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MINING CUSTOMER KNOWLEDGE FOR CHANNEL AND PRODUCT SEGMENTATION

Shu-Hsien Liao, Yin-Ju Chen, and Hsiao-Wei Yang
Department of Management Sciences, Tamkang University, New Taipei City, Taiwan, Republic of China

□ *Segmentation is particularly challenging in current markets. Hence, companies operating on consumer markets face significant implementation complexities. However, successful implementation of market segmentation is reported problematic, despite being extensively researched and widely acknowledged as a powerful concept in practice. The desired outcome, and the knowledge discovery of market segmentation, is to reap the benefits of competitive advantage. This study takes Computers/Communications/Consumer (3C) products as an example and uses a two-step data mining approach to the cluster analysis and association rules to analyze customer channels and product segmentation. Moreover, we look at what kinds of products and brands customers of different segments prefer and how these preferences differ in relation to varying channel types. Thus, this study finds some 3C product-buying behavior patterns, including customer purchase preferences and customer purchase demands, in order to generate different 3C segmentation marketing alternatives.*

INTRODUCTION

In recent years, the rapid increase in channel patterns has led to diverse types of retail channels competing with each other in the customer market (Balasubramanian et al. 2005). A business's sales channel strategy could influence consumer's sales channel preferences. It provides a new direction for business strategies in that they could play an important role in consumer sales channel preference development. When a business offers multiple sales channels, its customers can compare sales channels either within or outside of the same corporate business (Muthitacharoen, Gillenson, and Suwan 2006). Thus, the proliferation of channels has created new challenges for research, including understanding how consumers may be segmented with

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Address correspondence to Shu-Hsien Liao, Department of Management Sciences, Tamkang University, No. 151, Yingjuan Rd., Danshuei Dist, New Taipei City, Taiwan 251, Republic of China. E-mail: michael@mail.tku.edu.tw

respect to their information search and purchase behavior in a multichannel environment (Konus, Verhoef, and Neslin 2008).

In terms of segmentation, market segmentation has been defined as "...an ongoing and iterative process of examining and grouping potential and actual buyers with similar product needs into subgroups that can then be targeted with an appropriate marketing mix in such a way as to facilitate the objectives of both parties" (Mitchell and Wilson 1998, p. 431). Market segmentation is frequently appraised as an effective strategic marketing tool (Weinstein 2006) and reflected in the well-known segmentation, targeting, and positioning (STP) conceptualization of the market segmentation process (Kotler 1996). The concept is valuable because of its ability to assist in the understanding of markets (Weinstein 2006) and selection of target markets (Sarabia 1996). Having a clear segmentation plan can reportedly help managers devise marketing programs to meet the specific needs of different segments of customers (Doyle and Saunders 1985).

In addition, segmentation is particularly challenging in current markets (Bonoma and Shapiro 1984; Chéron and Kleinschmidt 1985; Mitchell and Wilson 1998; Freytag and Clarke 2001), because (1) heterogeneity among customers is more pronounced and visible as a result of frequent communication, (2) social interaction characterizes the exchange and complicates stimulus–response patterns, (3) customers stimulate back to a larger extent by communicating needs and wants directly, (4) relations are multiplex, generating multiple stimulus channels, (5) offerings are more complex and frequently developed in interaction, and (6) segments are more unstable. Hence, companies operating in consumer markets face significant implementation complexities (Boejgaard and Ellegaard 2010). However, successful implementation of market segmentation is reported problematic, despite being extensively researched and widely acknowledged as a powerful concept by practice (Dibb and Wensley 2002; Palmer and Millier 2004). The desired outcome, and the knowledge discovery of the implementation of market segmentation, is to reap the benefits of competitive advantage (Goller, Hogg, and Kalafatis 2002), in other words, to gain market share and/or sell more. But these benefits of market segmentation strategy cannot be reaped if the segmentation plan cannot be implemented.

Customers play an important role as business assets. Most of the parties involved in sales, such as the commercial websites, retailers and channels, are aware of the need for businesses to acquire better customer knowledge (Tapscott and Ticoll 2003; Matsuo 2009). However, this is easier said than done because customers' knowledge is known only to 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. Inefficient utilization renders the data collected useless, causing databases to become "data dumps" (Keim et al. 2004). Thus, finding ways to effectively process and use data for customer knowledge discovery is an artificial issue that calls for new techniques to help analyze, understand, or even visualize the huge amounts of stored data gathered from business and scientific applications. Among the new techniques developed, data mining is a process of discovering significant knowledge from large amounts of data stored in databases, data warehouses, or other information repositories (Keim et al. 2004). Customer knowledge extracted through data mining can be integrated with customers and products knowledge from research and can be provided to describe customer profiles and purchase behaviors. Thus, it can serve as a reference for product development, product promotion, and customer relationship management. When effectively utilized, such knowledge extraction can enable enterprises to gain a competitive edge by producing customer-oriented goods that increase customer satisfaction (Ben David and Sterling 2006).

