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Mining shopping behavior in the Taiwan luxury products market

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ABSTRACT

The rapid growth of Taiwan's economy has been accompanied by the country's developing market for luxury products. To successfully establish the new market demand chain for the luxury industry in Taiwan, it is essential to understand customer preferences. Thus, this study uses an association rules approach and clustering analysis for data mining to mine knowledge among luxury product-buying customers in Taiwan. The results of knowledge extraction from data mining, illustrated as knowledge patterns, rules and knowledge maps, are used to make recommendations for future developments in the luxury products industry.

1. Introduction

In physics, a spectrum is the series of colored bands diffracted and arranged in the order of their respective wave lengths by the passage of white light through a prism or other diffracting medium (Liao, Chen, & Hsu, 2009). Outside of physics, a spectrum is a condition that is not limited to a specific set of values, but can vary infinitely within a continuum. Since the word saw its first scientific use within the field of optics to describe the rainbow of colors in visible light when separated through a prism, it has been applied by analogy to many other fields. In most modern usages of spectrum there is a unifying theme between extremes at either end. An effective visualization tool, especially for stakeholders or managers, is a brand spectrum diagram highlighting where the company's brands and products are situated in relation to other competitors.

Conspicuous consumption was highly prominent in the late 1990s and early years of this decade. Many consumers regarded brand image sometimes as being more important than quality. However, consumer behavior began to change in the middle of the decade as the availability of information made it easier for consumers to learn about and compare products and consequently, to become more discerning (Bellaiche, Mei-Pochtler, & Hanisch, 2010). In commerce, businesses use branding to differentiate their product and service offerings from those of their competitors (Baker, 1979; Dibb, Simkin, Pride, & Ferrell, 2005; Kotler, 1994). The brand incorporates a set of products or service features associated with that particular brand name (Baker, 1979) and identifies the product/service in the market. Brands are part of consumers' lives and organizations' strategies. It is widely accepted that consumers buy brands rather than products. As a consequence, competition no longer occurs at the core-product level, but on the basis of the added attributes that the brand represents. These attributes are diverse in nature and can be either physical or psychological. Nevertheless, they are ultimately the reason why the customers buy Nike instead of Reebok or vice versa in specific market segmentation. Thus, we ask: does a customer have a spectrum of brands or products as preference frequencies in their purchasing decision (Liao et al., 2009)?

In commerce, customers function crucially as business assets. Most of the parties involved in sales are aware of the need for businesses to acquire better customer knowledge, such as information about customers' shopping experiences. However, access to such information is not straightforward since customer knowledge is largely concealed within the customers. It is available but not accessible, and there is little possibility of exploring the full volume of data that should be collected for its potential value. The greatest opportunity to access this knowledge in a more comprehensive way is to use the data that is collected to build long-term relationships with customers. In previous studies, many data-mining models have been presented such as classification, estimation, predictive modeling, clustering/segmentation, affinity grouping or association rules, description and visualization, as well as sequential modeling. Similarly, there have also been numerous application methods, including association rules, sequential patterns, grouping analysis, classification analysis and probability heuristic analysis (Ben-David & Sterling, 2006; Bhattacharyya, Jha, Tharakunnel, & Westland, 2011; Liao, 2003, 2005; Liao et al., 2009; Liao, Chen, & Tseng, 2009; Musaev, 2004; Prinzie & Van den Poel, 2005). Thus, customer knowledge extracted through data mining can be integrated with information about luxury product shopping experiences and demand chain promoting knowledge and then provided to companies in the luxury products industry.

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Accordingly, the purpose of this study is to investigate the following research issues on product and brand spectrum in the luxury products market of Taiwan. Specifically, the aims of the study are: (1) to introduce the luxury products market in Taiwan; (2) to describe explicitly the conceptualization behind the knowledge represented in a knowledge base, the data for which is gathered by means of questionnaire. The customer and luxury products database developed on the basis of the data collected provides information about basic consumer data, consumer behavior, brand preference and luxury product purchasing; (3) to implement a data-mining approach to acquire customer information; (4) to understand customer knowledge using association rules and clustering analysis; and (5) to depict the product and brand spectrum of the luxury products market in Taiwan.

There are two data-mining stages implemented in this study. The apriori algorithm is a methodology which consists of the association rules for data mining implemented to mine knowledge from luxury product-shopping customers. Knowledge extracted from data-mining results is depicted as knowledge patterns and rules and utilized to make shopping recommendations to the luxury products industry. Following that, cluster analysis using the *K*-means algorithm is undertaken to explore segmentation clustering and to make recommendations about effective promotion and sales designs for marketing to customer clusters. The rest of this study is organized as follows: in Section 2, the background to the luxury products market in Taiwan is presented. This is followed in Section 3 by a description of the methodology used in the study, including the research framework, data sources, and database design. Section 4 presents the data-mining approach, association rules, clustering analysis, and data mining tool – SPSS Clementine, while Section 5 presents the data-mining results. This is followed by Section 6, which describes research findings and managerial implications. Finally, Section 7 presents a brief conclusion.

2. Luxury products market

Since the early 1990s, the market for luxury products has been growing at an unprecedented pace (Truong, Simmons, McColl, & Kitchen, 2008). The 2005 estimates by the Boston Consulting Group (BCG) reached $840 billion worldwide for luxury products. With private consumption growing at a rate of 11 per cent per annum (Jin et al., 2010), the BCG has argued that the global market for luxury products is close to €1 trillion (Bellaiche et al., 2010).

The luxury products industry, which has been the dominant market in Europe and North America, is witnessing fresh momentum with the growth of the Asian market. In particular, the economic growth of China has led to a significant increase in the consumption of luxury products (Kim, Kim, & Sohn, 2009). Although the meaning of true luxury varies among individuals, for the majority of consumers the term connotes rarity, quality and refinement (Bellaiche et al., 2010). In recent years, accompanying the continued growth of the Asian economy has been the rapid expansion of the luxury products industry in that region. As the Asian luxury products market represents almost half of the global luxury products market, the concerns about the luxury products industry has become widespread (Kim et al., 2009). Annual luxury products consumption has reached $2.7 billion dollars in Taiwan, ranking the country among the top five in the Asian region in this respect (Smith, 2009).

As mentioned previously, with the rapid growth of the Taiwanese economy has come the development of the luxury products market in Taiwan. This economic development has given more potential buying power to the Taiwan market. To successfully establish the new market demand chain for the luxury products industry in Taiwan, it is essential to understand customer preferences. Irrespective of the specific tools and methods used to develop successful outlet malls, customer orientation is a prerequisite (Lengnick-Hall, 1996).

