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MINING USER KNOWLEDGE FOR INVESTIGATING THE FACEBOOK BUSINESS MODEL: THE CASE OF TAIWAN USERS

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□ *Social network sites (SNS), as web-based services, allow users to make open or semi-open profiles within the systems they are part of, to see lists of other people in the group and to see the relations of people within different groups. Facebook is essentially an online social network site in which individuals can share photographs, personal information, and join groups of friends. This study investigates the experiences on Facebook of various users in Taiwan. Their degrees of confidence were often demonstrated by word-of-mouth disseminations about the social network site. Further, this research looks at how the reputations of Facebook proprietors and their affiliates were disseminated through relationship marketing for formulated social network marketing in its business model concerns. Therefore, this study uses the a priori algorithm as an association rules approach, and cluster analysis for data mining. We divide Facebook users into two groups of contributors and lurkers by their profiles and then find each group's social network community information utilization and online purchase behaviors for investigating the Facebook business models.*

INTRODUCTION

Social network sites (SNS), as web-based services, allow users to make open or semi-open profiles within the systems they are part of, to see lists of other people in the group, and to see the relations of people within different groups. The terminology and structure of such communication networks differ between sites (Boyd and Ellison 2007). Facebook, which is a popular social network site, is one of the most commonly used social sharing sites today, having millions of users (Mazman and Usluel 2010; Bicen and Cavus 2010; Ross et al. 2009). In 2011, Facebook had more than 750 million active users, 50% of whom logged on to Facebook on any given day (Facebook

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2012). Facebook is clearly one of the most popular tools for social communication (Ross et al. 2009). Facebook is essentially an online social network site in which individuals can share photographs, personal information, and join groups of friends (Bicen and Cavus 2011).

Social networks refer to composites of a large number of individuals in groups as well as the interactions and relationships that exist among the groups and individuals (Iacobucci and Hopkins 1992; Yu, Venkatraman, and Singh 2003; Kim et al. 2008). Marketers rely on social networks to spread marketing messages in both business-to-business (B2B; Mouzas 2006) and business-to-consumer (B2C; Brown and Reingen 1987) markets. Individuals in social networks act as business communication channels (Ryu and Han 2009) to disseminate and exchange information (Brown and Reingen 1987; Ardissono et al. 2003). Social networks influence consumer behavior in various aspects, such as information search strategies, decision-making processes, and consumption decisions (Flynn, Goldsmith, and Eastman 1996; Nongaillard and Mathieu 2011). Therefore, social networks are an extremely important channel for virtual community marketing.

Recently, the emerging channel of social networking marketing (SNM), such as Facebook, Twitter, and Epinions, has attracted the attention of marketing practitioners and researchers. These sites permit users not only to express comments and opinions on products, people, organizations, and many other entities, but also enable users to build various social relationships. With these social relationships, opinions will have greater impact on users than those expressed on other channels (such as shopping websites) because people believe or more easily accept the opinions of those with whom they have social relationships (Lu, Zhao, and Wang 2010). In addition, the influence of opinions on SNM can be disseminated more widely and quickly than that of other channels. Thus, some user opinions captured on SNM can greatly influence other users' buying decisions or their views on certain companies.

Thus, many business entities have recently come to recognize this phenomenon, and some companies have begun to identify certain users of SNM to conduct online marketing and reputation management (Miller and Dickson 2001) in e-commerce and e-business. For companies to better utilize SNM for cost-effective, targeted marketing and reputation management, they must address an important question, given the huge number of social network users and companies' limited budgets: Which users' opinions will most influence others' actions? If the most influential group of target users could be identified, companies could consume minimal resources to improve product sales and enhance their reputations (Xu et al. 2012).

In contrast to traditional direct marketing, SNM recognizes that links between consumers exist. As a result of the availability of gigantic databases of customer information today, companies now are able to target their customers taking into account their interrelatedness. Traditional marketing research does not reveal these social connections among consumers and, thus, cannot take advantage of links between customers. These interdependencies are measured through implicit links (e.g., matching on demographic attributes, geographic links, etc.), or through explicit links (e.g., communications between actors, family ties, etc.; Hill, Provost, and Volinsky 2006). Although SNM offers clear advantages over the direct marketing business model, the use of social network information and knowledge in predicting consumer behavior is a very recent issue (e.g., Hill, Provost, and Volinsky 2006; Manchanda, Xie, and Youn 2008; Subelj, Furlan, and Bajec 2011; Benoit and Poel 2012).