In previous studies, there are many data mining models such as classification, estimation, predictive modeling, clustering/segmentation, affinity grouping or association rules, description and visualization, as well as sequential modeling. Similarly, there are also many application methods, including association rules, sequential pattern, grouping analysis, classification analysis, and probability heuristic analysis (Mehta and Bhattacharyya 2004; Prinzie and Van den Poel 2005; Ben David and Sterling 2006; Huang et al. 2009; Liao, Ho, and Yang 2010; Liao, Chen, and Lin 2011; Lee and Estivill-Castro 2011; Vidulin and Gams 2011; Liao et al. 2012; Liao, Chu, and Hsiao 2012). Thus, through research, knowledge of customers extracted through data mining can be integrated with channel and product segmentation knowledge and then possible segmentation alternatives can be proposed to companies.

Accordingly, this study investigates how channel attributes, product attributes, and information searches result in the channel and product preferences of the customer. According to the different product categories, we look for the reason that customers choose the same single-channel or multichannel for buying. In addition, this study implements a two-step data mining approach and cluster analysis and association rules as analysis approaches for data mining. By doing so, we analyze customer adumbration and find variables, such as reasons for channel selection, reasons for product selection, product categories, information searches, and the type of channels used in the analysis of channel segmentation and product segmentation. In addition, with the rapid development of Computers/Communications/Consumer (3C) products in the Taiwan market, 3C products and information of customers have come closer to everyday life. Therefore, this study investigates customer purchase information related to 3C products. This study attempts to understanding customer demand for products and channels, and what kinds of services and products the customers hope the distributors and manufacturers provide. Finally, this study finds some models, including different clusters of channels and product bundling, so that sellers can launch more programs and services to attract customers in the early marketing strategy using a knowledge discovery approach.

The rest of this study is organized as follows. In "Methodology," we present the methodology, including system design, conceptual database design, and physical database. "Data Mining – A Two-Step Approach" introduces the proposed two-step data mining approach, which includes the cluster analysis and K-means algorithm and association rules. The first step is to generate customer profiles using the clustering method and the second step investigates possible channel and product segmentation by implementing association rules. "Data Mining and Results" are presented in the next section. "Research Findings and Managerial Implications" follow, and the final section presents a brief conclusion.

METHODOLOGY

System Design

According to the system design shown in Figure 1, this study incorporates data regarding customer database, channel database, and product database into the data mart, and analyzes the overall database by using two-step clustering and association rules as a data mining approach to find the target customers. With the development of diversified technology, enterprises consider customer knowledge management in marketing and service, and then provide appropriate channels for different customer needs.

Conceptual Database Design

The concept of the relational databases was first developed in the 1970s by Codd to represent interrelated data in the form of a table (Codd 1970). The representation of data in an interrelated table has hence become the main characteristic of the relational databases. Relational databases organize data as a collection of tables in which all data relationships are represented by common values in related tables. These databases can relate data stored in one table to data in another, as long as the two tables share a common data element. The tables appear similar to flat files, but the information in more than one file can be easily extracted and combined with Structured Query Language (SQL), which is the standard data

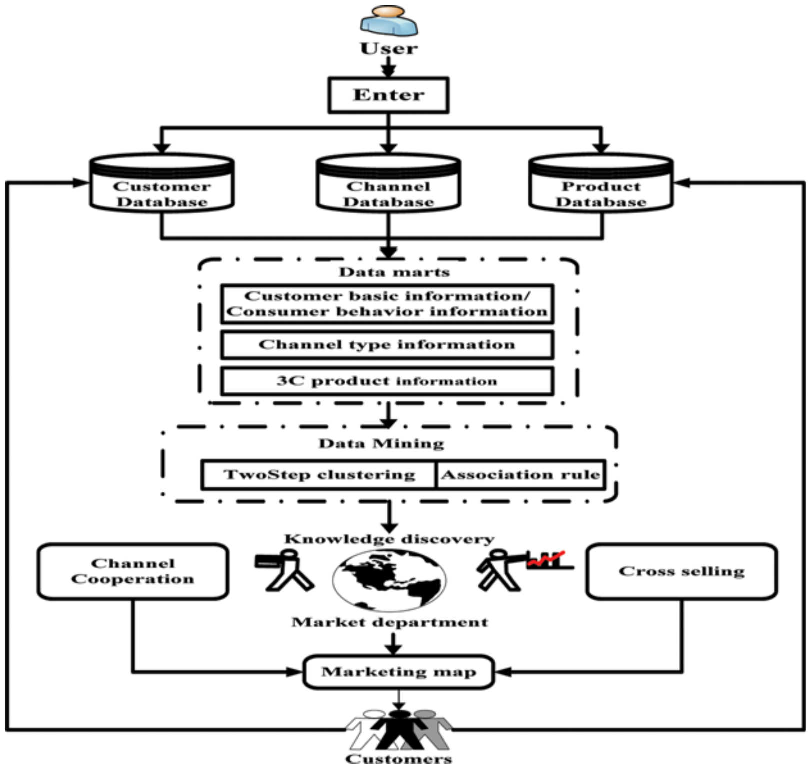


FIGURE 1 System design. (Color figure available online.)

manipulation language for relational database management systems. Many organizations maintain relational databases, and because relational patterns reliably portray patterns embedded within databases, relational patterns can be utilized by organizations to support a variety of efforts for building their database management systems (Tsechansky et al. 1999). Some research articles have shown that the association rules of relational databases can provide a useful method for mining knowledge in different application areas (Berzal et al. 2001; Thabtah, Cowling, and Hammoud 2006). In this study, Figure 2 is the Entity and Relationship (E–R) diagram of conceptual database diagram, which provides a conceptual data model for the relational database design and contains 13 entities, 7 relationships, and 77 attributes.