According to Morgan Stanley Croup's Global Industrial Classification Standard (GICS), luxury products include apparel, accessories, jewelry, and watches. In this paper, focus is placed on bags in the accessories category.

3. Methodology

3.1. Research framework

Due to the difficulty in obtaining luxury-product customer and sales information, this study uses a designed questionnaire to collect research data. The *K*-means algorithm is used to sort customers into clusters in order to generate association rules for each cluster. On the basis of the results of the study, recommendations to the luxury industry market about how to open up effective new services and sales are made.

3.2. System framework

Having collected past customer data to establish a database system, we analyze the entire database system by data mining to find the relationship between luxury product-buying customer behavior and luxury product-buying patterns, including consumer shopping preferences and demand consideration. The aim of this approach is to enable businesses to further understand luxury product-buying experience/patterns, rather than the psychology and orientation of experienced luxury product-buying customers. The objective in so doing is to make suitable marketing suggestions that are capable of providing customers with their preferred products and services, while reducing marketing costs and increasing business profits for companies. The system framework is shown in Fig. 1.

In this study, the design and operation of a physical database is used to construct a relational database. This is achieved by entering data into the table through Microsoft Access 2003. Unlike general database software, which uses standard structured query language (SQL), rendering it incapable of accommodating large numbers of people online simultaneously, Microsoft SQL 2005 has the capability to satisfy this need because each type of data storage and processing is different. With the Microsoft software, it is possible for manufacturers to design a driver for all types of language using standard SQL, and then to access their database through a regional network so as to provide programming language access to the information database system. Microsoft's console provides an open database link (open database connectivity; ODBC), allowing administrators to manage a variety of ODBC drivers (Fig. 2).

3.3. Questionnaire design and data collection

The database and questionnaire were developed based on customer needs, wants, and the requirements of this research. The questionnaire contained six parts: customer information; individual lifestyle and gain information channel; individual luxury product-buying experience; product-promotion activities; brand cognition; and consumer perception. These categories were designed to enable researchers to understand the relationships affecting customer characteristics, luxury product-purchasing motivations, luxury product-choice, and promotional activities in which customers usually participate through marketing channels. Due to poor accessibility to actual consumption quantity data for many luxury products, questionnaires were used in this research to implement the sampling survey. The research sample consisted

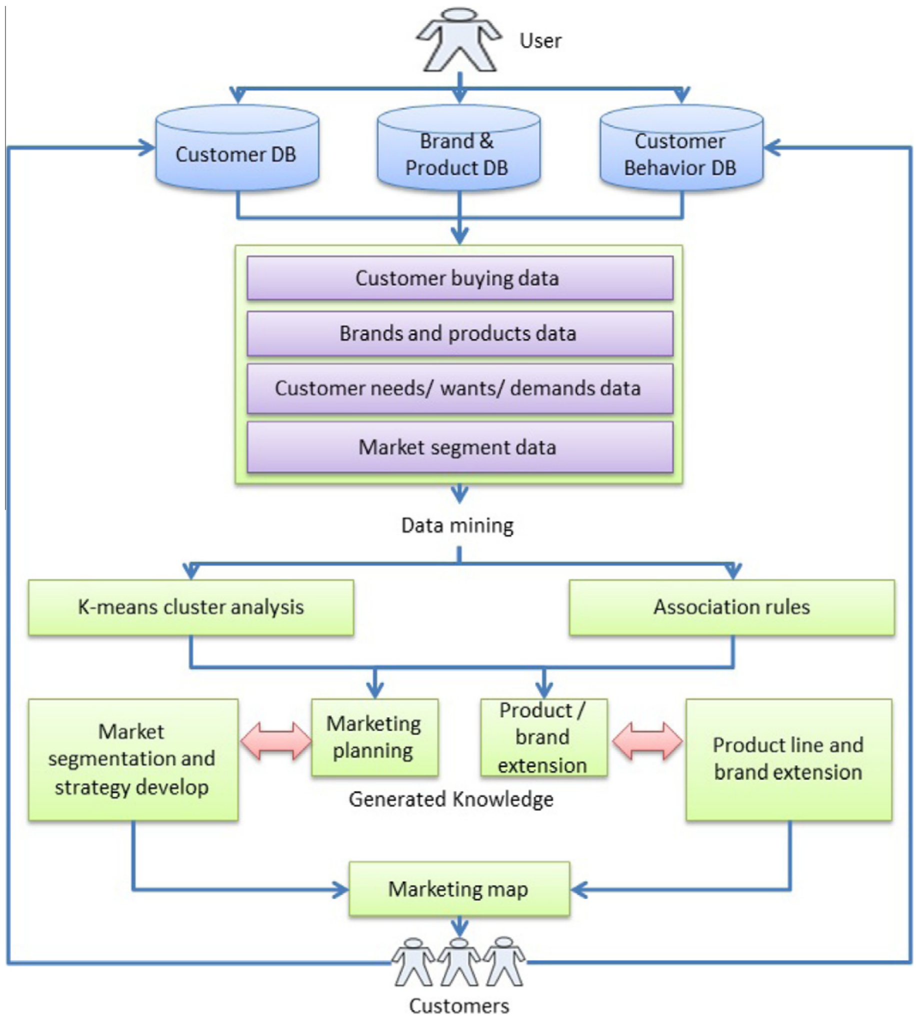

Fig. 1. System framework.

principally of members of the public with experience of purchasing luxury products.

The sample size, in the pilot stage was 10, and luxury brand senior members were used as a pilot standard. Answers were used to modify the questions and answer options in the questionnaire, and formed the basis for administering the official questionnaire. An online survey company was used to collect and audit the data. In total, 1951 questionnaires were returned, of which 5 were rejected because they were either incomplete or invalid. This left a total of 1946 valid questionnaires, yielding a valid completed rate of 99.7%.

4. Data mining

4.1. Association rules – Apriori algorithm

As stated in Agrawal, Imieliński, and Swami (1993), discovering association rules is an important data-mining issue. Consequently, there has been considerable research into using association rules in the field of data-mining problems. The association rules algorithm is used mainly to determine the relationships between items or features that occur synchronously in databases. For instance, if people who buy item X also buy item Y, there is a relationship between item X and item Y, and this information is useful for decision makers. Therefore, the main purpose of implementing the association rules algorithm is to find synchronous relationships by analyzing random data and using these relationships as a reference during decision making. The association rules are defined as follows (Wang, Chuang, Hsu, & Keh, 2004):

Make I = the item set, in which each item represents a specific literal. D stands for a set of transactions in a database in which each transaction T represents an item set such that $T \subseteq I$. That is, each item set T is a non-empty sub-item set of I. The *association rules* are an implication of the form $X \rightarrow Y$, where $X \subset I$, $Y \subset I$ and $X \cap Y = \Phi$. The rule $X \rightarrow Y$ holds in transaction set D according to two measure standards – *support* and *confidence*. Support (denoted as $Sup(X,D)$) represents the rate of transactions in D containing the item set X. *Support* is used to evaluate the statistical importance of D; the higher its value, the more important the transaction set D is. Therefore, the rule $X \rightarrow Y$ has *support* $Sup\ (X \cup Y, D)$, which represents the rate of transactions in D containing $X \cup Y$. Each rule $X \rightarrow Y$ also has another measuring standard called Confidence (denoted as $Conf(X \rightarrow Y)$), representing the rate of transactions in D that contain X as well as Y; that is, $Conf(X \rightarrow Y) = Sup(X \cap Y)/Sup(X,D)$.

