Mining Consumer Knowledge from Shopping Experience: TV Shopping Industry

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Abstract: *TV shopping becomes far much popular in recent years. TV nowadays is almost everywhere. People watch TV; meanwhile, they are more and more accustomed to buy goods via TV shopping channel. Even in recession, it is thriving and has become one of the most important consumption modes. This study uses cluster analysis to identify the profiles of TV shopping consumers. The rules between TV Shopping spokespersons and commodities from consumers are recognized by using association analysis. Depicting the marketing knowledge map of spokespersons, the best endorsement portfolio is found out to make recommendations. By the analysis of spokespersons, period, customer profiles and products, fourbusiness modes of TV shopping are proposed for consumers: new product, knowledge, low price and luxury product; the related recommendations are also provided for the industry reference.*

Keywords: *Consumer knowledge, data mining, TV shopping, association rules, clustering.*

Received July 23, 2014; accepted June 26, 2016

1. Introduction

Commercially available since the late 1920s, the television set has become familiar in households, businesses and institutions, particularly as a vehicle for advertising, a source of entertainment and news. Since the 1950s, it has been the main medium for shaping public opinion. In recent years, Internet television has seen the rise of television available via the Internet. Today, TV is almost everywhere. People watch it; meanwhile, they are more and more accustomed to buy goods via TV shopping channel. Therefore, following by retail and supermarket, TV shopping is well-known because of the third revolutionary change in sales [13]. It is a significant change from an entity store to a virtual one. In fact, in the past 20 years, TV shopping has become one of the fastest growing businesses. Now, TV shopping becomes a more important business rather than entity shopping [11, 15, 21].

To increase the perception and credibility of products and brands, TV shopping usually employs a spokesperson or a host for promotion. Traditionally, selecting a spokesperson is usually in accordance with the personal impression of the business management or marketing departments. Theoretically, a spokesperson recommendation system aims to establish a sense of trust in customers on the endorser, further to build or transfer the trust to the promotional products [5]. According to e-Marketer researches, 90% people believe the recommendations from people they trust [16]. Therefore, industries can find a better spokesperson and product portfolio out in accordance with the preferences of consumers but not the business management's or marketing departments'. Marketing combined with a spokesperson for sales promotion is frequently used and useful to meet consumers' perception and credibility on the products. Thus, the spokesperson and products ought to work hand and glove for effectively persuading customers to buy the products [12].

General information, shopping experience, preference of spokespeople, products and brands of customers are important for enterprises. However such information is not concrete but abstract. Then, collecting such information and the way to handle them become chief missions for the industry. New technology is needed for analysis and understanding. Visual graphic is one of the methods to settle these data [17]. Besides, data mining is a very useful and effective method to deal with the problem. The purpose of data mining is to find valuable information out from big data [6, 9, 10]. In recent years, data mining has attracted the attention of the information industries and society. It is extensively used in many fields, such as fraud detection, financial projections, crime and behavior recognition [1, 4]. With the more frequent and diversified business conducts, the application of data mining has been seen everywhere. With the characteristics of handling much factual data and establishing the analysis models without the assumptions of the data, data mining is applied in broader ways [9, 20, 28].

In addition, a spectrum is used to show the strength of products' and spokespersons' preference of customers. In physics, a spectrum is a 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. In most modern usages of spectrum, there is a unifying theme between extremes at either end [18]. 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 too ther competitors [27]. Marketing research frequently cited the measure of the spectrum to measure the preferences of consumers. The spokesperson of this study, for example, each consumer has specific preference ranking from strong to weak. This relationship of the specific preference ranking will produce a similar spectrum gradient phenomenon. The front end of the preference spokesperson ranking means that consumers have a strong preference for this spokesperson and vice versa. This study names such a ranking as spokesperson spectrum.