Physical Database

In this study, the design and operation of the physical database are used to construct a relational database through Microsoft Access 2007, which was

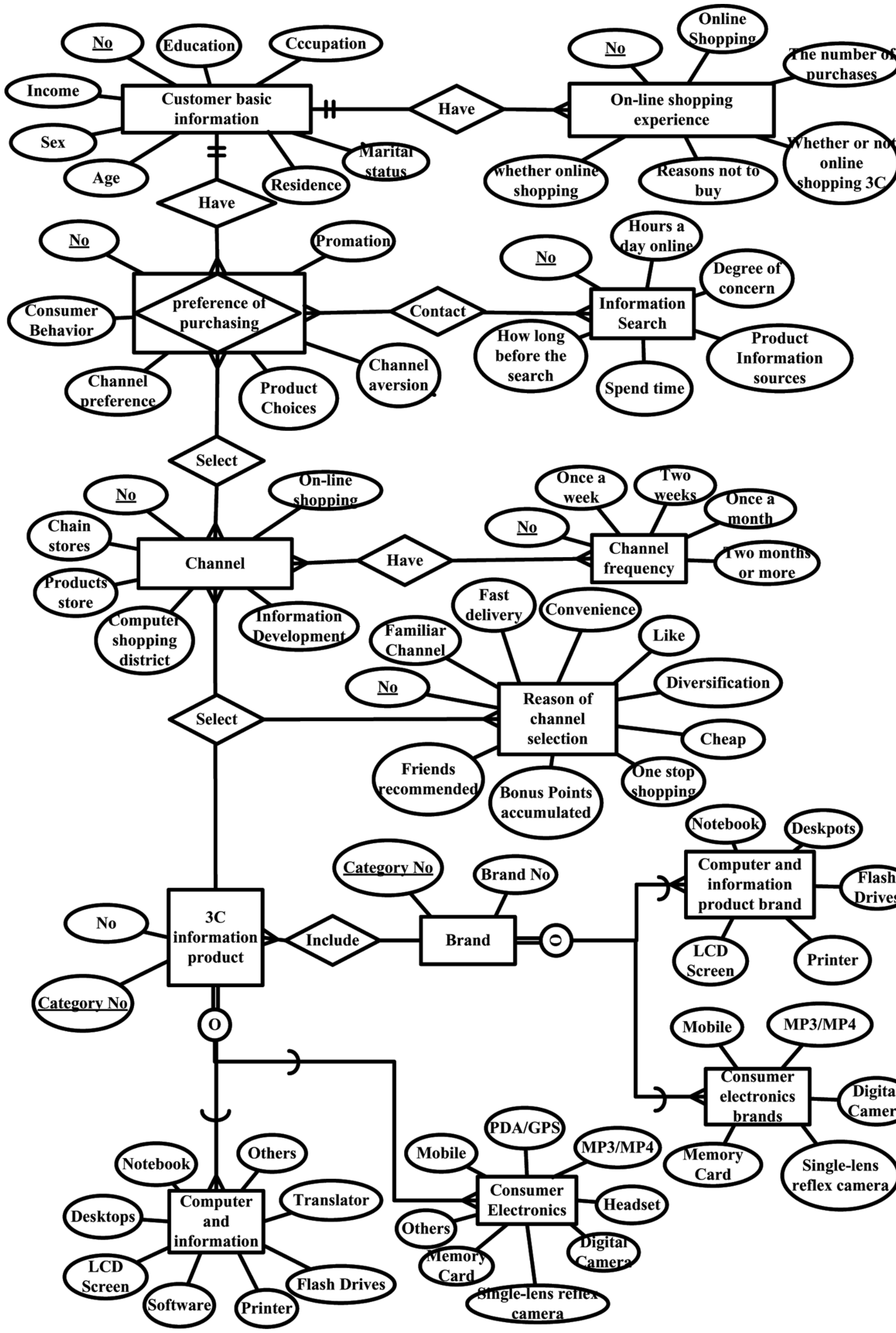


FIGURE 2 Conceptual database design: E–R model.

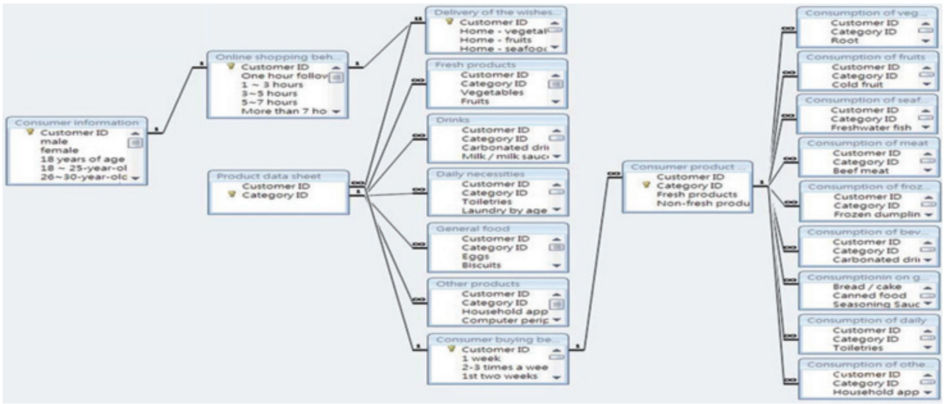


FIGURE 3 Physical database design. (Color figure available online.)