In this case, $Conf(X \rightarrow Y)$ denotes that if the transaction includes X, the chance that the transaction also contains Y is relatively high. The measure confidence is then used to evaluate the level of confidence about the association rules $X \rightarrow Y$. Given a set of transactions D, the problem of mining association rules is to generate all transaction rules that have certain user-specified minimum support (called *Min sup*) and confidence (called *Min conf*) (Kouris, Makris, & Tsakalidis, 2005). According to Agrawal and Shafer

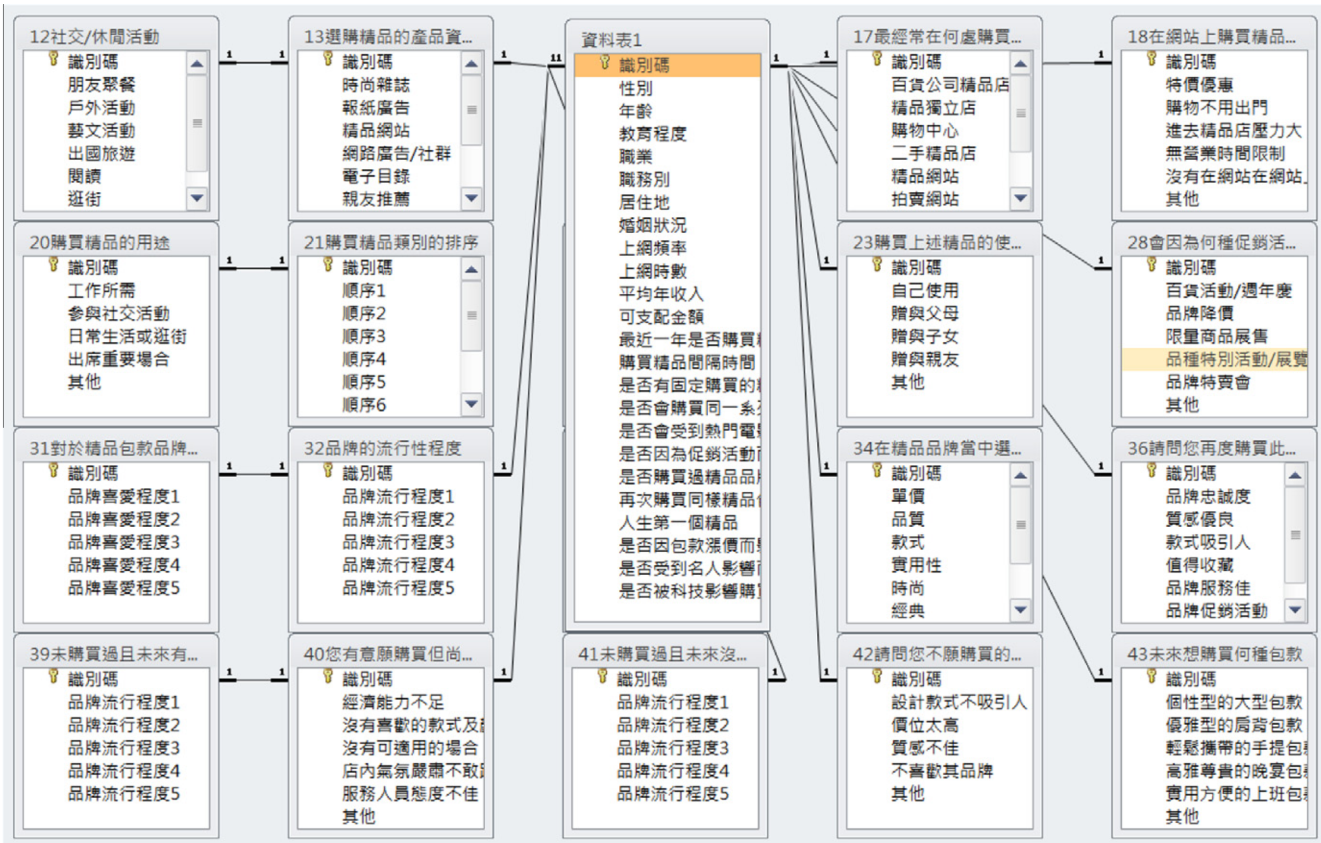

Fig. 2. Physical database designs.

(1996), the problem of mining association rules can be decomposed into two steps. The first step is to detect a large item set whose support is greater than Min sup; and the second step is to generate association rules, using the large item set. Such rules must satisfy two conditions: $Sup(X \cup Y, D) \geqq Min\ sup$, $Conf(X \to Y) \geqq Min\ Conf$.

To explore the association rules, many researchers use the Apriori algorithm (Agrawal et al., 1993). In order to reduce the possible biases incurred when using these measure standards, the simplest way to judge the standard is to use the *lift* judgment. *Lift* is defined as: $Lift = Confidence(X \to Y)/Sup(Y)$ (Wang et al., 2004).

4.2. Clustering analysis – K-means algorithm

The process of partitioning a large set of patterns into disjointed and homogeneous clusters is fundamental in knowledge acquisition. It is called *clustering* in most studies and is applied in various fields, including data mining, statistical data analysis, compression and vector quantization. The *K-means* is a very popular algorithm and is one of the best for implementing the clustering process. *K*-means clustering proceeds in the following way: firstly, *K* number of observations are randomly selected from all *N* number of observations according to the number of clusters and become centers of the initial clusters. Secondly, for each of the remaining $N–K$ observations, the nearest cluster is found in terms of the Euclidean distance with respect to $xi = (xi1, xi2, \ldots; xip, \ldots, xiP)$. After each observation is assigned to the nearest cluster, the center of the cluster is re-computed. Finally, after the allocation of all observations, the Euclidean distance between each observation and the cluster's center point is calculated to confirm whether or not they have been allocated to the nearest cluster. Several studies have discussed implementation of the *K*-means algorithm for cluster analysis as a data-mining approach (Ture, Kurt, Turhan Kurum, & Ozdamar, 2005; Vrahatis, Boutsinas, Alevizos, & Pavlides, 2002).