This study mainly applies data mining to analyse consumers' experience of TV shopping. Using cluster analysis to depict consumers' profiles, and applying association rule for the recommendations of products which set spokes person preference and period preferences as variables, different clusters purchasing preferences and product's combinations is found out. More specific recommendations in accordance with the research results are suggested then. Based on research background and motivation, TV shopping consumers in Taiwan are presented as the research objects to reach the research purposes:

1. Developing questionnaires of consumers' TV shopping experience, their preferences of TV channel, spokesperson, shopping period and product, trading mechanisms and shopping satisfaction.
2. Respectively establishing the potential development of TV shopping and targeting two groups in which find out the patterns of consumers' behavior in TV shopping and give recommendations.
3. Based on consumer profiles and preferences depicting the knowledge map of spokesperson and marketing, the purchasing motivation of TV shopping, the trading mechanism, the recommended spokespersons and products in different clusters are discovered for identifying the best combination of endorsement and giving recommendations.
4. Converting knowledge into the spokesperson and product spectrum, the ranking of spokesperson in customers is gained successively. Using the spokesperson and product spectrum strategy analysis chart, the proposal for the business model is made.

2. Shopping Industry in Taiwan

Originated in the local television station in the Mid-western United States, TV shopping became a commercial marketing until the late 1980s [23]. For marketing, the TV shopping industry promotes products to obtain profits. Engel *et al*. [7] explained that TV shopping industry has been a business channel in the cable system but not an entertaining television program. Its content was broadcasted as the nature of commerce. The purpose was to sell products for more profits. Via various shooting angles of products, TV shopping offered a clear product packaging image for consumers. In addition, a host presented a detailed demonstration and introduction of products. Some of TV shopping channels even gave a live show so that consumers could ask any questions about products by telephone inquiries [23]. Consumers got reliable information from their favorite host in the TV shopping show. The higher the credibility of the host, the higher purchase intention of consumers was [22].

TV shopping industry in Taiwan has developed since 1990s. In the early stage, because of the expensive cost of leased channels, the products with poor quality and the transaction disputes, TV shopping industry gradual declined. In 1999, there was a drastically change because of ET-mall. ET-mall succeeded owing to the real operating through television by using scenarios design and program strategies as well as a live broadcast. Meanwhile, the interaction with customers was increased by attractive men and women or a credible host. While the interaction between consumers and the host increased, customers were more interested in the program and the products so their purchase intention and behavior rose [8].

Table 1. Profiles of TV shopping companies in Taiwan.

Name	ET-mall	momo	ViVa	U-Life
Channels	5	3	1	5
Found	1999	2004	2005	2011
Authorized Capital (US $)	90millions	36millions	3millions	33millions
Market channels	● Internet ● Catalog ● Mobile phone	● Internet ● Catalog ● Shop ● Depart. store	● Internet ● Catalog	● Internet ● Catalog
Members	More than 4 million people	More than 3 million people	About 1.3 million people	About 0.85 million people

There were simple descriptions for four Taiwanese TV shopping companies (show as Table 1), which are ET-mall, momo, ViVa and U-Life.

1. Et-mall, established in August 1999, shares five channels with U-Life. In December 1999, it had live shows. In the following year, catalog shopping was offered. Virtual channel information platform constructed by EHS could provide 3000 online shopping services. Its members now are more than 4 million people.
2. momo TV, established in June 2004 by Fubon Financial, has three shopping channels. Fubon Financial offers a wide range of products, which are

more than ten thousand kinds. Also, Fubon Financial is the first company offering consumers online insurance services. Its members are more than 300 million people.

3. ViVa TV, established in August 2005, is now a TV shopping channel. Its main claim is to provide consumers a good shopping experience constantly. Shopping channels comprise TV, website and shopping catalog. Its members are approximately 1.3 million people.
4. U-Life shopping channel, established in November 2009, shares five channels with ET-mall. Its members are estimated about 85 million people.

3. Research Methods

3.1. Research Architecture

This study built an analytical database based on questionnaires which collected consumers' TV shopping experience. The database contained consumers' basic information, their purchase experience, their spokesperson and product preferences and the trading mechanism. First, K-means algorithm of cluster analysis was used to depict consumers' profiles. Then, Apriori algorithm of association analysis was used to find out the correlation amongst the spokesperson, the merchandise combination and customers' satisfaction of TV shopping. Finally, marketingsuggestions and recommendation mechanismswere proposed based on the consumers' knowledge map. System architecture is shown as Figure 1.