used to enter data in the table (Figure 3). Although general database software cannot accommodate too many people online simultaneously, Microsoft SQL 2005 can satisfy this need, because general database systems use standard structured query language (SQL). Because each case of data storage and processing is different, in order to give the programming language access to the information database system, manufacturers design a driver for all types of languages using standard SQL, and then access their database through regional networks. Microsoft's console provides an open database link (open database connectivity; ODBC), so administrators can manage a variety of ODBC drivers. In fact, a total of 900 samples of consumer data were randomly selected for data mining from December 1, 2010 to January 31, 2011 on a 3C-firm database in Taiwan.

DATA MINING: A TWO-STEP APPROACH

Cluster Analysis and K-Means Algorithm (Generating Customer Profiles)

The process of partitioning a large set of patterns into disjoint and homogeneous clusters is fundamental in knowledge acquisition. It is called *clustering* in most studies and it has been 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 order. First, the K numbers of observations are randomly selected from all N number of observations according to the number of clusters, and these become centers of the initial clusters. Second, 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 recomputed. 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. In addition, several studies have discussed implementation of the k-means algorithm for cluster analysis as a data mining approach (Ture et al. 2005).

Association Rules (Investigating Channel and Product Segmentation)

Discovering association rules is an important data mining problem (Agrawal, Imilienski, and Swami 1993), and there has been considerable research on using association rules for data mining problems (Gallo et al. 2007). The association rules algorithm is used mainly to determine the relationships between items or features that occur synchronously in databases. For instance, during a trip to the shopping center, if the people who buy item X also buy item Y as well, there exists a relationship between item X and item Y. Such 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 to use these relationships as a reference for decision-making. The association rules are defined as follows (Wang et al. 2004):

Make $I = \{i_1, i_2, \ldots i_m\}$ 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 nonempty subitem 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 the transaction set D according to two measurement 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, and the higher its value, the more important the transaction set D is. Therefore, the rule $X \rightarrow Y$ which has support Sup$(X \cup Y, D)$ 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 both X and Y. That is, Conf$(X \rightarrow Y)$ = Sup$(X \cap Y)$/Sup (X, D).

In this case, Conf$(X \rightarrow Y)$ denotes that if a transaction includes X, the chance that this transaction also contains Y is relatively high. The measure of 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 used to generate all transaction rules that have certain levels of user-specified minimum support (called Minsup) and confidence (called Minconf) (Kouris et al. 2005). According to Agrawal and Shafer (1996), the problem of mining association rules can be divided into two steps. The first step is to detect a large item set whose support is greater than Minsup, and the second step is to generate association rules, using the large item set. Such rules must satisfy the following two conditions:

1. $\mathrm{Sup}(X \cup Y, D) \geq \mathrm{Minsup}$
2. $\mathrm{Conf}(X \rightarrow Y) \geq \mathrm{Minconf}$

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

DATA MINING AND RESULTS

Data Mining for Marketing Segmentation and Customer Adumbration

Market segmentation mainly involves clustering of customers with high similarity, helping enterprises to focus on the targeted market, provide services, then to pursue further growth opportunities in the market. Clustering is a widely used technique, the goal being to partition a set of patterns into disjointed and homogeneous clusters. This study employs two-step cluster analysis and divides customers into two groups to distinguish the reasons for choosing 3C products and the types of channels, as shown in Figure 4.

The clusters were called Cluster-1 or the working cluster (466 samples) and Cluster-2 or the student cluster (437 samples). The customer profiles and characteristics are as follows.

1. Working cluster (Cluster-1)
   Customers in Cluster-1 were mainly composed of "working people" with an age range between 26 and 35, and their occupations were in information technology, finance and insurance, and manufacturing. Their average monthly income was between NT$20,001 to 40,000. Customers

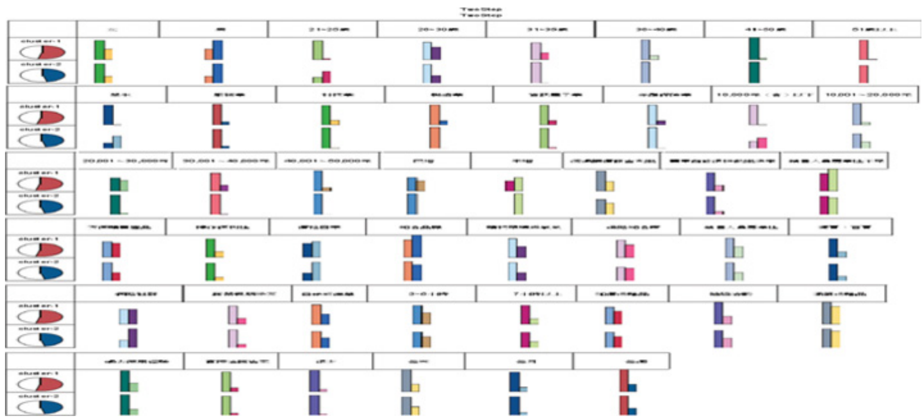


FIGURE 4 Two-step clustering results. (Color figure available online.)

believed that ease of buying products is important and usually purchased products made by well-known brands. The shopping environment and atmosphere were the reasons for customers to select channels. They expressed disapproval of the lack of sales professionals. The Internet community, catalogs, and past experiences were the main sources of information for customers. Customers in this group checked information about 3C products on a weekly basis.