4.3. Data mining tool, SPSS Clementine

In this study, SPSS Clementine is employed as a data-mining tool for analysis. The difference between SPSS Clementine and other software is that its data processing is carried out through the use of nodes, which are then connected together to form a stream frame. In addition, data visualization can be presented to users after the mining process is completed. SPSS Clementine's visual interface invites users to apply their specific business expertise, which leads to more powerful predictive models and shortens time-to-solution (SPSS, 2003).

5. Results

Market segmentation is defined as a marketing technique that targets a group of customers with specific characteristics, and pursues the growth opportunities of further markets. This study therefore applies clustering analysis to segment "basic consumer information" and "consumer behavior and reason". During the analysis, the system divides all the items or data of high similarity into several clusters; however, as large disparities exist among these subject clusters, the goal is to distinguish the purchase product behavior of the different groups of customers.

This study uses *K*-means algorithm cluster analysis to group data in the grouping variables: "basic consumer information" and "consumer behavior and reason." The Apriori algorithm is then used to carry out cluster analysis on each cluster group. Fig. 3 shows the results of the *K*-means clustering approach. According

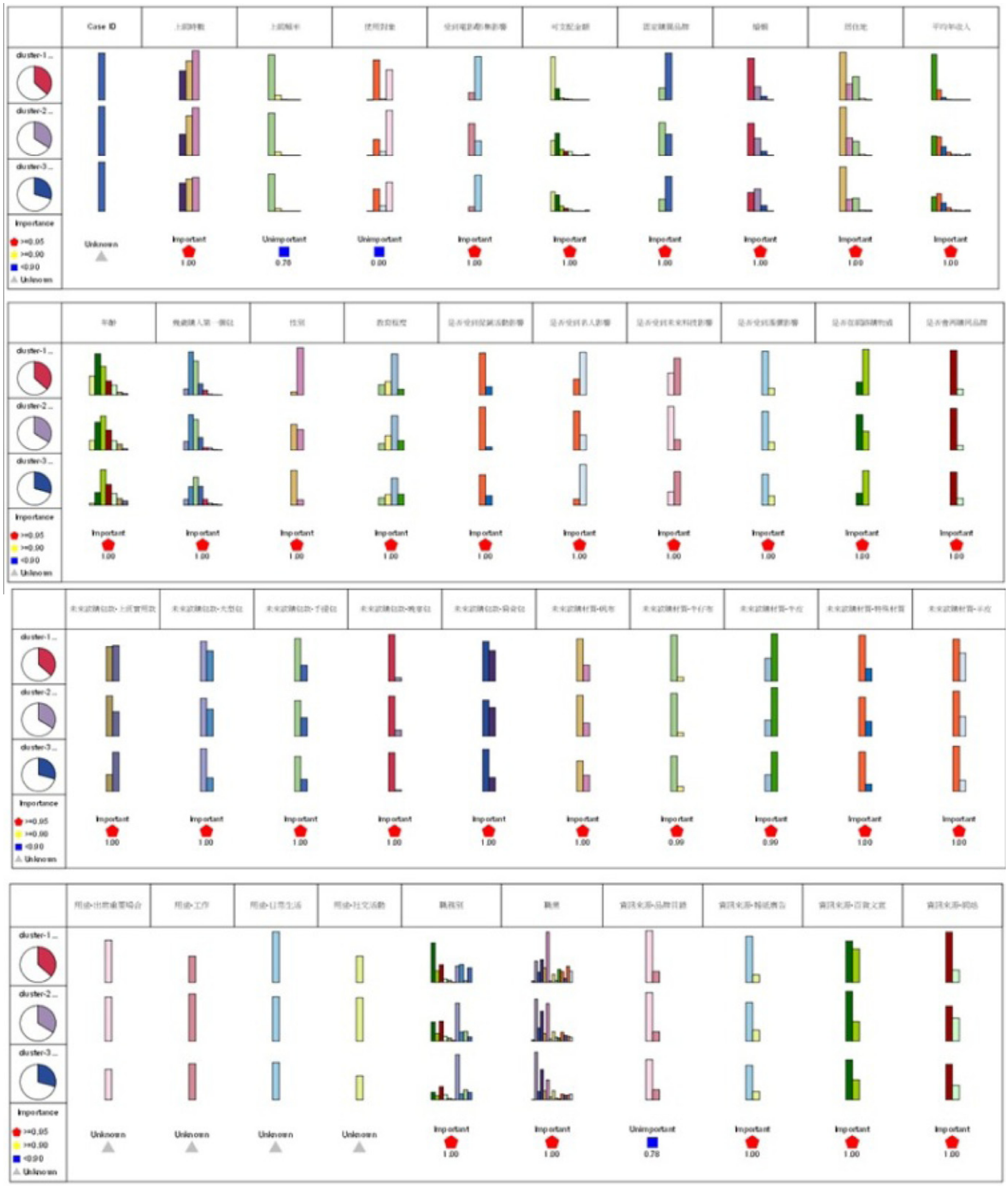

Fig. 3. *K*-means clustering results.

to the characteristic of group data, Cluster-1 (772) is named "pragmatism of consumption groups", Cluster-2 (637) is named "maturity frequency of consumption groups", and Cluster-3 (537) is named "fashion of consumption groups". The profile and characteristics of customers are shown in Table 1.

5.1. Cluster-1 consumer product and brand spectrum

5.1.1. Product spectrum

The relationship diagram presents the complexity of relationships among decision-making variables. All possible combinations

Table 1
Customer profile and characteristics of clusters.

	Cluster-1	Cluster-2	Cluster-3
Sample size	772	637	537
Named	Pragmatism of consumption groups	Maturity of consumption groups	Fashion of consumption groups
Gender	Female-dominated	Male-dominated	Female-dominated
Age	26–30 years	31–35 years	31–35 years
Level of education	University	University	University
The types of work	Service industry/Administrative	Information and electronic industry/ Manufacturing	Service industry/ Manufacturing
The average monthly family income	under 50,000 dollars	51,001–75,000 dollars	Under 50,000 dollars
Frequency of consumption on luxury products	2 years	1 year	1 season
Luxury products information source	Fashion magazine, department stores DM	Fashion magazine	Fashion magazine

of decision-making variables and the degree of relationship between two or more columns are presented in this diagram, the lines in which express the accumulated frequency of each variable sequence in relation to each cluster of consumers. If the line is thicker, the accumulated frequency is higher. The level of relationship in the web diagram was unclear and so had to be adjusted, which was achieved by altering the threshold value of the relationship between the variables as shown in Fig. 4.