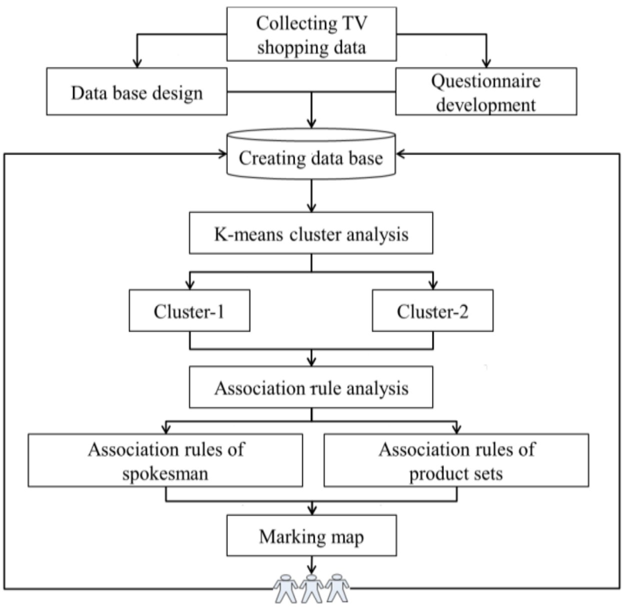

Figure 1. System architecture.

3.2. Questionnaire Design and Data Collection

This study collected customers' consumption information by questionnaires. To create a database, a marketing survey was conducted to collect related information mainly from the public that was with TV shopping experience. Data mining was applied to find out customers' demands and preferences for a reference of the decision-making and TV shopping recommendation mechanism.

A pilot test was used before the full-scale research project to test the design which then could be adjusted. It was a potentially valuable insight. Anything that missing in the pilot study could then be added to the full-scale test to improve the chances for a clear outcome. The test was carried out on TV shopping senior members; the sample size was 45. In the questionnaire survey, 1,165 questionnaires were returned in total, in which 136 were rejected because they were either incomplete or invalid. 1,029 questionnaires were valid so that the valid completed rate was 87.86%.

3.3. Association Rule Analysis-Apriori Algorithm

Agrawal *et al.* [2] has learned that association rules were an important data-mining issue. The association rules algorithm was mainly used to determine the relationships between items or features that occurred synchronously in databases. For instance, if people who bought item X and Y, there was a relationship between item X and Y; this information was useful for decision makers. Therefore, the main purpose of the association rule algorithm was to find out the synchronous relationships for decision making. The association rules are defined as follows [26]:

Make I be the item set, in which each item represents a specific literal. D stands for a set of transactions in the 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 transactionset D is. Therefore, the rule $X \rightarrow Y$ has support $Sup(X \cup Y, D)$, which represents the rateoftransactionsin D containing $X \cup Y$. Each rule $X \rightarrow Y$ also has another measuring standard called Confidence (denotedas $Conf(X \rightarrow Y)$), representing the rate of transactions in D that contain X as well as Y; that is:

$$Conf(X \rightarrow Y) = Sup(X \cap Y) / Sup(X, D) \quad (1)$$

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.) [14]. According to Agrawal and Shafer [3], the problem of mining association rules could be decomposed into two steps. The first step was to detect a large item set whose support is greater than Min-sup; and the second step was to generate association rules, using the large item set. Such rules must satisfy two conditions:

$$Sup(X \cup Y, D) \geq Min\,\text{sup} \tag{2}$$

$$Conf\,(X \rightarrow Y) \geq Minconf \tag{3}$$

To explore the association rules, many researchers used the Apriori Algorithm [2]. In order to reduce the possible biases incurred when using these measure standards, the simplest way to judge the standard is to usethe lift judgment. Lift isdefined as [26]:

$$Lift = Confidence(X \rightarrow Y) / Sup(Y) \tag{4}$$

3.4. Cluster Analysis-K-means Algorithm

The process partitions a large set of patterned into disjointed and homogeneous clusters as 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 methods for implementing the clustering process [19]. K-means clustering proceeds in the following way: firstly, K numbers of observations are randomly selected from all N number 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. 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 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 [24, 25, 29].

4. Results

4.1. Customer Profiles

This study used K-Means algorithms to cluster customers, and then named Cluster-1 as Future buyer, and Cluster-2 as Target customer. Results for 2 clusters' profiles are shown in Table 2.