In addition, among the new techniques developed for business intelligence, data mining is the process of discovering significant knowledge such as patterns, associations, changes, anomalies, and significant structures from large amounts of data stored in databases, data warehouses, or other information repositories (Hui and Jha 2000; Keim et al. 2004). In the literature, 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 patterns, grouping analysis, classification analysis, and probability heuristic analysis (Berson, Smith, and Thearling 1999; Mehta and Bhattacharyya 2004; Liao 2005; Divsalar et al. 2011; Kumar 2012; Liao, Chu, and Hsiao 2012; Sudha and Bhavani 2013). Knowledge of SNS users extracted through data mining can be investigated for business models, and SNM knowledge extracted from research and then provided to SNS businesses, thereby serving as a valuable reference for building their profit model.

This study investigates various user experiences from Taiwan on Facebook. Their degrees of confidence were often demonstrated by word-of-mouth disseminations about the SNS. Further, this research looks at how the reputations of Facebook proprietors and their affiliates were disseminated through relationship marketing for formulated SNM in its business model concerns. Based on these considerations, the purposes of this research can be simplified as follows: (1) to segment Facebook users by their social network community information utilization behaviors; (2) to explore the interrelationships existing between participation motives and the utilization of social-networking tools employed by SNS users; (3) to explore the information about how online purchase distribution channels shared on the SNS impacted on other users' intended purchases; (4) to segment SNS users by their behaviors, so corporations can develop a pertinent marketing proposal that mixes and matches appropriate interactive tools on SNS; (5) to devise an effective service mechanism for developing an integrated social network marketing model.

The rest of this article is organized as follows. “Research Design” introduces the proposed research design, which includes the system framework, system architecture, database development, and questionnaire design. “Data Mining” introduces the data mining approach, including the association rules and cluster analysis. “Data Mining Result” presents the data mining process and the analyzed results. “Implications” describes research findings, managerial implications. Finally, a brief conclusion is presented in “Conclusion.”

RESEARCH DESIGN

Research Framework

The research framework in this study is shown in Figure 1 which delineates the outline of a questionnaire to trace the behaviors of Facebook users

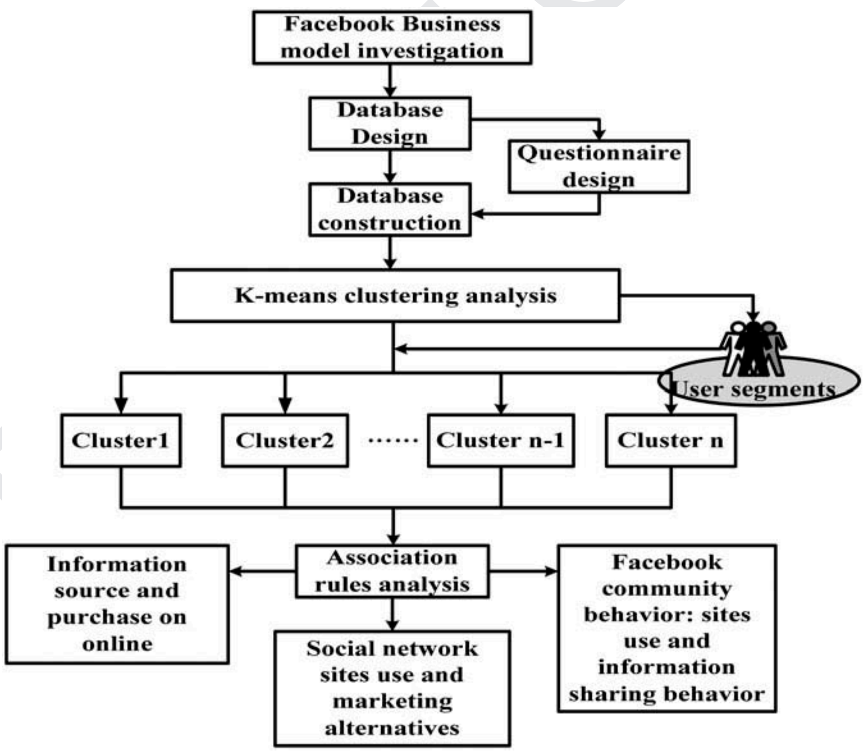

FIGURE 1 Research framework.

in using the site's interactive tools to share information. The questionnaire promoted the collection of data, which was later compiled into a comprehensive database for analyzing the utilization behaviors of Facebook users. The researchers began by conducting an actual field study on the behaviors of Facebook communities, where preliminary and secondary data were collected. Specific database requirements were considered. The answered questionnaires collected data that embodied the architecture of the databases, and the constructed databases were used to categorize users by their behaviors shown in the collected data. A priori algorithm association rules were employed for analyses through which the analogy and disparity characterized by the inherent behaviors of Facebook users were investigated through the contexts of "Information Source and Purchased Items" and "Facebook Community Utility Operative Attitude." A proposal that recommended marketing strategies for the Facebook social network community was developed.

