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Identifying high-value airlines customers for strategies of online marketing systems

An empirical case in Taiwan

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Abstract

Purpose – The purpose of this study is to discover valuable customers for enterprises. The international market of Taiwan airlines can be enhanced; thus, this study aims at Taiwan's airline market as a research area.

Design/methodology/approach – This research uses data mining technologies with a proposed model to analyse airline customer values for big data online marketing systems, such as customer relationship management (CRM) system. The research applied supervised apriori algorithm, socio-economic variables and a proposed model to discover the rules/markets.

Findings – The results show that eight markets were discovered and three association rules were established for business systems of airlines.

Originality/value – The valuable travellers/markets can be discovered by this research. By collecting shoppers' transactional data, global online CRM and point of sales (POS) systems can be big data marketing systems. The research framework can be easily applied in online CRM/POS or big data marketing systems for international airlines; however, it is for other global businesses as well.

Keywords Association rules, Customer value, Data mining technologies, CRM marketing, CRM and POS systems, Big data online marketing systems

Paper type Case study

1. Introduction

Based on the well-known Recency, Frequency, Monetary (RFM) model (Hughes, 1994), Chiang (2012) proposed the positive and negative profit variables for identifying customer values of internet shopping retailers. In other words, the RFM model can be developed for various businesses. Hence, businesses can develop their profit variables for evaluating customer values effectively. According to businesses' operation procedures, they can replace the RFM variables with proper profit variables for judging customer values. However, as mentioned above, the customer values can be estimated by positive or negative variables.

Data mining technologies are widely used to identify customer values, which are typically applied to front and back systems, such as online big data marketing systems, customer relationship management (CRM) systems, point of sales (POS) systems and online analytical processing (OLAP) systems. Customer profiles of memberships and transaction records are usually analysed to judge customer values and to increase customer loyalty. With the front and back systems, businesses can analyse customers for their customer values. Therefore, businesses can divide them to achieve optimum target markets. In addition, businesses can improve customer values and loyalty through the marketing strategies of information systems (Berry and Linoff, 2004; Kotler and Keller, 2016).

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The concept of the front and rear systems is applied to economy-class passengers to refine their customer values and to identify some useful models. The RFM model can estimate customers, which can also be applied to market clustering as well. The supervised apriori algorithm (SAA; Chiang, 2011) is based on the Apriori algorithm (Agrawal *et al.*, 1993), which is an appropriate method to apply as a classifier for transactional and socio-economic variables in this study. Thus, the procedure of this search can be applied easily in a CRM or marketing system.

For applications of big data marketing in international retail companies, CRM and POS systems can be important data marketing systems because they collect large data per day. Therefore, marketing systems use data mining and machine learning to discover customer knowledge. However, data mining technologies use data analysis and machine learning methods to analyse data to create useful models. Data mining technologies are widely used in CRM/POS or big data marketing systems to find customer knowledge and increase their contributions, which typically include classification, prediction, estimation, association/decision, grouping and visualization (Linoff and Berry, 2002).

The RFM model consists of three profit variables, which can also be a clustering method in accordance with the customer values. Businesses can plan to extend their customers' life cycle (Berry and Linoff, 2004) by implementing marketing projects in various ways to improve purchasing rates, increase sales of high-price product or retain customers to become long-term customers.

As mentioned earlier, customers could be partitioned into a few clusters by the RFM model. Businesses generally implement various marketing plans in optimum target markets (high-value clusters) to improve their shopping frequencies, to gain monetary benefits or to attract them to be long-term customers. Usually, customer values can be estimated by the model, if RFM variables are profit variables for businesses.

This study applies SAA (Chiang, 2011; Agrawal *et al.*, 1993) to process socio-economic variables and a proposed model: Frequency, Travelling times, Family members (F-T-FM) profit model/variables to create association rules. Hence, this research adopts data mining technologies for clustering, classification and rule analysis to create useful models.

2. Literature review

2.1 RFM model

RFM model was defined by Hughes (1994), where R (Recency) was defined as "recent purchasing time"; F (Frequency) was defined as "average frequency of purchasing in a specific period"; M (Monetary) was defined as "average amount of purchasing in a specific period".

The RFM is a method for analysing customer value. It is typically used for database marketing and direct sales and is particularly focused in the retail industries and services industries (Fader *et al.*, 2005).

The RFM model can be applied in the field of market segmentation for finding some high-value customers (Goodman, 1992). For example, Lin and Tang (2006) applied the model to analyse customers of music products. They classified homogeneous customers in a cluster. This study partitions each variable of the model to be two levels: High (H) and Low (L) level. Thus, there were about eight clusters established.