1. Cluster: Future Buyer Cluster-1 was around 26 to 35 years old. Their education level was university and graduated; their profession was in IT and service industry. They never bought goods from a TV shopping channel. The average monthly family income was between US $ 165-330 and between US$ 330-1,650. They paid much attention to the quality of goods and took personal privacy seriously. So, they had no confidence in TV shopping about the quality of goods and the security. Then, the use of cash on delivery and chain store pickup or manufacturer's quality assurance might increase their purchase intentions.
2. Cluster: Target Customer Cluster-2 comprises married office ladies, around 36 to 45 years old. They worked at manufacturing industry or financial industry. Their education level was College and above. The average monthly family income was between US$ 330-1,650. Their purchase motivations were sale promotions, product discount and time saving. They were willing to spend US$35~100 on necessities and entertaining products. They daily spent 2~3hours to watch TV. Besides, they preferred cash on delivery and online credit card.

4.2. Association Analysis of TV shopping Spokesperson

A hot commodity was very difficult to identify from many commodities in TV shopping. To choose favorite goods was not an easy job for consumers. In this study, the spokesperson, the merchandise mix and the satisfaction were used to explore the influence of different spokespersons and satisfaction for the consumer product selection. In Taiwan, Spokesperson-A was Jung Ssu, Spokesperson-B was Ching Li, Spokesperson-C was Chieh-Ling Jen, Spokesperson-D was Niu Ma, Spokesperson-E was An Yu, Spokesperson-F was Fei Yu, and Spokesperson-G was Yu-Teng Lin.

1. Spokesperson's analysis of Cluster-1Cluster-1 had never bought a product via TV shopping. They liked TV and movie stars. The top 3 options respectively were Spokesperson-B, Spokesperson-A and Spokesperson-C. The association rule of spokespersons is shown in Table 3. Spokesperson-A attracted unmarried people who watched TV one hour per day and also attracted married male. Cluster-1's married female customers preferred to watch Spokesperson-B's TV shopping program at 22:00~22:59. The popularity of the host, the situation of endorsement and the price strategy were significant for fresh Cluster-1. Figure 2 shows the strength and complexity of relationship between the spokespersons and input variables. The stronger the relationship, the darker color of the line is. The

more complex the relationship, the denser the lines are.

2. Spokesperson's analysis of Cluster-2 Cluster-2 was interested in necessities. They highlighted the convenience of shopping and practicality of products, such as the service provided by household utensils shops, storage products and pots. They preferred high-profile celebrities. The top 3 spokespersons were Spokesperson-B, Spokesperson-D, and Spokesperson-E. The association rules of spokesperson are shown in Table 4 and Figure 3. Female had a positive relationship with Spokesperson-D, whose education level was university. Married female customers had a positive relationship with Spokesperson-E, who had a show at 23:00~23:59. That meant each spokesperson had particular customers. So, different products should be matched with different spokespersons for the marketing strategy.

Table 2. Customer profile and characteristics of clusters.

	Cluster-1	Cluster-2
Sample size	418	482
Named	**Future buyer**	**Target customer**
Gender	Male (55%)	Female (70%)
Age	26~35 year-old (43%)	36~45 year-old (45%)
Level of education	University (37%) Graduate school (21%)	Vocational school (25%) University (31%)
Types of work	Service industry (19%) IT industry (18%)	Manufacturing industry (18%) Financial industry (16%)
Married status	Unmarried (57%)	Married (67%)
Average monthly family income (US $)	Between 165～330 (25%) and between 1,000～1650 (28%)	Between 330～1650 (70%)
TV shopping experience	No (79.5%)	Yes (89.1%)
Average spending (US $)	Below 33 (90%)	Between 33~100 (67%)
Never TV Shopping reason	Shopping process complicated (63%) The uncertainty of the quality of commodities (89%)	Personal information may outflow (72%)
Payment type	Pay on delivery (50%) Pay by online credit card (33%)	Pay on delivery (41%) Pay by online credit card (43%)
Recommended type	Friends and relatives recommended (68%) Manufacturer's quality assurance (74%)	Manufacturer's quality assurance (83%) Public figure endorsements (66%)
Promotion type	Cash discount (71%) Layaway plan (74%)	Cash discount (92%) Gift (67%)
Future willingness to use the TV shopping	Will be used in the future (61%)	Will be used in the future (83%)

Table 3. Association rules of Cluster-1's spokesperson (min-sup.=20%;min-conf.=20%).