System Architecture

The system architecture of this research is shown in Figure 2; it comprises three distinct databases: "Tools Utilization Behavior Database," "Information Participation Database," and "Consuming Preference Database." These three databases translated into the two features in the data market. These two features represented the "Information Source and Purchased Items" and "Facebook Community Utility Operative Attitude." The data market was processed by data mining procedures to categorize users, and association rules analysis yielded three knowledge components: defining the utility aspect of "Tool Value Knowledge Component"; defining the information impact aspect of "Effective Information Medium Knowledge Component"; and defining by the Facebook community aspect of "Facebook Community Attitude Knowledge Component." These knowledge data components embodied the marketing map that facilitated the strategic concepts in the proposal for the operation of an appropriate social network community marketing campaign.

Database Design

The concept of relational databases was first developed in the 1970s by Codd to represent interrelated data in the form of a table (Codd 1970). It applied the concept of entity in business environments, in which the data attributes between entities and their relationships were explored to interpret events that happened and messages that ensued. The term *entity* is used to describe an important object, event, or concept existing within a corporation for its ontological objectivity. Data attributes are used to describe entities'

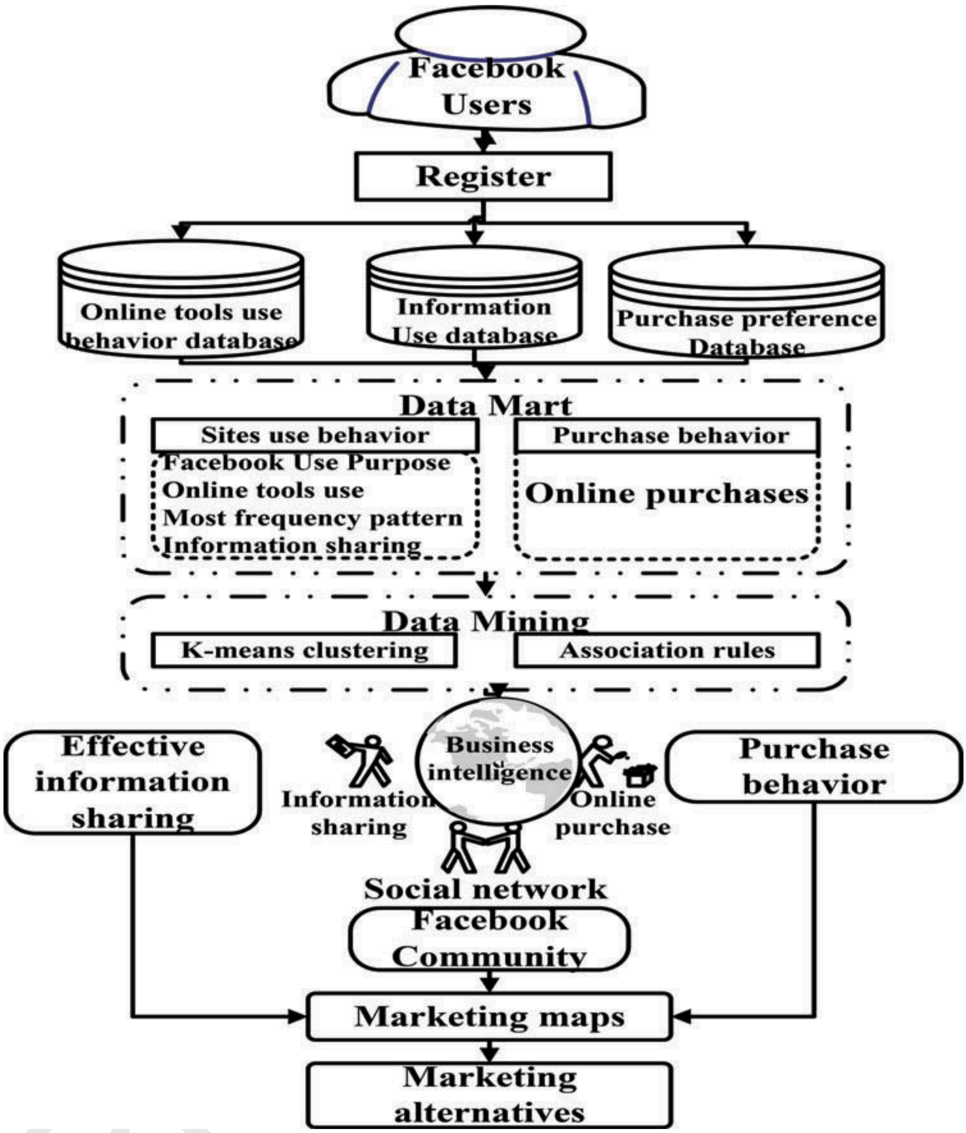

FIGURE 2 System architecture.

characteristics. Figure 4 is the concept database for this research; it is the concept-entity database that was derived from the integration of categorized attributes. The interrelationships among these attributes were explored by the formulated questionnaire that gave rise to seven entities, three existing relationships, and sixty-seven attributes. In this study, the relational database contains 6 entities, 5 relationships, and 59 attributes. Figure 3 shows the conceptual databases.