For processing the RFM analysis of consumer in various industries, Miglautsch (2000) pointed out an important point of view for 1-1-1: more than 50 per cent of customers shop only one time in many stores. Su *et al.* (2006) applied RFM model in comprehensive industries and found the high-value customer was only about 18.59 per cent, and it is also in line with the well-known 80/20 rule.

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Moreover, in the research field of classifying and segmentation with the RFM model, Cheng and Chen (2009) used the RFM model and K-means algorithm into the Rough set theory for mining accuracy classification rules. The results of their research can be used to drive a CRM system for an enterprise.

The RFM model can also be applied in specified industries, for example, Chao and Yang (2003) applied Back-Propagation Neural Network on the transactions of the medical equipment industry based on the model; Shih and Liu (2003) applied Analytic Hierarchy Process (AHP) to determine the weights of the model and sorted the customer life value. This research found eight customer clusters, and two types of golden customers. Moreover, Wong and Chung (2007) applied the RFM model and the decision tree algorithm to analyse domestic airline passengers in Taiwan. The results of their research could identify value passengers and might help domestic airlines of Taiwan for their ticket sales.

For applications of the RFM model, McCarty and Hastak (2007) applied Chi-square Automatic Interaction Detectors (CHAID) algorithm and logistic regression on the model. Their research found that the CHAID algorithm tended to be superior to the model when the response rate is low.

For research of clustering by the RFM model, Ravasan and Mansouri (2015) applied weighted RFM model to segment customers of an auto insurance company into four patterns: best, new, risky and uncertain. Maskan (2014) applied a proposed weighted RFM model on internet-service-provider users. In Maskan's research, the customers were partitioned into five markets accurately. Also, Koudehi *et al.* (2014) applied the K-means clustering, Self-Organizing Map (SOM) algorithm (Kohonen, 1990) and weighted RFM model to discover some valuable customer segmentations for the purpose of marketing strategy.

Besides, regarding the study of market segmentation of the RFM model, Chiang (2011) applied an improved model on market segmentation. Chiang's research was for mining useful customer value. Instead of the RFM variables, Chiang's research proposed the Recency, Frequency, Monetary, Discount and Returning variables model to identify customer value for online stores' market. However, the RFM model is not proper for any industry. Researchers can improve and apply it on a variety of retail industries.

2.2 Customer value applications

Bauer and Hammerschmidt (2005) stated that customer value is to estimate profits via total possible cash flows on individual customers for business. Hence, Linoff and Berry (2011) indicated that customer value is the difference between profit and cost of customers for many retail businesses. Han *et al.* (2012) also pointed out that customer value is profit of customer to business. Thus, assessment of customer value consists of some attributes that can be used to calculate customers' past or expected future profits (Chiang, 2013).

However, for improving customer satisfaction, Gudem et al. (2013) pointed out that businesses should know what products are demanded in markets for increasing growth rates. Furthermore, for enhancing customer values, Pynnönen *et al.* (2014) concluded that retailers should provide full service solutions for all types of customers.

Zalaghi and Varzi (2014) proposed a method to identify customer loyalty. Their study used K-means clustering to segment customers. Loyalty of each customer was estimated via a weighted model (weight RFM model, RFM model based). Via estimating the customer value (RFM model), their research results indicated that customers were classified into 16 groups with profit rate.

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2.3 Apriori algorithm applications

In 2003, Chen *et al.* applied the RFM model to partition customers for obtaining higher value customers. Their study employed the apriori algorithm to analyse relationships among pharmaceutical products for mining possible product portfolios of sales. The results found eight product portfolios that can increase shopping amount from 2.5 to 4.5 products.

As for the research of online shopping behaviours, Yang and Lai (2006) applied basket market analysis on online shopping behaviours, their research data were collected from a POS system and their research results found significant association rules for decision-making of bundling sales.

For enhancing CRM system, Gong *et al.* (2007) applied Apriori algorithm on a CRM system of a carpet company for reducing invalid records and scanning times. The CRM system was improved for saving the time efficiently.

Association rules can also be applied in discovering patterns for developing new product. For example, Liao *et al.* (2011) used Apriori algorithm and clustering method on marketing system of an international travel agency in Taiwan. Their research discovered customer knowledge patterns, and the patterns can be applied to developing new travel products for travel agencies.