Rule	Sup	Conf	Lift	Consequent	Antecedent
R1	27.51	20.00	1.64	Spokesperson-A	Unmarried, 1 hour daily watching TV
R2	20.09	27.38	1.63	Spokesperson-B	Married, Female, 22:00~22:59
R3	25.83	69.44	1.43	Spokesperson-A	Male, Married
R4	21.77	65.04	1.39	Spokesperson-C	Female, University

Table 4. Association rules of Cluster-2's Spokesperson (min-sup.=20%;min-conf.=20%).

Rule	Sup	Conf	Lift	Consequent	Antecedent
R1	20.12	25.77	1.80	Spokesperson-D	University, Female
R2	34.85	26.78	1.65	Spokesperson-E	Married, Female, 23:00~23:59
R3	21.99	27.35	1.55	Spokesperson-B	to 3 hours daily watching TV, Married, 23:00~23:59

Table 5. Association rules of Cluster-1's products combination (min-sup.=20%;min-conf.=20%).

Rule	Sup	Conf	Lift	Consequent	Antecedent
R1	21.05	23.86	2.77	18~25 year-old	Unmarried, Cubilose, Seal storage bags, GPS navigator
R2	21.29	26.96	2.12	Medical industry	Bedding, Gold painting, Foreign tour, Seal storage bags
R3	21.29	37.09	2.09	IT industry	Unmarried, Clam essence, Tachograph
R4	21.53	23.33	1.95	Financial industry	Razor, Cubilose
R5	20.81	28.73	1.90	Education level is senior high school	Bicycle, Toad embellishment, Mop
R6	20.09	21.42	1.90	41~45 year-old	Motorcycle, Cubilose, Massage chair

Table 6. Association rules of Cluster-2's products combination (min-sup.=20%;min-conf.=20%).

Rule	Sup	Conf	Lift	Consequent	Antecedent
R1	31.57	34.09	1.92	IT industry	Unmarried, Cubilose
R2	34.68	31.03	1.75	IT industry	Unmarried, GPS navigator
R3	31.81	34.58	1.64	Education level isInstitute	Unmarried, Tachograph

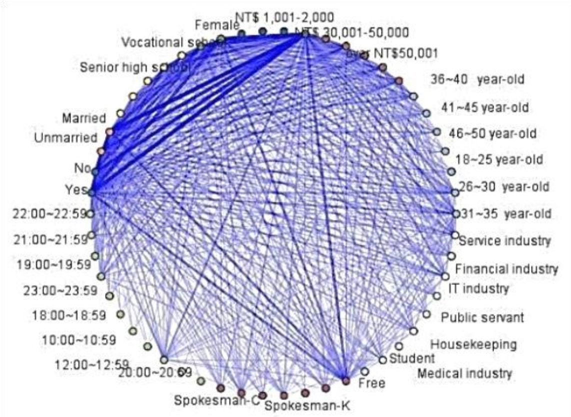

Figure 2. Cluster-1 web graph of spokesperson and shopping periods.

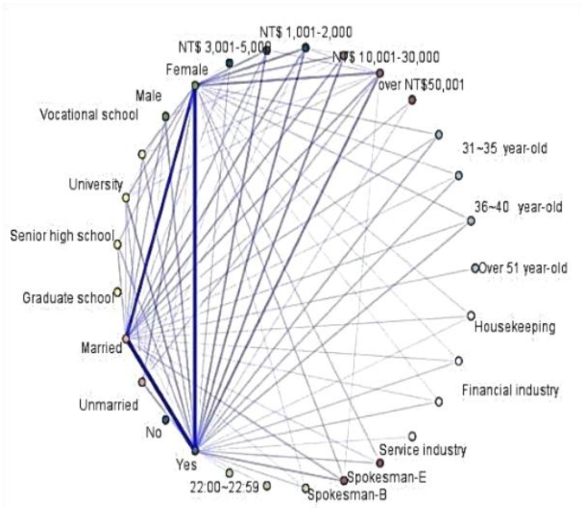

Figure 3. Cluster-2 web graph of spokesperson and shopping periods.

4.3. Association Analysis of Products Combination

At this stage, owing to proposing recommended combinations, the significant association rules were found out through the relationship between the merchandise mix and three decision variables - the age, the type of work, and the level of education.