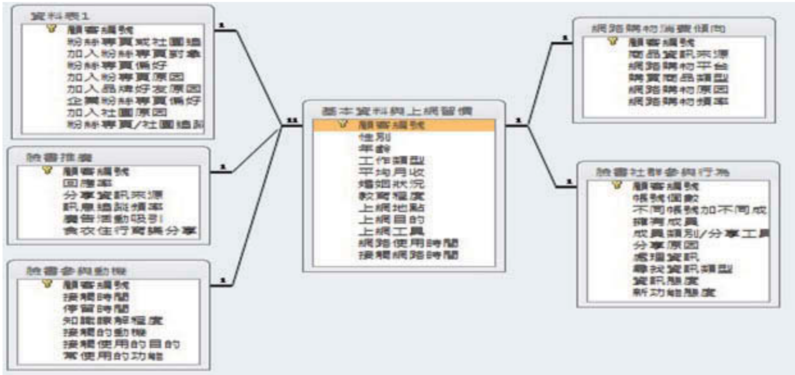

FIGURE 3 Relational database.

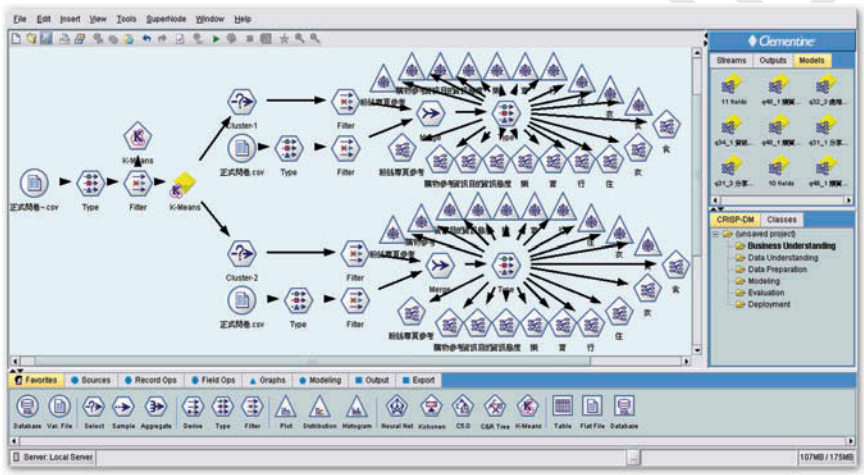

FIGURE 4 Data mining model and process diagram.

Questionnaire Design and Analysis Tool

The databases for this research were constructed through a surveyed questionnaire under randomized sampling. The questionnaires used online distributions that reached relevant social network communities in order to explore various online behaviors of Facebook users. There were six structural components in the questionnaire encompassing basic information of Facebook users: (1) participating motive for the Facebook community, (2) participating behavior in the Facebook community, (3) Facebook promotion, (4) online shopping preference, (5) Facebook brand support fan page, and (6) group tracking. In addition, other issues investigated included sites for online shopping channels, purchased items, information-gathering behavior, and the degrees of acceptance for online channels. This research employed the SPSS Modeler to analyze data using k-means clustering, followed by application of the a priori algorithm on each cluster to analyze association rules. These data mining models and processes are summarized in Figure 4.

DATA MINING

Association Rules

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. 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 $I = \{i_1, i_2, \cdots i_m\}$ 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_$\mathrm{Sup}(X, D)$) 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 $\mathrm{Sup}(X \cup Y, D)$ 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 $\mathrm{Conf}(X \rightarrow Y)$), representing the rate of transactions in D that contain both X and Y. That is,

$$\mathrm{Conf}(X \rightarrow Y) = \mathrm{Sup}(X \cap Y)/\mathrm{Sup}(X, D).$$

In this case, $\mathrm{Conf}(X \rightarrow Y)$ 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, Makris, and Tsakalidis 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. $\text{Sup}(X \cup Y, D) \geq \text{Min sup}$

2. $\text{Conf}(X \rightarrow Y) \geq \text{Minconf}$

To explore association rules, many researchers use the a priori algorithm (Agrawal, Imilienski, 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 $\text{Lift} = \text{Confidence}(X \rightarrow Y)/\text{Sup}(Y)$ (Wang et al. 2004).