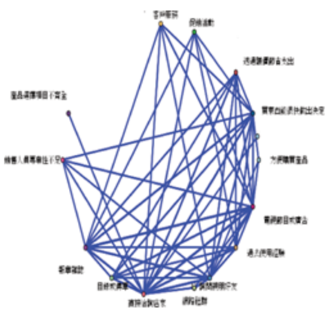
2. Student cluster (Cluster-2)
   Customers in Cluster-2 were mainly composed of "students" with an age range between 21 and 25, and their occupation was student. Their average monthly income was below NT$10,000 or between NT$10,001 to 20,000. They liked to save by bargaining and they chose products based on price factors. Customers in this group selected channels based on sales professionals and channel awareness. They expressed disapproval of incomplete product selection items. The Internet community was the main source of information for customers. Customers in this group checked information about 3C products on a daily basis.

Channel Segmentation Analysis

This study uses two-step cluster analysis for contour-based segmentation of customer adumbration and then uses channel characteristics as subsegments. By association rules, the channel is chosen as a consequent to generate a channel selection factor for each cluster. We then propose the kind of customer behavior and the main considerations of products involved in preferred channel attributes.

Table 1 shows the association rules of channel segmentation of Cluster-1 when purchasing 3C products. This cluster takes sales professionals as the

TABLE 1 Association Rules of Channel Segmentation of Cluster-1



Rule	Cons	Antecedent			
R1	Sales professionals	To seek the views of others	Lack of professionalism	Functional use	Product quality
R2	Sales professionals	To seek the views of others	Lack of professionalism	Product quality	–
R3	Sales professionals	To seek the views of others	Internet community	Lack of professionalism	Product quality
R4	Channel awareness	Like online shopping	Gift with purchase		
R5	Channel awareness	Like online shopping	Product options are incomplete		

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

first consideration when choosing channels to purchase products. They also like to seek the views of others; therefore, when negotiating sales, they also attach great importance to the views put forward. Therefore Cluster-1 disapproves of sales staff lacking professionalism. Because Cluster-1 consists of office workers with stable income, therefore, they emphasize functional use and quality product.

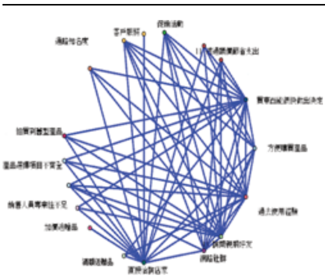
Table 2 shows the association rules of the channel segmentation of Cluster-2 when purchasing 3C products. This cluster takes channel awareness as the first consideration when choosing channels to purchase products. After selecting the channel, they make a decision soon and they dislike pressure from sales staff.

Product Segmentation Analysis

When the products and services are different, the suppliers will have different trading methods, leading to separation of the market. When all the products have different features, then the supplier can provide different products and services to different segments of customers. Therefore, this study uses customer adumbration for contour-based segmentation, with product features used as a subsegment. The product selection factors act as a consequent to find product attributes in their preferences, considering each cluster and what kind of promotion activities are the most effective in different groups.

Under the condition of min sup: 15%; min conf: 80%, Table 3 shows the association rules of the channel segmentation of Cluster-1 when purchasing 3C products. As shown in the table, this cluster takes product quality as the value orientation of products. Moreover, it is particularly evident that the male customers think highly of the professionalism of sales and customer

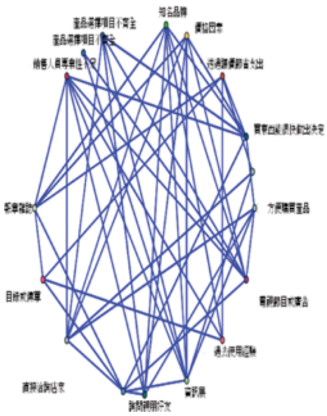
TABLE 2 Association Rules of the Channel Segmentation of Cluster-2



Rule	Cons	Antecedent				
R1	Channel awareness	Make a decision soon	Pressure from sales staff	–	–
R2	Channel awareness	Convenience to purchase products	Buy old products	–	–
R3	Channel awareness	Catalog or flyer	To seek the views of others	Price factors	Internet community
R4	Channel awareness	Convenience to purchase products	Buy old products	Product quality	–

min sup = 10%; min conf = 65%.