1. Products combination analysis of Cluster-1Cluster-1 had never bought a product via TV shopping. They were serious about the quality of products and their own privacy. The favorite products' pattern of these customers was shown in Table 5. For example, in rule R1, unmarried customers in 18~25years old, liked products of cubilose, seal storage bags and GPS navigator. So, if one of these was bought, the other two products could be recommended as the products in the merchandise mix. In rule R2, customers in medical industry liked products of bedding, gold painting, foreign tour and seal storage bags. The merchandise mix of IT or financial industry is shown in Table 5.
2. Products combination analysis of Cluster-2 Cluster-2 was interested in necessities. They highlighted the convenience of shopping and practicality of products. In Table 6, the terms of "education level was institute," "unmarried," and "tachograph" got a positive relation. So, the merchandise mix of "GPS navigator or Cubilose" was offered for Cluster-2 to attract unmarried customers in IT industry.

5. Conclusion and Suggestions

5.1. Conclusion

TV shopping channel has gradually become one of the important commercial channels. The information of consumption's habit has been longing for the industry. However, the operator's experience was very limited to hold such information. Only if making good use of data analysis coupled with the operators' experience, the valuable information could be turned into useful knowledge. The knowledge then could yield more valuable knowledge map to assist operators to predict the market.

Operators learnt the situation of sales from sales quantity of the products. However, what shopping concern of consumers could not be known by the trading process. This part had had depend on the integration of key knowledge and the understanding of consumers' mind. That might create better operation mode in a rapidly changing market. In order to meet consumers' want and need, this study suggested that TV shopping operators should attach importance to the preferences and needs of consumers, rather than just want to sell their products to customers.

5.2. Managerial Implications

Based on data mining concepts, this study divided consumers into "Future buyer" and "Target customer". According to the variables of the spokesperson, shopping hours and commodity, customers' satisfaction and TV shopping service of each cluster were described. Marketing knowledge map was intended to assist the operators to learn the consumers' preferences and satisfaction. Then, market segmentation and future sales-oriented recommendations promised well. In addition, such knowledge could be used for valuable decision-making and increased the value of the enterprise business intelligence.

5.3. Spectrum of Spokesperson

There was a specific preference of spokesperson for every consumer. The closer the left of the spokesperson, the stronger the preference was. The closer the right of the spokesperson, the weaker the preference was.

The strength of this preference was similar to the gradient of the spectrum so this study called such phenomenon as the spokesperson spectrum. The operators needed to accurately grasp the preference of consumer on products to find the competitive endorsement goods from all products in TV shopping. TV shopping industry wanted to find out the cause-and-effect relationship from a variety of statistical analysis. Through the marketing knowledge map of spokespersons, the information of spokesperson, shopping hours and product categories were put in order in accordance with consumers' preference. Cluster-2, the Target customer as the example is described below.

- The sequential order of the preference spokesperson: Spokesperson-B, A, E, D, and F.
- The sequential order of the consumption hour: 20:00, 21:00, 22:00, 23:00, and 19:00. All periods were from after work to midnight.
- Strong preference in early channels of ET-mall and momo.
- Inclined to buy household goods, 3C appliances and leisure sports goods.

Via the questionnaire analysis of consumers, spokesperson, consumer time, shopping channels, product categories were used to draw the market knowledge map of spokespersons of TV shopping, which shown in Figure 4. For "Future buyer" and "Target customer," suggestions were given as follows:

1. Establishing the identification of consumers: while consumers bought goods, they measured their own needs but also concerned about the appearance, communication skills and professional competence of the spokesperson. For example, Spokesperson-B as a TV shopping expert was also a TV presenter, a model, and a stage director. Endorsement by high-profile entertainers or professionals could improve the corporate image to get better financial revenue.
2. Generating the perception difference: the types of products offered by each TV shopping channel was

slightly different. There were larger differences because of advertising, promotion and the spokesperson spectrum. It was named as perceptual difference. For example, married male customers with higher education preferred watching the program of Spokesperson-E endorsing household goods and entertaining 3C products in the evening. The industry then could learn such customers' preference in selecting the spokesperson and the products. Meanwhile, according to the marketing map of spokesperson, sales activities could be set well for customers to get a better spokesperson image.