Cluster Analysis

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 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).

DATA MINING RESULT

Questionnaire Background

This research began with questionnaire distribution from September 10, 2011 to February 15, 2012. A total of 622 questionnaires were answered and returned. After discarding incompletely, inappropriately, or exceedingly answered questionnaires, the remaining 600 questionnaires were incorporated into the database. The return rate for the questionnaires was 98%.

By analyzing the surveyed users' data, it was found that this database had a higher proportion of male participants (51.5%) than female participants (48.5%). For age, 30% of the adults were between 31 and 35 years of age, and 24.5% were between 26 and 30 years of age. Most were university graduates, comprising 54% of the surveyed users, and those with completed postgraduate studies comprised 21%. The largest group worked in financial and IT-related industries, comprising 20.5% of the total surveyed users. Those with disposable incomes around NT $30,001 – NT $40,000 comprised 57% of the surveyed users.

With regard to their online behaviors, 77% of the surveyed users had used the internet for more than nine years, followed by those who had used it for more than seven years. These users with less exposure comprised 15% of the total surveyed users. There were 71% of the users who surfed the internet for three to five hours each day. The most popular device for surfing was a desktop computer (55%). The popular locations chosen for surfing were on campus or the office, (48.36%) and at home (45.07%; multiple answers permitted). There were 38.54% of the users who searched for specific information as their main purpose for surfing the internet. These were followed by users searching for information on job requirements (23.68%). Social requirements were also noted among these users (21.16%).

Cluster Analysis

Cluster analysis for data mining was applied to categorize Facebook users according to their community participation behavior and sharing patterns. The data were analyzed by a k-means clustering algorithm under 11 cluster variables that included "Facebook Community Participation Behavior," "Facebook Promotion," "Online Purchase and Consuming Preferences," "Brand Tracking," and others. The a priori algorithm was applied to determine the associations between each cluster.

Contributors: Contributors are the most passionate members from the community who aggressively contribute user-created contents. They are the most active participants within the community, they share searched information on Facebook using its tools, and they remain logged on for longer times. In Facebook communities, the enthusiasm of these contributors drive the process of information creation, posting, and sharing that converge all interactive movements of exchange among those involved, and in the roles of these contributors.

Lurkers: Lurkers are the less active participants in Facebook, who share only the information and contents in which they are interested. Their partial sharing behaviors in Facebook community participation depict their roles in information tracking and sharing demanded information. However, compared to contributors, lurkers had less extensive effects on Facebook's participation value.

In consonance with the six structural components construed in the questionnaire, 58 subcomponents were created, including "User Basic Information," "Social Network Community Participation Motive," "Social Network Participation Behavior," "Facebook Promotion," "Online Purchase and Consuming Preference," and "Brand Tracking." These subcomponents became the foundation for the process of clustering. The data samplers were incorporated into the SPSS Modeler, where a k-means clustering algorithm partitioned the database constituents into two clusters: Cluster 1 (297 data entries), and Cluster 2 (303 data entries). The clustering results are shown in Figure 5.

This study employs a k-means clustering algorithm for analyses, and 11 structural components from the formulated questionnaire were used as the clustering variables. This was followed by the association analyses conducted by the a priori algorithm, as shown in Table 1.

Association Rules Analysis

In research, eight structural components were derived from the relational database, where these components' associations were investigated. These eight structural components are "Basic Information–Online Habits," "Various User Categories," "Community Participation Motive," "Utility

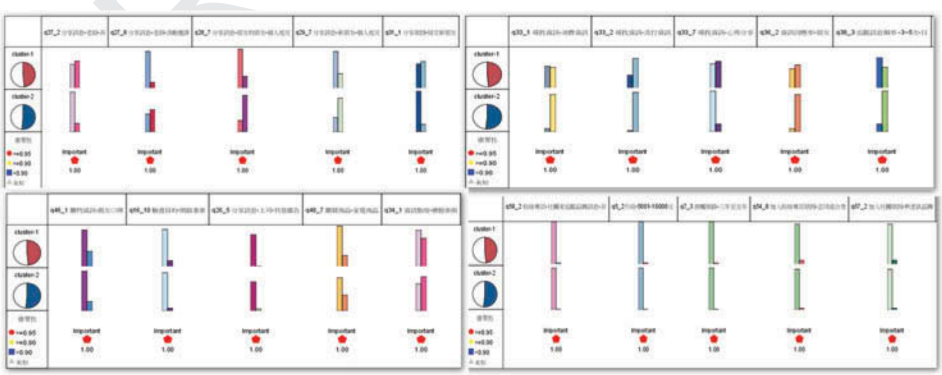

FIGURE 5 K-means clustering analysis.