TABLE 3 Association Rules of Product Segmentation of Cluster-1



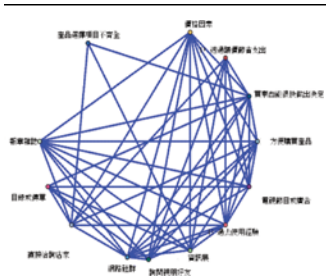
Rule	Cons	Antecedent		
R1	Product quality	Sales professionals	Customer Service	–
R2	Product quality	Sales professionals	Customer Service	Cash discounts
R3	Product quality	Sales professionals	Male	–
R4	Product quality	Sales professionals	Male	Cash discounts
R5	Product quality	Product selection is not complete	Customer Service	Male
R6	Product quality	Sales professionals	Lack of professional-ism	Male
R7	Product quality	Convenience to purchase products	Customer Service	Male

min sup = 15%; min conf = 80%.

services as the first considerations when choosing a channel to purchase products. In addition, cash discounts increase product sales.

Under the condition of min sup: 28%; min conf: 80%, Table 4 shows the association rules of the channel segmentation of Cluster-2 when purchasing 3C products. As shown in the table, this cluster takes product price as the value orientation of products and price factors are the most important reason for purchasing products. Therefore, they look for businesses to provide the most preferential prices. Also, they consider pressure from sales to be very annoying. Free gifts with purchases as promotions increase the purchasing power of customers.

TABLE 4 Association Rules of Product Segmentation of Cluster-2



Rule	Cons	Antecedent			
R1	Price factors	Gift with purchase	Pressure from sales staff	Shop around	–
R2	Price factors	Gift with purchase	Shop around	–	–
R3	Price factors	Gift with purchase	Shop around	Cash discount	–
R4	Price factors	To seek the views of others	Pressure from sales staff	Shop around	Cash discounts

min sup = 28%; min conf = 80%.

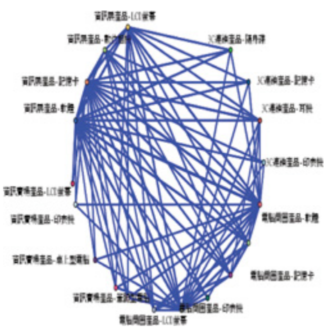
Channel and Cross-Selling Analysis

Mining different association rules with channel segmentation and product segmentation, we further attempt to understand the correlation between channel and product. For example, when customers buy products in a channel, they buy other products as well. Looking at the degrees and sources of product information searches, we then propose customers channels and product lines and bundle products for manufacturers with different channels and associations.

Under the condition of min sup: 16%; min conf: 80%, Table 5 shows that Cluster-1 purchases digital cameras through two channels: information development and computer shopping districts. They also buy memory cards through the same channels. Therefore, information development and computer shopping districts can sell digital cameras and memory cards together.

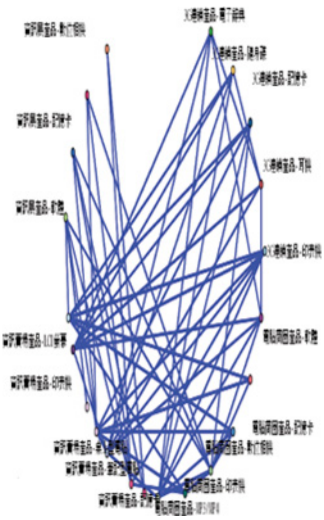
Under the condition of min sup: 13%; min conf: 80%, Table 6 shows that Cluster-2 purchases LCD screens through information marketplaces. They also buy desktops through the same channel. Therefore, LCD screens

TABLE 5 Association Rules of Channel and Cross Selling of Cluster-1

	Rule	Cons	Antecedent		
	R1	Information development – Digital cameras	Information development – Memory cards	–	–
	R2	Computer shopping districts–Digital cameras	Computer shopping districts – Memory cards	Computer shopping districts–Printers	–
	R3	Computer shopping districts–Digital cameras	Computer shopping districts–Memory cards	Information marketplace–Product diversification	–
	R4	Computer shopping districts–Printers	Computer shopping districts–LCD screens	Internet community	–
	R5	Information marketplace–Notebooks	Computer shopping districts–LCD screens	Computer shopping districts–Printers	Internet community

min sup = 16%; min conf = 80%.

TABLE 6 Association Rules of Channel and Cross Selling of Cluster-2



Rule	Cons	Antecedent		
R1	Information marketplace–LCD screens	Computer shopping districts–Software	Information marketplace–Desktops	–
R2	Information marketplace–LCD screens	Two weeks ago	Information marketplace–Desktops	Information marketplace–Product diversification
R3	Information marketplace–Desktops	Within a week	Information marketplace–LCD screens	–
R4	Information marketplace–LCD screens	Computer shopping districts–Product diversification	Information marketplace–Desktops	Internet community
R5	Information marketplace–LCD screens	Two weeks	Information marketplace–Desktops	Internet community

min sup = 13%; min conf = 80%.

and desktops can be sold together in the information marketplace channel. In addition, two weeks before customers purchase LCD screens, they begin to search for detailed product information about LCD screens through the Internet community.