Fig. 5 shows each luxury product's accumulated frequency for Cluster-1 (pragmatic of consumption). The preference degree significance was produced by the accumulated frequency multiplied by the weighted score. Based on the preferences of test objects for luxury products, Spectrum 1 to Spectrum 10 represent the sequence of bags, apparel, leather, shoes, jewelry, watches, sunglasses, accessory, others, and other apparel accessory. The data showed that pragmatic consumer prefer bags above all other luxury products, and tote bag is consumers' favorite among bags (79% of Cluster-1).

Table 2 shows execution results with 1% minimum support and 80% minimum confidence, which produces two significant product relationship combinations. Based on the association results for customers who usually purchase bags, cross-selling with practical sunglasses or valuables watches products is suggested. This group of consumers, having relatively low monthly disposable income and being unaffected by celebrities, movies or television series when making purchases, has a more conservative and rational buying characteristic. Therefore, sales rates for this type of customer can be enhanced by companies introducing product combinations and cross-promotion under the rules detailed below.

5.1.2. Brand spectrum

The analysis results show that 772 test objects in Cluster-1 Pragmatism of consumption) consumed bags, and the brand preference level of significance was produced by accumulated frequency times weighted score. The advertisement perception spectrum, sense of reality spectrum, and brand recall spectrum were produced based on the test objects' preference sequence for bag products shown in Fig. 6.

Table 3 shows execution results with 2% minimum support and 80% minimum confidence, which produce two significant luxury

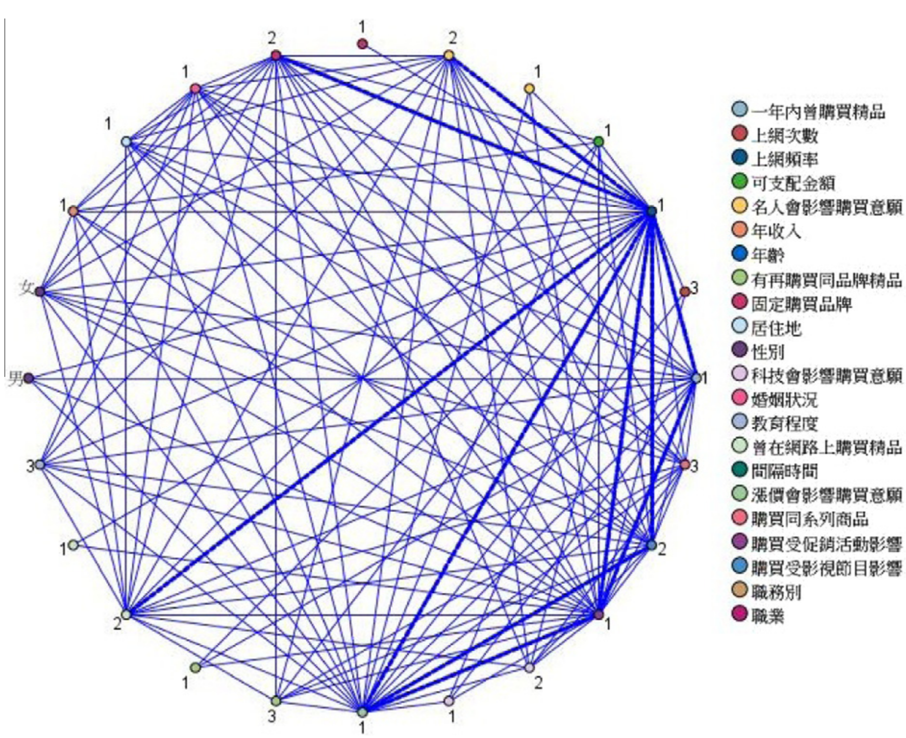

Fig. 4. Cluster-1 luxury product association diagram.

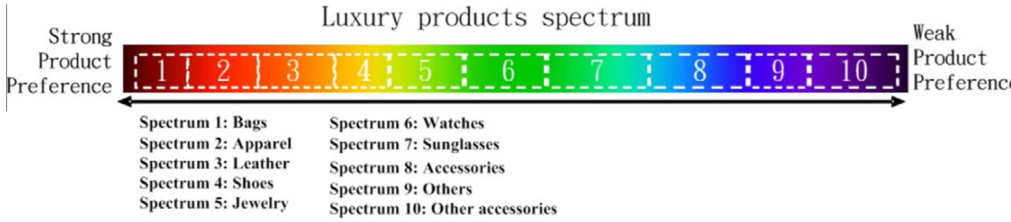

Fig. 5. Cluster-1 luxury products spectrum.

Table 2
Association rules of product preference of Cluster-1.

Rule	Sup.	Conf.	Lift	Consequence	Antecedent	
R1	10.02	82	1.049	Bags	Sunglasses	
R2	1.603	100	1.279	Bags	Sunglasses	Watches

Min sup. = 1%; Min conf. = 80%.

product-brand purchase behavior relationship combinations. In terms of strongest relation to pragmatism, pragmatism and better service were the most important factors among pragmatic consumers when purchasing bags. In addition, pragmatism and better service produced a gained value of 1.389.

Therefore, with respect to the pragmatic group, it is suggested that companies should improve service quality, as well as create better shopping experience and environment to attract consumers' attention. The pragmatic group's brand loyalty will be earned through more considerate service and enhanced brand image.

5.2. Cluster-2 consumer product and brand spectrum

5.2.1. Product spectrum

Fig. 7 shows each luxury product's accumulated frequency for Cluster-2 (maturity of consumption). The preference level of significance was produced by the accumulated frequency multiplied by the weighted score. Based on the preferences of test objects for luxury products, Spectrum 1 to Spectrum 10 represent the sequence of apparel, bags, watches, leather, shoes, jewelry, sunglasses, accessories, others, and other apparel accessories. The data show that mature consumers prefer apparel above all other luxury goods, with the skirt being consumers' favorite luxury apparel (58% of Cluster-2).

Table 4 shows execution results with 15% minimum support and 50% minimum confidence, which produces two significant product relationship combinations. Based on the association results for customers who usually prefer apparel, cross-selling with shoe and bag products is suggested. These groups of consumers are mature, male information and electronic industry engineers or manufacturing engineers, aged between 31 and 35 years, with stable monthly disposable incomes. Most of them consider professional image and personal preference to be most important. It is advised that for this cluster, clothing, footwear fashion sense and professional style should be displayed in a coordinated way.