Since the studies regarding the improvement of the Apriori algorithm, Chiang (2010) applied the Apriori algorithm to supervised database. The objective of Chiang's paper was to discover behaviours of community course-selection. The fuzzy cluster method was applied to segment students, and the improved supervised-fuzzy-apriori (SAA, Chiang, 2008) was applied for generating fuzzy association rules. The rules can be used on marketing projects of university community curriculums.

However, for retail industries, association rule is a useful data mining technology, which can help retailers to generate customer shopping-behaviour rules (Bilgic *et al.*, 2015). These useful rules can be applied to marketing or CRM systems to effectively implement the target marketing strategy.

For applications of the Apriori algorithm, Sarvari *et al.* (2016) used k-means clustering, Apriori algorithm, SOM clustering algorithm and weighted RFM model to analyse shopping data from a global pizza restaurants chain for application of CRM system. Via the Apriori algorithm, their research extracted association rules and the best customer purchase behaviour pattern. Also, the results were applied on some scenarios and the best ones were identified. The best scenario showed that monetary (M) factor was the most important factor for clustering among the RFM analysis results.

Regarding applications of the Apriori algorithm on on-line recommendation systems, Liao and Chang (2016) applied AHP model, Apriori algorithm with rough set theory on on-line shopping customers for recommendation system. Their research found four preference association rules of online shoppers, and these rules can be applied on two patterns for online recommendation systems.

3. Methodologies

3.1 Research logic

The research applies socio-economic variables and proposed F-T-FM model to the analysis process. Via the SAA, the socio-economic variables are oriented into the F-T-FM markets to establish useful association rules (Figure 1).

3.2 Questionnaire design, data collection and sample size

A questionnaire could be high validly if it refers to some analogous studies and discusses with scholars and experts as well (Creswell, 2008). The measurement of validity of this

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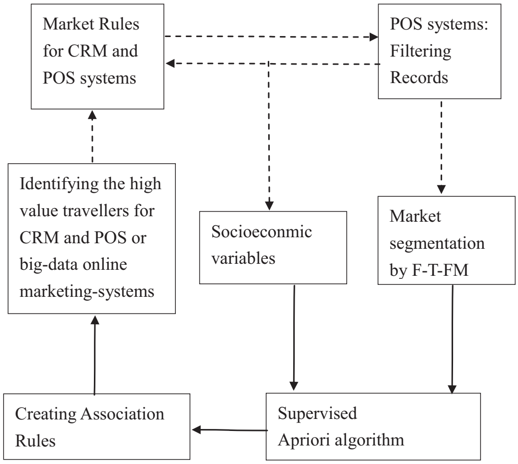

Source: This Research

Figure 1. Research logic (solid lines)

questionnaire uses content validity. Definition of Content Validity is that a questionnaire designed with highly representative of a research.

The questionnaire of this research refers to the results of discussing with the airline's managers and scholars in this field. The RFM model is not applicable to any business. The model is proper for retail business (Chiang, 2017). Thus, the questionnaire is designed by using a proposed F-T-FM model (the variables are listed as follows) and the socio-economic variables. The socio-economic variables refer to the question items of membership forms of EVA Airways and China Airlines (Lin and Liu, 2008; Chiang, 2012). In the research of Lin and Liu (2008), they designed the questionnaire by the RFM variables and question items in membership form of airlines (EVA Airways and China Airlines) for exploring online booking behaviour of air passengers.

The F-T-FM model is designed as follows:

- *Frequency (F)*. Frequency for travel times in the past 36 months. There are five selections: 0 ~ 2 times, 3-4 times, 5-6 times, 7-8 times, over 9 times.
- *Travelling times (T)*. Travelling times in high season in the past 36 months. There are five selections: 0 ~ 1 time, 2 times, 3 times, 4 times and over 5 times.
- *Family members (FM)*. Family members travelling together in the past 36 months averagely: one traveller, two travellers, three travellers, four travellers and over five travellers.

For focusing the market of the economic class of Taiwan air passenger market (EVA and China Airlines in Taiwan), the study uses a questionnaire method to collect data. The questionnaire consists of two parts: the F-T-FM model and the socio-economic variables.

All collected data will be the first-class data from the experienced passengers with the purposive sampling method. The sample size is measured by the equation $n = Z^{2}{}_{\alpha/2} \times P(1 - P)/e^2$, where n is the sample size, confidence interval 95 per cent (Z: 1.96), e: 0.05, P-ratio P: 0.5 (Triola and Franklin, 1994).