RESEARCH FINDINGS AND MANAGERIAL IMPLICATIONS

Research Findings

This study examines the concept of multichannel service output with regard to different needs and buying behaviors for differentiate channels and products. This study incorporates customer behavior data related to the purchasing of 3C products, information searches, purchase channels, and product category information to establish a relational database. This study uses cluster analysis and association rules to analyze the entire database and then divides the customers into two groups with small differences within the groups and large differences between clusters. This study uses two steps to sort customers into clusters and generate association rules. We then find different channel properties and product attributes for the adumbration of different customers' purchasing of 3C products. To further understand consumer patterns in different channels, this study explores buying, bundling products, levels and sources of information search ability, and the possibilities of industry alliances and channel cooperation among different manufacturers. The results show that different clusters care about different channel properties and product attributes. Furthermore, among the different segmentations of customers and their preferred channels, there are significant differences among the correlations of bundling products.

Through the implementation of data mining, this study first divided the customers into two groups, and then, according to the customer characteristics, performed cluster analysis on the two groups. A marketing

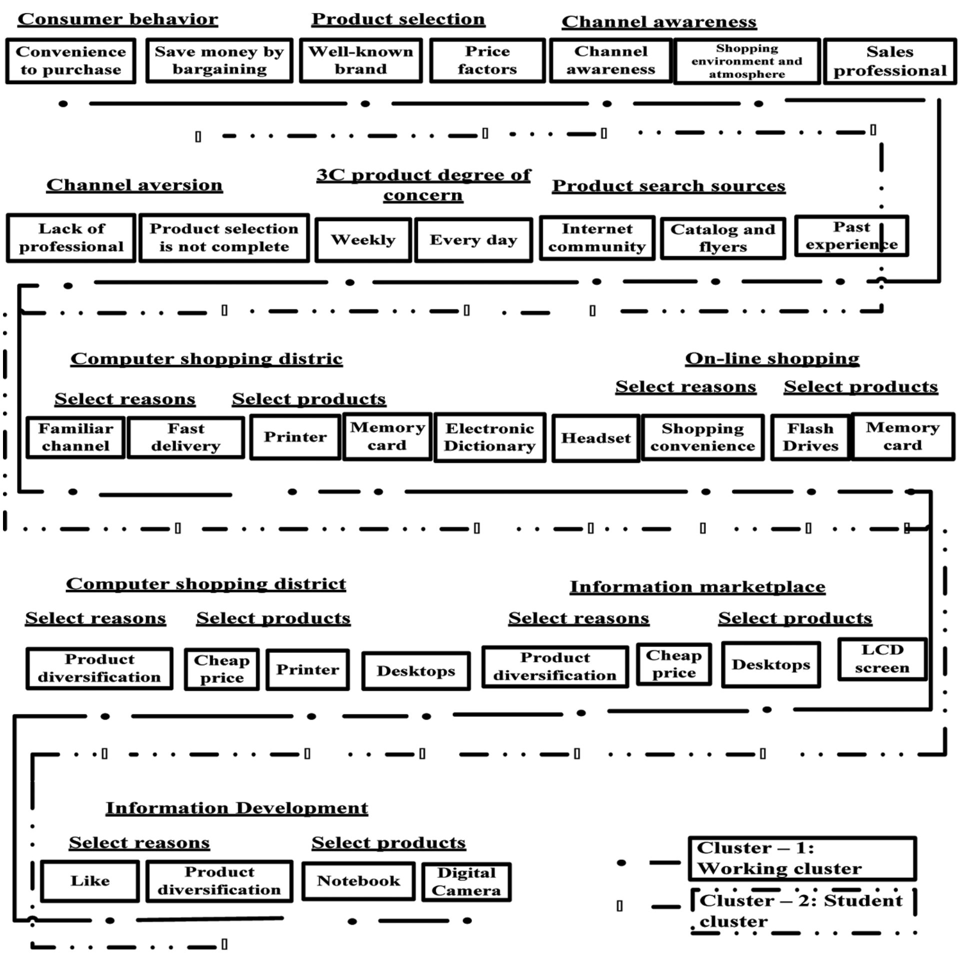


FIGURE 5 Marketing knowledge map – cluster analysis and association rules.

knowledge map includes cluster analysis and association rules, as shown in Figure 5. Using a marketing knowledge map to generalize these two categories of customers, we can clearly see the different customer behaviors and channels, the reasons for product selection, sources of information searches, and degrees of concern. This enables us to understand the reasons behind the customers' product choices and why they have purchased in different channels.

Customers in Cluster-1 were mainly composed of "working people." Their sources of information were the Internet community and past experience. Customers in Cluster-2 were mainly composed of "students," and the Internet community was their source of information. Cluster-1 and Cluster-2 both use the Internet community as a source of information. This means that the Internet community is a very important search channel for every group. Therefore, we propose that manufacturers provide information in the Internet community when new products enter the market. In addition, manufacturers can target customers in the working people cluster by advertising in special magazine issues that market to that group. Customers in the working people cluster also like to seek the views of others when purchasing 3C products. Thus, distributors can train staff with sales experience to satisfy customer demand. In addition, to discuss customer behavior by channel, the products purchased by the customers who purchase through online shopping and at computer shopping districts are the same. Although the two clusters purchase through the development of information channels, the main customers were composed of "working people," who liked impulse buying. In addition, this study shows that the reasons for choosing the same channel among different clusters are different, so each channel of each distributor should be aimed at customers of different clusters with different sets of standards about services and products.