5.2.2. Brand spectrum

Analysis results show each bag brand's accumulated frequency for Cluster-2 (maturity of consumption), with the data demonstrating that 637 test objects in Cluster-2 consumed apparel. The brand preference level of significance was produced by accumulated frequency multiplied by weighted score. The advertisement perception spectrum, sense of reality spectrum, and brand recall spectrum were produced based on the test objects' preference sequence for bag products shown in Fig. 8.

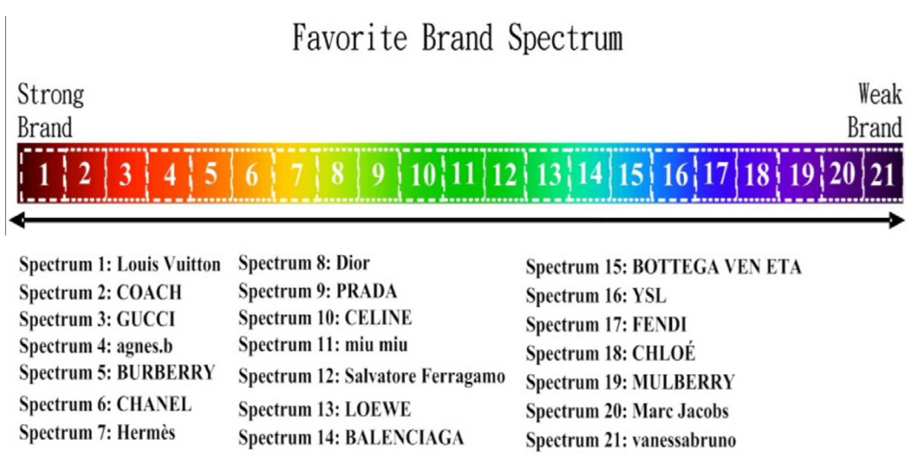

Fig. 6. Cluster-1 favorite luxury brand spectrum.

Table 3
The Luxury products brand purchase behaviors of Cluster-1.

Rule	Sup.	Conf.	Lift	Consequence	Antecedent		
R1	2.204	81.82	1.389	Pragmatism	Better services		
R2	2.004	80.00	1.267	Style of goods	Brand loyalty	New style goods	Prices

Min sup. = 2%; Min conf. = 80%.

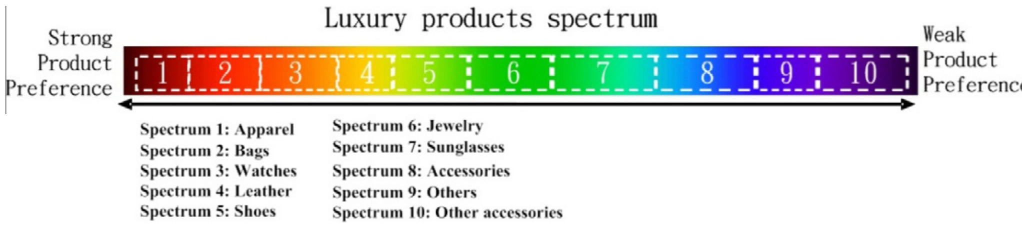

Fig. 7. Cluster-2 luxury products spectrum.

Table 4
Association rules of product preference of Cluster-2.

Rule	Sup.	Conf.	Lift	Consequence	Antecedent	
R1	42.182	62.069	1.246	Apparel	Shoes	
R2	19.515	53.416	1.088	Apparel	Shoes	Bags

Min sup. = 15%; Min conf. = 50%.

Table 5
The luxury products brand purchase behaviors of Cluster-2.

Rule	Sup.	Conf.	Lift	Consequence	Antecedent
R1	14.909	71.545	1.399	Products style	Attraction by shape
R2	29.333	70.248	1.020	Quality	Sense of reality

Min sup. = 10%; Min conf. = 70%.

Table 5 depicts execution results with 10% minimum support and 70% minimum confidence, which produce two significant luxury product-brand purchase behavior relationship combinations. In terms of strongest relation to product style, attraction by shape, quality, and sense of reality were the most important factors among mature consumers when purchasing apparel. In addition, product style and attraction by shape produced a gained value of 1.399.

Therefore, it is suggested that companies should enhance the quality of goods and introduce a more professional user style in order to attract the attention of mature consumers.

5.3. Cluster-3 consumer product and brand spectrum

5.3.1. Product spectrum

Analysis results show each luxury product's accumulated frequency for Cluster-3 (fashion of consumption). The preference level of significance is produced by accumulated frequency times weighted score. Based on the preferences of test objects for luxury products, Spectrums 1–10 represent the sequence of apparel, bags, watches, leather, accessories, shoes, jewelry, sunglasses, other apparel accessories, and others (Fig. 9). The data demonstrate that fashionable consumers prefer over all other luxury goods apparel, especially dresses (61%) and coats (52%), the most popular among luxury apparel.

Table 6 shows execution results with 1% minimum support and 70% minimum confidence, which produces three significant product relationship combinations. Based on the association results for customers who usually prefer bags, cross-selling with shoes, jewelry, leather, and watch products is suggested. These groups of consumers are older service industry staff and manufacturing staff, aged between 31 and 35 years who generally have a monthly disposable income. Most of them consider fashion style to be important, and are easily influenced by celebrities, movies or television series. Since such consumers are willing to invest more than in products, the industry should highlight the fashionable nature of bags, leather goods, and shoes.

5.3.2. Brand spectrum

Analysis results reveal each bag brand's accumulated frequency for Cluster-3 (fashion of consumption), the data showing that 537 test objects in Cluster-3 consumed apparel. The level of significance for brand preference is produced by accumulated frequency multiplied by weighted score. The advertisement perception spectrum, sense of reality spectrum, and brand recall spectrum are produced based on the test objects' preference sequence for bag products shown in Fig. 10.

Table 7 shows execution results with 10% minimum support and 70% minimum confidence, which produce three significant product relationship combinations. In terms of strongest relation to quality, sense of reality and collection were the most important factors among fashionable consumers when purchasing apparel; in addition, sense of reality and collect the brand products produce a gained value of 1.262.