TABLE 1 K-means Clustering Results

Algorithm	K-means Clustering	
Cluster	Cluster 1	Cluster 2
Participant	Contributors	Lurkers
Sample Size	297	303
Sharing Member Category Sharing Tools	Classmate: Wall Status Event Invitation; Shared link.	Class: Group Wall; Shared Link.
	Friend: Wall Event Invitation; Shared Link; Photo Album.	Friend: Group Wall Event Invitation; Shared Link.
	Colleague: Wall Event Invitation; Shared Link.	Colleague: Fan Page; Form Group Wall.
Information	Brand Information Tracking.	Meeting new acquaintances.
Sharing Purpose	Socializing with Friends Exchange of Profit.	Facilitate Networking Brand Information Tracking.
Means in Receiving Information	Aggressively Express Personal Contention.	Just for Reading.
	Reaffirm with the Liked Button Shared Link.	Reaffirm with the Liked Button. Shared Link.
Searched Information Content	Consumer Information Fashion Information.	Fashion Trends Knowledge Gaining.
	Knowledge Information.	Shared What Learn.
Attitude to Trending Information	Aggressively Participated.	Do not reject to and do not aggressively.
	Continuously Pay Attention.	Participated.
Sharing Information Category/Sharing Method	Dining: Personally Written and Posted Group Shared Information.	Dining: Shared Other's Posts, Shared Link.
	Fashion: Group shared Information Fan Page.	Fashion: Shared Other's Posts, Shared Link.
	Living: Personally Written and Posted; Create Fan Page.	Living: Create Fan Page, Shared Link.
	Travel: Personally Written and Posted Group Shared Information.	Travel: Shared Other's Posts, Create Fan Page.
	Educational: Shared Other's Posts Fan Page.	Educational: Shared Other's Posts, Group Shared Information.
	Entertainment: Personally Written and Posted Group Shared Information.	Entertainment: Create Fan Page, Shared Link.
Motive for Joined Fan Page	Discount and Promotion, Other's Recommendation.	Unique Content; Savvy Brand Updates.
	Administer Latest Brand Update.	
Motive for Joined Group	Discount or Promotion; Administer Latest Brand Update.	Brand Information Other's Recommendation.
		Interesting or Entertaining Content.
Joined Brand Fan Page	7-Eleven; Costco; Starbucks; Eslite Book Store; IBM Apple.	7-Eleven; Costco; Eslite Book Store.

Sharing Information," "Online Purchase and Consuming Preference," "Facebook Promotion," and "Fan Page/Group Brand Tracking." Figure 6 describes the association rules analysis model.

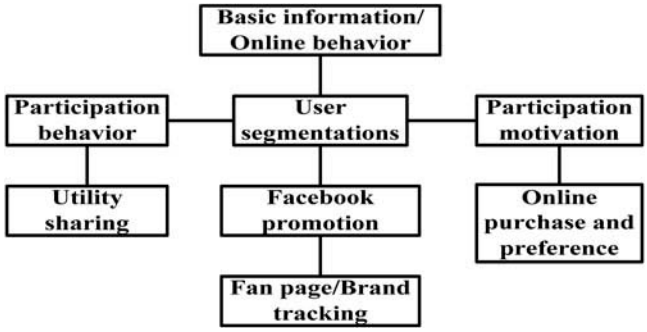

FIGURE 6 Association rule analysis model.

Sharing-User Category and Sharing Tool

Many users use Facebook tools to acquire information and then share this information with other Facebook users via the site's tools. The questionnaire employed the consequent structural components such as "Classmate, Friend, and Colleague," and the antecedent structural components such as "Dining, Fashion, Living, Travel, Educational, and Entertainment," in order to conduct association rules integration.

Under the criterion for minimum antecedent support of 40% and minimum rule confidence of 50%, four significant association rules were derived, as shown in Table 2. All the lift values were greater than 1, and **the levels of associations** are **shown** in the association diagram in Figure 7. This research found that when contributors shared information about dining, most of the shared information was personally written and then posted or linked to websites shared. Event invitations were then sent to friends and classmates to complete the sharing process. However, for sharing among colleagues, the shared information was personally written and posted to groups for information dissemination via walls and shared links.

Under the criterion for minimum antecedent support of 40% and minimum rule confidence of 40%, three significant association rules were

TABLE 2 Contributor-Sharing User Category and Sharing Tool (Dining-Cluster 1)

Rule	Lift	Support	Confidence	Consequent	Antecedent
R1	1.206	43.5	60.92	Classmate-Event Invitation.	Dining-Personally Written and Posted. Dining-Shared Link.
R2	1.133	44	80.46	Friend-Event Invitation.	Dining-Personally Written and Posted. Dining- Shared Link.
R3	1.126	49.5	63.63	Colleague-Wall.	Dining-Personally Written and Posted.
R4	1.16	44.0	55.68	Colleague-Shared Link.	Dining-Group Shared Information.

