. The intelligent system established by this study encompasses different types of service; therefore, customers can research services required in each stage of their trip. Through data mining, the level of association between different services and different types of service can be determined to offer one-stop service that quickly tends to the various needs of individual customers.

6. CONCLUSION

6.1 Conclusion remarks

According to service-dominant logic, in the competitive global market, companies have begun

to enhance their competitiveness by emphasizing the crucial strategic information that can be gleaned from identifying the value generated by their services. Compared with the actual products, companies have begun to place greater value on the service they or their products provide. For such services to more effectively fulfill the requirements of consumers, companies have allowed customers to participate in the creation of services. When customers use the intelligent system proposed in this study, data of services used and travel records become feedback for this system. That is, this system is capable of learning, which enables its recommendations to more effectively meet the requirement of customers and improve the relevance of recommended services.

The majority of current intelligent systems or platforms use product information and features as filters instead of considering the value services provide for companies and customers (Luo et al., 2019). To address this, the service intelligent system established in this study analyzes the service preferences of customers to identify services that meet their requirements. Moreover, the value of services is quantified to recommend high-value services to the customer. Accordingly, the service intelligent system of this study identifies items strongly associated with valuable services based on the service value of customer preferences, and recommends them to the customer.

The RFM model was employed to analyze customer value. Companies can analyze value from customer data to identify target customers. The service intelligent system established in this study used the RFM model to analyze valuable customers and services. This process began by identifying prominent customers who were the most loyal to a particular service. Then, services with the highest interaction level under a particular service value for prominent customers were identified. Finally, valuable services were analyzed and identified to be recommended to suitable customers, who were identified by association rules.

6.2 Contribution and implication

The main contributions of this study are as follows. Companies offer various services to fulfill the different needs of customers. However, establishing a method to provide valuable services and record the value created by these services

remains a challenge. Previous recommendation platforms have been designed from companies' points of view and base recommendations on product features. Therefore, recommended products cannot always meet the requirement of customers. Although services are highly valued now, recommendation platforms based on service value have not been established. Therefore, this study aimed to fulfill customer service needs. Particularly, this study employed service-dominant logic as the foundation and service values as references. Then, the RFM model and association rules were applied to identify core customers and identify valuable services. Finally, service values were classified for customers to receive high-value service recommendations that meet their needs.

To compete in today's competitive market and shorten product lifecycles, companies design and offer relevant services to apply to their products to enhance company competitiveness. The value of these services is created when customers use them. However, it is difficult to quantify service value. Therefore, companies often struggle to document the services that customers consider valuable; thus, systematic analysis and sharing of such data are even more challenging. This study applied the RFM model to analyze the service course of customers. High-value services and their values were quantified and documented. In this way, valuable services were compiled and organized and thus ready for recommendation to other customers with similar requirements.

Furthermore, the following implications are detailed. Using the intelligent system established in this study, companies can quantify the service value created through customer use and analyze the contributions of different services to the customer and company. To establish this system, this study employed service value as the reference for search and quantified this value by the RFM model for the company to understand the importance of each service. A company can further analyze the influence of each service on the customer and company and invest the appropriate resources to continue improving service value. Additionally, companies can enhance competitiveness through strategic alliances with other companies.

Other tourism recommendation platforms focus mainly on recommending a particular type of

service (e.g., accommodations or restaurants). However, tourists must make a variety of travel plans, including recreation, accommodation, and transportation. Therefore, the search cost for such customers is considerably high. The intelligent system established in this study allows companies to integrate services of various types; for example, companies can offer one-stop platforms integrating services needed for a trip such as recreational activity, accommodation, and transportation to recommend valuable and high-quality services that meet the requirements of the customer. In this way, the search cost for customers is minimized, and customers can find required services as quickly as possible.

6.3 Research limitation and future research

Although tourism data from the Tourism Bureau comprised data from 2001 through 2014, 2001 through 2009 were inconsistent and missing some data. Therefore, this study adopted only data from 2010 through 2014 to avoid errors in the experimental results. Additionally, future studies can focus on the following two research directions. First, although the present study investigated the Taiwanese tourism industry, several factors valued by the tourism industry were not considered. Future studies are recommended to consider additional factors and analyze the weight of such factors to improve the effectiveness of the recommendations to meet the requirement of the customer. Second, future studies can use the present study as a foundation to determine applications in other service sectors. By combining key factors in different service sectors, future studies can design novel and high-quality services and create diversified service values.

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