Managerial Implications

1. Single product multichannel marketing:
   In this study, the marketing knowledge map is drawn by association rules. Customers of Cluster-2 search for the next product under channel segmentation. There is no special attention factor determining their choice of products. Customers of Cluster-1 not only attach importance to customer service, but also pay attention to product selection. Therefore, focusing on the distributor's point of view to appeal to different clusters of customers, they should provide related services based on factors that customers take under consideration. In addition, focusing on the manufacturer's point of view, they should manufacture new products

to meet customers' needs and create business opportunities with products preferences valued by different clusters.

There are many factors affecting customers' choices to purchase 3C products and the purchasing channels they choose. Even with the same product, customers will have various reasons to choose to buy through different channels. Channel characteristic are major factors affecting customer purchasing. In particular, product selection and product information are key characteristics. Different segments of groups have different needs and buying processes as well as varying demands for services. Thus, multichannel segmentation can be used to create communication channels. Therefore, manufacturers should focus on product characteristics and customer characteristics in order to provide all customers of all segments with effective and appropriate services. By accomplishing this, in addition to providing required value to the customers, manufacturers can become competitive. Moreover, distributors not only provide for segmented customers with specific needs, but also effectively deliver services. Therefore, manufacturers should launch new products for office workers and develop marketing strategies based on the factors that customers emphasize, such as functional use and product quality.

2. New products to enter the market and multichannel services:

When product attributes are the main consideration for channel selection, the choice of Cluster-1 has certain requirements. On the contrary, for distributors, Cluster-2 pays special attention to these factors. They just hope the sales staff does not apply too much pressure when selling products. From the promotion point of view, because Cluster-2 focuses on price, hence, they look for the cheapest store. Therefore, cash discounts change nothing for Cluster-2. Contrarily, gifts with purchases can stimulate purchasing power. In addition to emphasis on the quality of the product itself, they also hope that 3C distributors provide better service quality. Today, 3C products have become more diverse, product life cycles are getting shorter, there are different manufacturers of similar products, and price differences are getting smaller. In addition, virtual channels have become the future trend of development. Therefore, manufacturers not only need to provide customers with customized products, but also must enhance sales with service diversification through different distributors who are expected to provide better service quality. Moreover, customers purchase 3C products based on brand and price comparisons. Therefore, before distributors consider brands, they must first demand that the product manufacturer provide services. In addition, some customers do information searches, such as looking for their first choice of retail stores to examine products. They then use the Internet again to look for product information. Finally, they decide whether to buy the product. Therefore, distributors/channels can provide information about product attributes, product performance, and so on to the customer, or provide pre-sales and after-sales service and education to make customers aware that the information provided is also a requirement (Wierenga and Soethoudt 2010).

3. The channeling and bundling of products for sales:
   The product marketing segmentation shows that different clusters of customers purchase different products by different channels, but choose to buy multiportfolio products in the same channel, for example, buying a digital camera with a memory card and buying an LCD screen with a desktop. These are some complementary products, therefore customers purchase bundled products rather than a single product. It is suggested that distributors can use a mixed bundling strategy. That is, in addition to enabling customers to purchase individual products separately, they can also purchase bundled products. Different segmentations have different shopping patterns, in other words, Cluster-1 purchases digital cameras for high entertainment, and Cluster-2 purchases LCD screens and desktops for practical purposes. Therefore, manufacturers must first identify the target market and determine which markets must deal with the channel. Different product bundles and services can be provided through different channels, according to how information is accessed by different segments of customers, and then useful insights and information must be provided to them (Harris and Blair 2006).
4. Brand and manufacturer alliance:
   The product marketing segmentation shows that information marketplaces are the most relevant to brands, and customers prefer to purchase products from well-known brands or bundled products with high specifications. This means that, if the distributor has the customer selection information for each manufacturer and the brand's product specifications, they can launch bundled products based on the preferences for products. In addition, manufacturers and distributors not only build long-term trust and mutually beneficial relationships through alliances, but also enhance functionality and structural and social relationship links. Thus, the interaction between partners has become closer. Manufacturers can use partnerships with distributors to make distributors understand the characteristics of goods and then respond to product promotion activities with marketing strategy. Through this kind of relationship, the upstream manufacturer can get first-hand market information, getting closer to customers and potential customers. They can also sell existing products while introducing new products in new markets. Downstream distributors not only ensure a stable source of goods, but also allow distributors to provide customers better service and earn more profits. Manufacturer and brand alliances can enhance

their brand images and reputations, while reducing barriers to entering markets (Rao and Ruekert 1994).

CONCLUSION

There are many studies investigating market segmentation. However, only the minority really succeed. Only by creating a customer database, having the proper analysis approach in regard to the knowledge of customers and market and so on, can companies realize the customers' profiles and investigate them in different market segmentations. In this way, companies can stand out and find the key to success on sales and marketing. Thus, this study finds some Taiwan 3C product-buying behavior patterns, including customer purchase preferences and customer purchase demands, in order to generate different 3C marketing segmentation alternatives. Thus, these research results will provide companies a case example not only for channels but also for brand/manufactures with some useful references to illustrate potential customers, develop latent business possibilities, and maintain the loyalty of target customers with market segmentation knowledge discovery.

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