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3.3 F-T-FM model

The RFM model consists of Recency, Frequency and Monetary. Typically, the application of the model is to separate each of the variables into five levels. First level is the lowest level, and the fifth level is the highest level (Miglautsch, 2000). Nevertheless, five levels of the model can be divided into two levels for observing grades of customer values and markets clearly and easily (two levels of L and H, Lin and Tang, 2006; Chiang, 2014).

This research improves the RFM model to be more visible for the purpose of recognizing customer value in the international airline industry. According to the studies of Berry and Linoff (2004), and Chiang (2014), they indicated that the profit increasing is the basis of customer values. Thus, as mentioned earlier, three profit variables are proposed: frequency of travelling, travelling times in high season and number of family members (includes adults, kids and infants) are applied for realizing passengers' shopping behaviours and benefit of online airlines. As mentioned previously, each variable is divided into two levels (Low: L and High: H) and eight markets are the maximum number. Thus, the markets are from L-L-L to H-H-H.

3.4 Supervised apriori algorithm

Association rules are widely used in a variety of business and science managements. The most commonly used for mining association rules is the Apriori algorithm (Agrawal *et al.*, 1993). The purpose of the Apriori algorithm is to scan the database for combinations of related information candidates (Itemset). Afterward, to calculate support value for each itemset. The itemset is for determining whether the combinations are classified in the database for association rules group.

The research applied SAA (Chiang, 2011; based on Apriori algorithm, Agrawal *et al.*, 1993) to create high-value association rules. The SAA is used to mine association rules with clustered markets in this study.

The procedure of the SAA is shown as follows:

(1) Using cluster numbers to be a primary key to sort all possible combinations.

(2) To scan database and processing every record in turn. Data in the first cluster will be processed first.

(3) Candidate itemsets: Creating candidate itemsets in turn.

(4) To record itemset while it is greater than the minimum support; to delete itemset while it is less than minimum support.

(5) Minimal support: configuring minimal support.

(6) Exit while finishing all the data.

(7) Go to Step 2.

(8) End.

Support:

$$Support = (X / Y) \times 100\% \tag{1}$$

where:

Support = Support of X;
X = Times of X Itemset; and
Y = Numbers of all the data.

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Confidence:

If A and B → C

Then:

$$Confidence = \ Support\,(A,B,C)\,/\,Support\,(A,B)\ \times\ 100\% \tag{2}$$

where:

Confidence = Confidences of A and B → C;

Support (A, B, C) = Supports of A, B, C; and

Support (A, B) = Supports of A, B.

4. Empirical case

4.1 Air passengers' market in Taiwan

In accordance with the report of Tourism Bureau in Taiwan (2017), the outbound passengers were from 8,963,712 to 14,588,923 over the period from 2007 to 2016. As Table I shows, the inbound growth rates from 2007 to 2009 were lower than 6 per cent; hence, the outbound rates were even negative from 2008 to 2009. The outbound rates were declining from 2007 to 2009 because of the high cost of aviation fuel and airline crews, and the factor of global economic depression as well. However, the growth rates of the outbound passengers were 15.69 per cent in 2010, 1.79 per cent in 2011, 6.84 per cent in 2012, 7.94 per cent in 2013, 7.16 per cent in 2014, 11.30 per cent in 2015 and 10.66 per cent in 2016. That is, the rate was increasing up.

The inbound passengers were increasing progressively from 2007 to 2016. The inbound growth rates were declining from 5.58 to 3.47 per cent (from 2007 to 2008); the inbound growth rates were higher than 19 per cent in 2010, 2012 and 2014; hence, the growth rates were lower than 10 per cent in 2011, 2013, 2015 and 2016. However, the growth rate of outbound passengers in 2015 was 11.30 per cent, it has been the highest rate since 2011. But, the rate of inbound passenger in 2015 was only 5.34 per cent. As the Table I shows, both rates were decreasing from 2015 to 2016. The inbound growth rate in 2016 was 2.40, which was the lowest rate since 2007. That is, the airlines still have more space to enhance the rate.

For enhancing the growth rate, travel and airline industries in Taiwan (two major international airlines: EVA Airways and China Airlines) should implement more effective marketing projects on outbound and inbound passengers. Thus, the main costs of airline consist of fuels and crews can be balanced. Also, their profits can be increased.

4.2 Data collection and questionnaire description

The research uses purposive sampling method (Triola and Franklin, 1994) to be a data collection method. Data collection areas are in the largest international airports in Taiwan: Taoyuan International Airports. Economic class passengers of EVA Airways and China airlines were requested to fill out the questionnaires.