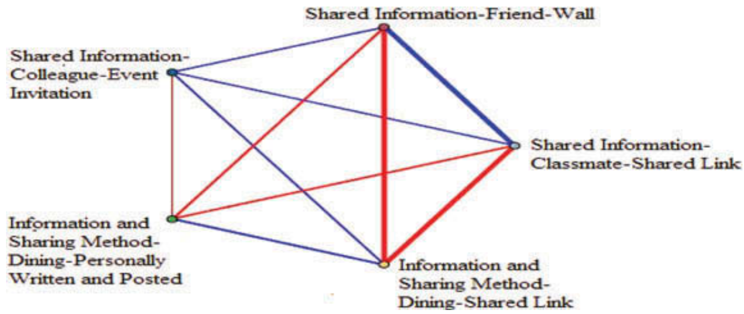

FIGURE 7 Contributors-sharing user category association diagram (Dining-Cluster 1).

derived, as shown in Table 3. All the lift values were greater than 1, and the levels of associations are shown in the association diagram in Figure 8. According to the association rules in Table 3, this research found that, concerning lurkers with respect to finding dining information, most used shared links for information sharing. However, for friends and classmates, the information was further shared through shared links and posts on their walls. In the respect of colleagues, these lurkers shared other's posted content, and then disseminated through posting on their walls.

TABLE 3 Lurker-Sharing User Category and Sharing Tool (Dining-Cluster 2)

Rule	Lift	Support	Confidence	Consequent	Antecedent
R1	1.259	78.5	91.932	Friend-Wall.	Dining-Shared Link.
R2	1251	78.5	93.843	Classmate-Shared Link.	Dining-Shared Link.
R3	1.058	46.0	59.783	Colleague-Wall.	Dining-Shared Other's Posted Content.

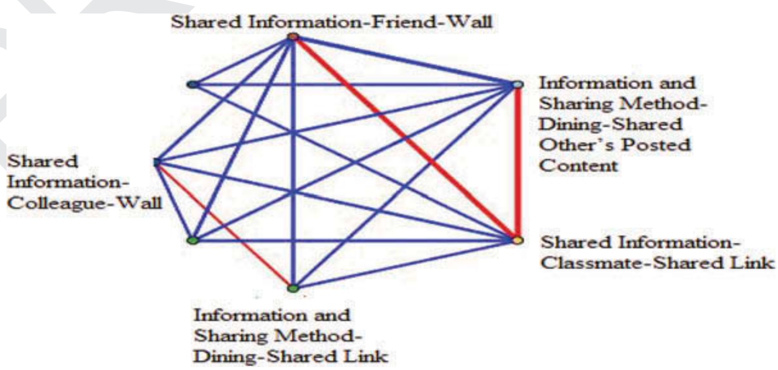

FIGURE 8 Lurker-sharing user category association diagram (Dining-Cluster 2).

Information Category and Attitude for Information

Facebook users of different categories also searched within Facebook, integrating the information uncovered in ways that disclosed their information handling behavioral preferences and attitudes. This research explored through the consequent structural components, such as "Method for Information Handling," and "Attitude Trending Information"; and through the antecedent structural components, such as the "Searched Information," for conducting the integration of association rules analysis.

Under the criterion for minimum antecedent support of 40% and minimum rule confidence of 40%, two significant association rules were derived. All the lift values are greater than 1, and the levels of associations are shown in the association diagram in Figure 9. According to the rules shown in Table 4, this research found that with contributors searching for knowledge information and consumer information, most of them participated with aggressive attitudes. When searching for consumer information, the majority of them chose to share links for the administered information.

Under the criterion for minimum antecedent support of 40% and minimum rule confidence of 40%, two significant association rules were derived. All the lift values were greater than 1, and the levels of associations are shown in the association diagram in Figure 10. According to the association rules in Table 5, this research found that when lurkers searched for trending

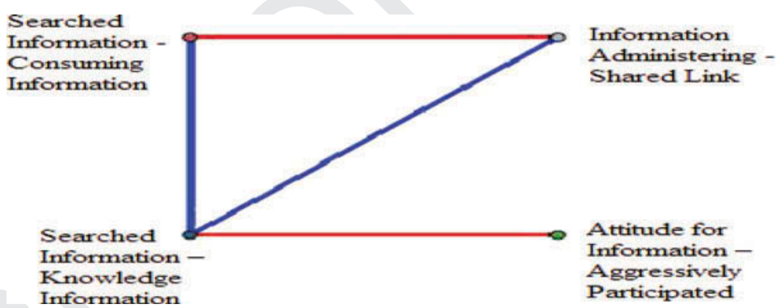

FIGURE 9 Contributor-information category association diagram (Cluster 1) .