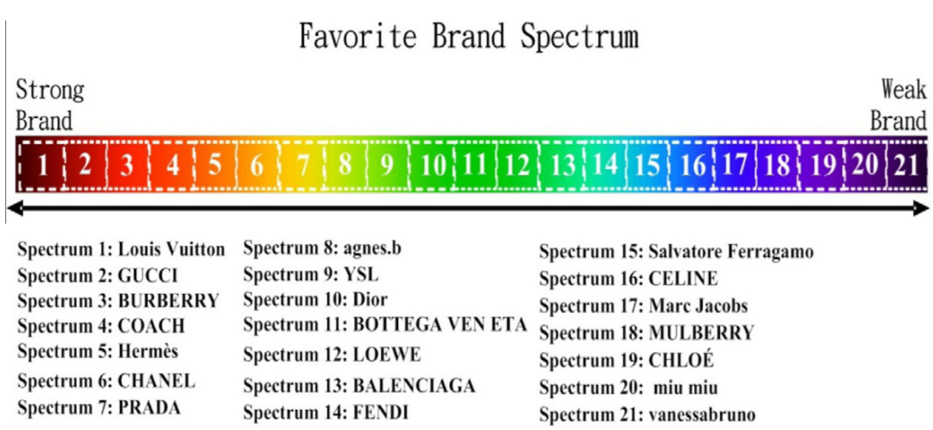

Fig. 8. Cluster-2 favorite luxury brand spectrum.

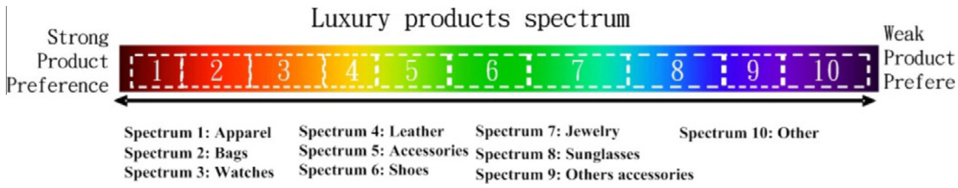

Fig. 9. Cluster-3 luxury products spectrum.

Table 6
Association rules of product preference of Cluster-3.

Rule	Sup.	Conf.	Lift	Consequence	Antecedent	
R1	31.833	70.202	1.002	Bags	Leather	
R2	1.125	71.429	1.019	Bags	Shoes	Jewelry
R3	4.341	74.074	1.057	Bags	Leather	Watches

Min sup. = 1%; Min conf. = 70%.

Table 7
The Luxury products brand purchase behaviors of Cluster-3.

Rule	Sup.	Conf.	Lift	Consequence	Antecedent	
R1	15.113	74.468	1.135	Quality	Collection	
R2	39.871	71.371	1.088	Quality	Sense of reality	
R3	10.289	82.812	1.262	Quality	Sense of reality	Collection

Min sup. = 10%; Min conf. = 70%.

It is important to note that the quality factor appears in three rules and the sense of reality factor appears in two, indicating that fashionable consumers pay considerable attention to these two factors. Collect the brand products is also a contributor.

Therefore, in terms of the fashionable group, it is suggested that companies improve brand strategies, create vivid slogans to attract consumers' attention, and also promote new products and the best quality. Brand loyalty among the fashionable group will only be earned through innovative product and package design along with an emphasis on product quality.

6. Research findings and managerial implications

6.1. Research findings

With rising living standards and advances in production capacity, the traditional "mass production" mode of operation can no longer effectively meet the needs of customers, who are looking for uniqueness, innovation, and novelty. The motivation behind a purchase originates from the affective domain and goes beyond the mere desire for the functional purpose of the product (Liao & Wen, 2009). In the current competitive environment, although merchants already use information systems to understand their customers, massive amounts of decentralized data create tremendous pressure. Data mining can direct businesses toward the next step based on tendencies and characteristics, rather than simply based on decision-makers' personal experiences. Databases nowadays are not just data storage; businesses should use data warehousing and utilize databases well for effective data mining. New trends in databases tend toward applications; therefore, utilizing data well does not simply concern computers and numbers; data are also tools for mapping out strategic plans.

In this paper, association rules and clustering methods are used to explore customers' shopping patterns. The products/brands spectrum provides ways to promote competence, reinforce brand properties, and perform strategic analysis and applications, enabling merchants to utilize the characteristics of the product spectrum to understand customers' preference sequences and their demands in the market. Using this information, merchants are then able to determine whether their product brands are ideal from their customers' perspective; to employ the product and brand spectrums to analyze their products and brands; and to draw up marketing plans to help them achieve a breakthrough in the market.

Fig. 11 shows the marketing knowledge maps of luxury products, and reveals the similarities and differences among the various customer clusters in terms of product and brand preferences and demands. The purpose of using a knowledge map to describe a marketing map for the product and brand spectrums is to enhance the beverage merchants' understanding of consumer behavior in the luxury products market. The following findings and suggestions are addressed in this particular study in regard to market segmentation in the luxury products industry:

(1) Bags rank in the top 3 of each cluster, indicating that they are the most favored of the luxury product categories for consumers. In light of this, it is possible for the industry to use the product spectrum as products with consider factors. Analysis of association rules reveals that the rules generated

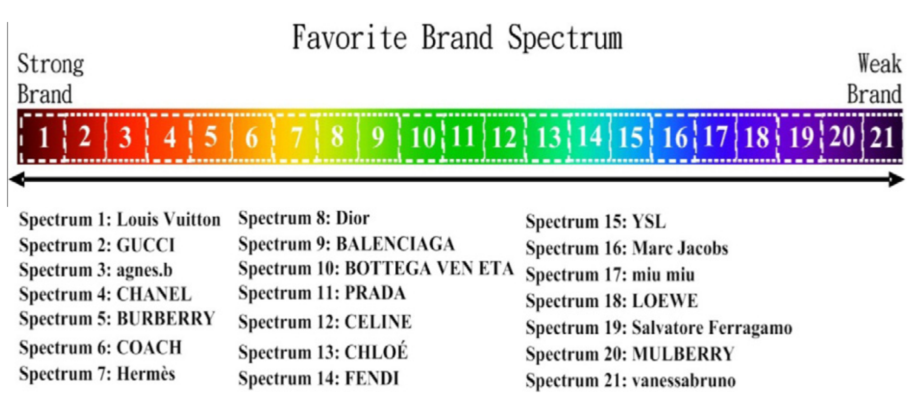

Fig. 10. Cluster-3 favorite luxury brand spectrum.