The minimum number of sample size was 384 after computing the equation: (Triola and Franklin, 1994). The questionnaires were filled out in August 2016. There were 478 questionnaires filled out and 13 invalid questionnaires deducted; thus, the valid questionnaires remained a total of 465. That is, the rate of the valid filling was 96.79 per cent.

The questionnaire was designed by the F-T-FM model (RFM model based) and socio-economic variables. Each of F-T-FM variables was designed to be five levels. The socio-economic variables are basic data consist of gender, age and income monthly.

The questionnaires were tested by the reliability test, and the Cronbach α is 0.8566. It means that the entire measurement of the reliability is fine because the value is larger than 0.7 (Nunnally, 1978).

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Table I.
Outbound and inbound passengers from 2007 to 2016 in Taiwan

Years	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Outbound passengers	8,963,712	8,465,172	8,142,946	9,415,074	9,583,873	10,239,760	11,052,908	11,844,635	13,182,976	14,588,923
Growth rate (%)	3.37	−5.56	−3.81	15.69	1.79	6.84	7.94	7.16	11.30	10.66
Inbound passengers	3,716,063	3,845,187	4,395,004	5,567,277	6,087,484	7,311,470	8,016,280	9,910,204	10,439,785	10,690,279
Growth rate (%)	5.58	3.47	14.3	26.64	9.34	20.11	9.64	19.11	5.34	2.4

Source: Tourism Bureau in Taiwan (2017)

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5. Research results

5.1 F-T-FM markets

Each of the F-T-FM variables are separated into five levels. The levels are from the lowest to the highest value (from 1 to 5). That is, they are from 1-1-1 to 5-5-5. Thus, the F-T-FM model can be observed clearly. For understanding the model clearly, five levels can be assigned into two levels (Low = L and High = H; Lin and Tang, 2006; Chiang, 2014). The F-T-FM markets are composed of three variables, and each variable is assigned two levels; thus, there is a total of eight markets ($2^3 = 8$ levels) should be discovered after processing the F-T-FM markets. The eight markets are from H-H-H to L-L-L. Hence, the H-L-H is the highest market share that has taken 26.5 per cent of the market; the L-H-L is the lowest share that has taken 2.4 per cent of the market. However, the three market shares are the H-L-H, H-H-H and H-H-L.

5.2 Supervised Apriori algorithm

The F-T-FM variables can be applied for passengers' clustering; thus, eight valid markets are clustered (partitioned) by the F-T-FM variables. The lowest market is L-H-L, which has taken 2.4 per cent of the market; that is, there is no empty market. Therefore, there is no invalid market eliminated. The steps of the procedure are shown below: First, the collected data are oriented into the eight valid clusters/markets via the SAAs (minimum support is assumed: 20 per cent). Second, the procedure is also dealing with a model evaluation: cross-validate (10 per cent for testing data, 90 per cent for training data). Consequently, there are three association rules for discovering high-value customers. The three association rules are created by using the SAA, which are illustrated in Table II.

6. Conclusions and suggestions

6.1 Conclusions

The research proposes a framework for discovering valuable memberships for online big data marketing systems or CRM/POS systems. The designed research framework can help airlines or other businesses. Businesses can partition memberships into some valuable markets by their customer value variables easily. The procedures of the discovering and analysis can be a daily routine in marketing systems (Bilgic *et al.*, 2015).

Because of the rates of the inbound passengers, they were lower even than 6 per cent from 2006 to 2008, and the rates of the outbound were also lower than 6 per cent from 2005 to 2009 (Table I). Therefore, the markets of air passengers need to be promoted by marketing plans of airlines or travel agencies. However, the growth rate of inbound international passengers in Taiwan still can be promoted. Thus, the objective of the research

Rule #	If	And	Income/per month	Individual or group	Then	Support (%)	Confidence (%)
1	Gender = Male	Age = 21 ~ 30	US$1,501 ~ 2,000	Group	Market = H-H-L	21.51	90.12
2	Gender = Female	Age = 31 ~ 40	Over US$3,001	Individual	Market = H-H-H	22.35	90.37
3	Gender = Female	Age = 21 ~ 30	US$2,500 ~ 3,000	Individual	Market = H-L-H	20.11	93.80

Source: This Research

Table II. Association rules for high-value economy-class passengers in Taiwan

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is to enhance the growth rate for the individual economy-class-passenger market in Taiwan. Airlines may implement marketing plans effectively to their online passengers for gaining profits, as well as for covering the expensive costs of fuel and airline crew.