3. Increasing the information's value: most of the business managers did not take advantage of the information, which includes many customers' knowledge and preferences, stored in the enterprise. Marketing strategy combined with customers' knowledge and preferences would have a higher value.

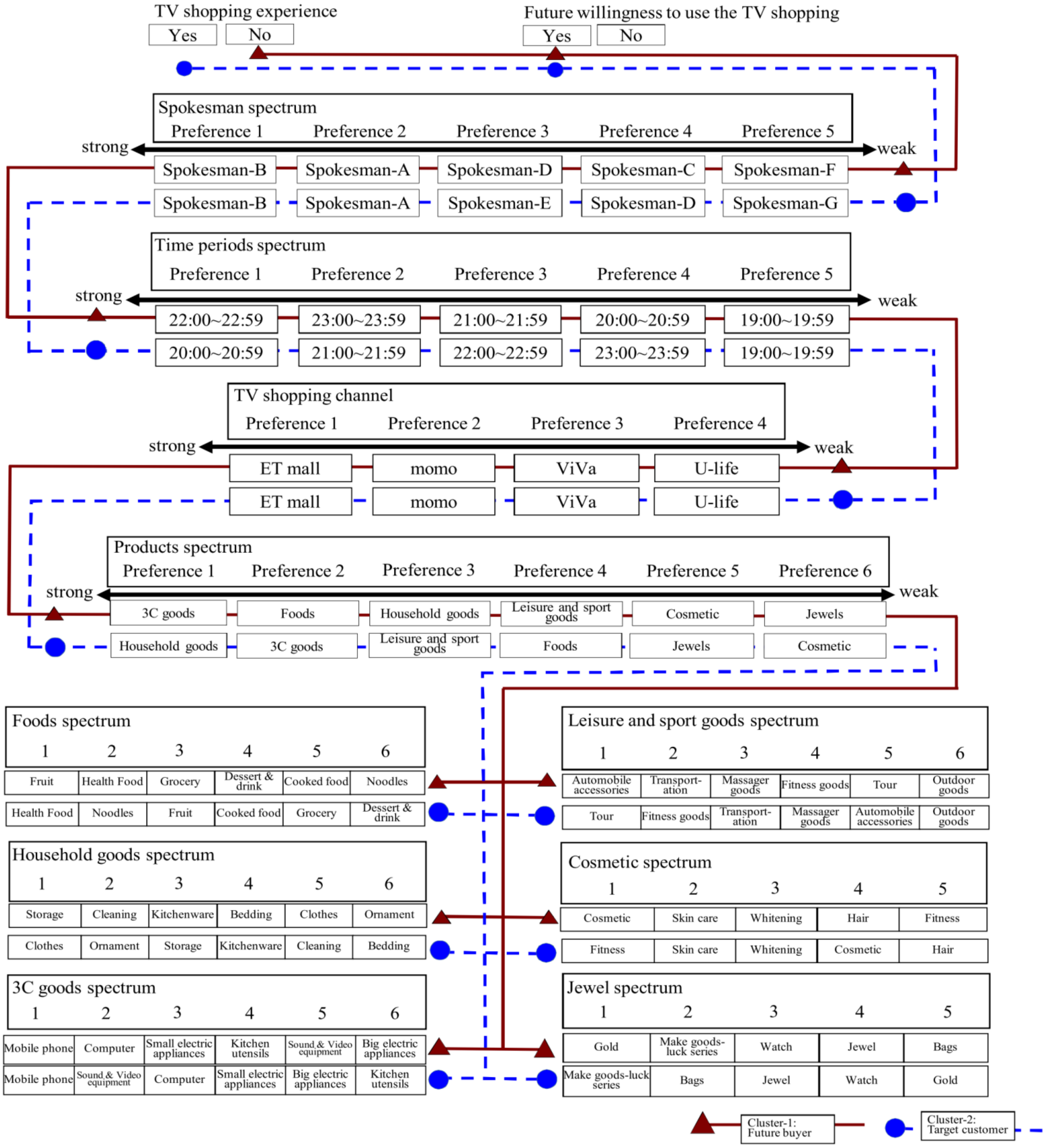

Figure 4. Spokesperson market knowledge map.

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