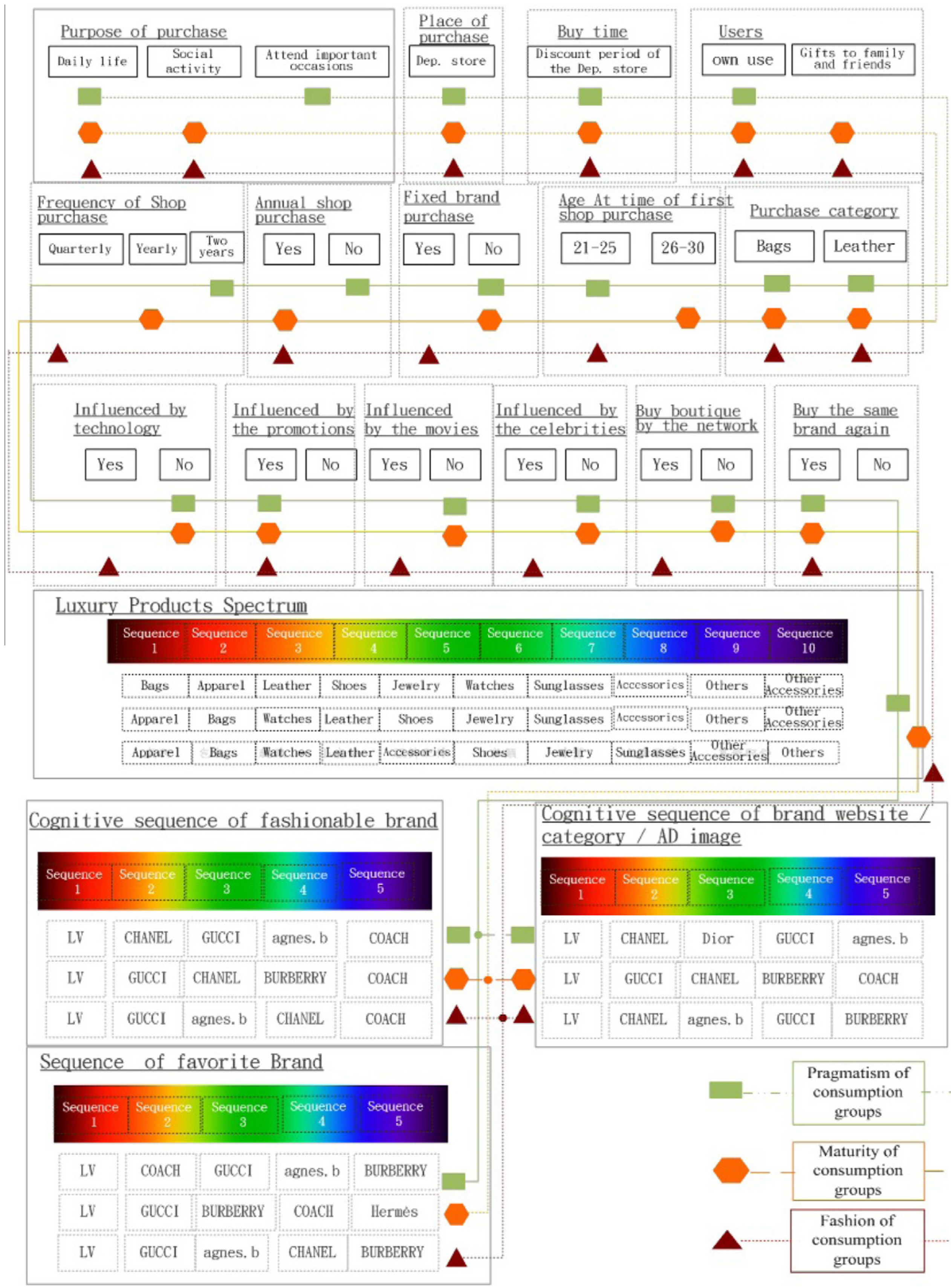

Fig. 11. Marketing knowledge map for luxury products market.

in the three clusters are not the same for each individual, suggesting that different consumer characteristics produce different product sets. Cluster-1 (pragmatism of consumption) consists of a combination of products that may be practical and lower-priced accessories or valuable watches. In Cluster-2 (maturity of consumption) with bag combination products can be stressed mature clothing and shoes; while in Cluster-3 (fashion of consumption), a combination of leather or jewelry is more appropriate.

(2) In this study, consumers perceive the best brand to be Louis Vuitton, especially in brand preference, brand awareness and brand of the popular website/catalog/advertising projects such as image recognition are more significant. However, the top 2 brands for each cluster are not the same. Therefore, the luxury industry should pay attention to the points of departure among the different clusters. For Cluster-1, to provide basic or entry-style products, it is important to build brand loyalty. For Cluster-2, attention should be paid to practicality, style and quality to attract consumers to purchase again. Finally, the luxury industry should provide the most popular styles to satisfy the preferences of Cluster-3.

(3) The brand spectrum suggests that merchants should use the product spectrum for reference while developing and positioning new products to launch customer-oriented innovations to meet customers' expectations, or utilize the characteristics of the product spectrum to perform strategic evaluations. A brand moving toward the higher levels in a sequence means that consumers in that market identify with the product. Merchants can benefit from brand recognition, which further promotes corporate image and fosters financial gain.

6.2. Suggestions

(1) Online shopping: in the three clusters in this study, the majority of consumers express preference for an online luxury product shopping experience; however, in the real world, luxury brand owners have yet to build such a shopping channel. Therefore, it is recommended that luxury brand owners be receptive to innovations including telephone shopping, or online shopping on their official brand websites as part of their brand marketing, access can be avoided by informal market share of competitors.

(2) Influence of celebrities and film: the purchase decisions of some consumers are influenced by celebrity clothing and brand exposure in films or television programs. Therefore, to exploit this, as luxury brands tend to be more appropriate brands for celebrities, companies should aim to increase the level of media exposure of their products in order to enhance consumer awareness of brand and product quality.

(3) Impact of promotional activities and price: in this study, buyers in each cluster are subject to the impact of price promotions; moreover, price for consumers is an important factor. Therefore, the luxury industry's brand with promotional activities in addition to discounts on merchandise outside of business owners, but also by brand activities, gift vouchers or unique products to attract consumers' attention.

7. Conclusions

In this research, customers were grouped and products were arranged in preference sequences, with luxury products being designated as brand objects in order to distinguish brand recognition levels among customers. Data analysis and segmentation revealed that product and brand sequences differed among the various customer clusters.

During the development process from product concept to actual product, the customer is able only to passively receive new information, and can only select from the products that are currently on sale in the market. Customers' needs and wants are sensitive and complex. If a firm is able to understand them, make the effort to fulfill their wants and provide friendly service, then the customer will be more supportive of the enterprise. Buying what is available on the market does not necessarily indicate that customers are satisfied with the current product because the customers' preferences and experiences have not been considered in developing the product; customers are able only to accept the product as it is. However, the extracting of customer knowledge from the market makes possible luxury product marketing that identifies the specific needs of groups of customers, and develops the right promotion and advertising approach for one or more market segments. This paper proposes the use of the Apriori algorithm of association rules, and *K*-means algorithm clustering analysis data-mining approach to mine customer knowledge from the database. Knowledge extracted from data-mining results is illustrated as knowledge patterns, rules, and maps that provide the basis of the recommendations detailed in the paper made to Taiwan's luxury products industry for future promotion and marketing strategies.

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