In regard to the growth rate of passengers, this study identified customer values of passenger for finding optimum target markets and enhancing their customer values. The research steps are as follows: First, eight valid markets are clustered by proposing profit variables (F-T-FM mode). Then, the socio-economic variables are oriented into the eight valid markets via the SAA. Finally, the research discovered three association rules of online economy-class passengers. However, these rules can be applied in CRM and POS systems of airlines for filtering the optimum target markets.

The F-T-FM variables are applied for clustering of online passengers; thus, eight valid markets are partitioned by the proposed customer values. Consequently, the top three high-value market are discovered, they are H-L-H, H-H-H and H-H-L.

Discussing about the practical aspects of this research, there are some features stated as follows. The data are easy to be collected via exist database of POS or CRM systems. The RFM model (variables) can be replaced with suitable variables for different type of business. In addition, the SAA is simple and easy to understand for industrial supervisors or administrators. Finally, the results are easy to apply on marketing plans. However, data analytics from raw data of POS or CRM can get more accurate analysis for marketing strategy.

Discussing about the theoretical aspects of this research, the application cannot be applied on shortly established businesses because their customer database is not enough for analysing. Hence, this application is not applicable for chain stores without customer membership system, such as convenient store industries. Furthermore, businesses can collect more information from social media to analyse customers and get more customer marketing knowledge.

6.2 Suggestions

In regards to the marketing applications for the three clusters, airlines may filter database of OLAP or CRM systems for identifying valuable memberships and passengers. Airlines may implement database marketing for these discovered markets. Furthermore, airlines can focus lower customer values of passengers for increasing the customer value from L to H, and to keep these passengers to be life-time valuable passengers.

Regarding applications of the association rules, for instance, in Taiwan, EVA Airways & China Airlines may identify memberships with conditions of Rule 1 (gender: Male, age: 21 to 30, monthly income: US\$1,501 $\sim$ 2,000, individual or group tour: group tour) that belong to the market H-H-L. How to enhance the level from Low to High? For EVA Airways & China Airlines, the Family Members (FM) variable in the Rule 1 is Low (L). It means that these passengers in this market are usually travelling alone. Thus, EVA Air & China Airlines or travel agencies can carry out marketing projects (such as discount) for family/friend groups (at least two passengers in a group) only for enhancing their FM variable into H level. The travelling times (T) variable of Rule 3 is L. It represents that these passengers are usually travelling in low season. Thus, EVA Air & China Airlines can execute promotions for a family group tour in high season to enhance them into H level.

If the frequency (F) variable is L, it represents that these passengers are not often travelling by international airlines. EVA Air & China Airlines can implement a promotion

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project before long vacations (such as summer and winter vacations, Chinese new year or spring break) for enhancing them into H level.

However, via the framework of this research, EVA Airways & China Airlines can estimate their passengers' markets without questionnaires. The EVA Airways & China Airlines can easily obtain the F-T-FM and socio-economic variables from their databases of memberships for finding the optimum target markets. The research proposes a framework to filter the value memberships for online big data marketing systems or CRM/POS systems of airlines/travel agencies or other businesses. Without applying a benefit segmentation analysis, the framework can help airlines easily to partition memberships into some value groups by their customer values. The valuable markets can be identified before implementation of new marketing projects. It can create an updated model of rules for enhancing customer values of the optimum target markets.

6.3 Managerial implications

- The research results can be applied on marketing systems or CRM systems for discovering valuable markets for businesses. Hence, the application of this research can be a sustainable system by machine learning (daily loop) in marketing systems.
- The logic of this research can discover customer value precisely and create rules for target markets. That is, customer values can be promoted to be higher by marketing plans via discovered rules.
- According to the research results, airlines may find it easy to discover customer values in their large-scale database for marketing systems. Besides, the discovered association rules (Table II) may be implemented on three different marketing plans for the discovered target markets.
- The research framework can be applied to other businesses for discovering marketing rules. They can accurately aim at their target markets for implementing marketing plans.
- Transaction records of a long-established business may include a big database of customer-shopping records. For a long-established business can apply the research logic on marketing systems for retaining existing customers and increasing customer values.
- The cost for retaining an existing customer is about one-fifth of the cost of developing a new customer (Kotler and Keller, 2016). As a result, businesses can retain existing customers by improving their marketing or CRM systems. However, this research can help companies to create their customer rules to improve their marketing or CRM systems. Businesses may focus on different market according to different rules.
- Businesses can increase lower customer values to middle level, while through the marketing plan, they can increase the medium level to higher level.

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