TABLE 4 Contributor Information Category and Attitude for Information (Cluster 1)

Rule	Lift	Sup.	Conf.	Consequent	Antecedent
R1	1.163	49.5	57.576	Trending Information Attitude - Aggressively Participated.	Searched Content-Knowledge Information. Searched Content-Consuming Information.
R2	1.039	70.0	57.143	Information Handling Method - Shared Link.	Searched Content-Consuming Information.

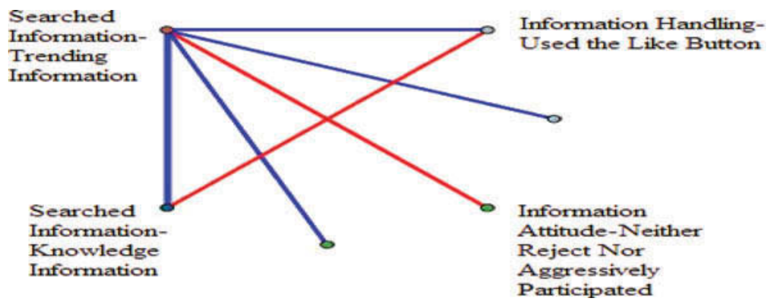

FIGURE 10 Lurker-information category association diagram (Cluster 2).

TABLE 5 Lurker-Information Category and Attitude for Information (Cluster 2)

Rule	Lift	Sup.	Conf.	Consequent	Antecedent
R1	1.051	83.5	51.497	Attitude for Trending Information-Neither rejected nor actively participated.	Searched Content-Trending Information.
R2	1.001	70.5	56.028	Information Handling Method-Used the Like Button.	Searched Content-Knowledge Information.

information, most of them had the attitude that they neither rejected nor actively participated in the sharing process. In the respect of searched knowledge information, most usually used the "Like" button to distribute the information.

Purchase and Information Reference Behavior

Under the criterion for minimum antecedent support of 40% and minimum rule confidence of 40%, three significant association rules were derived. All the lift values were greater than 1, and the levels of associations are shown in the association diagram in Figure 11. According to the rules shown in Table 6, this research found that contributors referred to social network community discussions in order to collect information about foods, drinks, and books purchased. For cosmetic products, these contributors usually gained information from blog opinions and recommendations, before making purchases.

Under the criterion for minimum antecedent support of 40% and minimum rule confidence of 40%, three significant association rules were derived. All the lift values were greater than 1, and the levels of associations are shown in the spider web diagram in Figure 12. According to the rules shown in Table 7, this research found that lurkers referred to bulletin board systems (BBS) discussions for information collection about commodities, foods, drinks, and books purchased. Q7

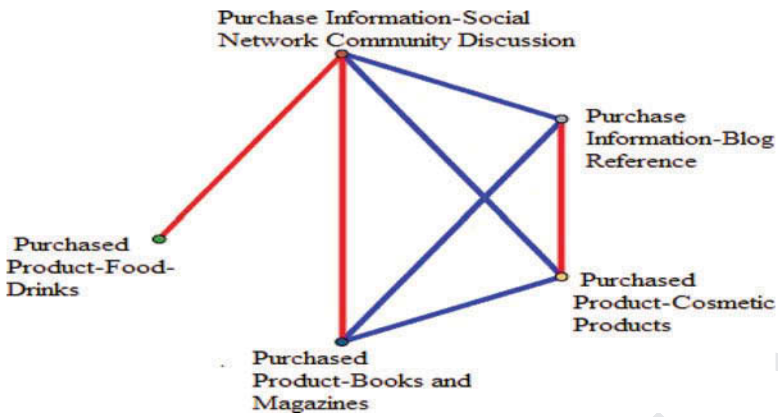

FIGURE 11 Contributor purchase-and-information behavior association diagram (Cluster 1).

TABLE 6 Contributor Purchase-and-Information-Reference Behavior (Cluster 1)

Rule	Lift	Sup.	Conf.	Consequent	Antecedent
R1	1.068	59.5	57.143	Product-Food Drink.	Purchase Information-Social Network Community Discussion.
R2	1.031	59.5	64.426	Product-Books and Magazines.	Purchase Information-Social Network Community Discussion.
R3	1.018	59.0	62.429	Product-Cosmetic Products.	Purchase Information-Blog Reference.

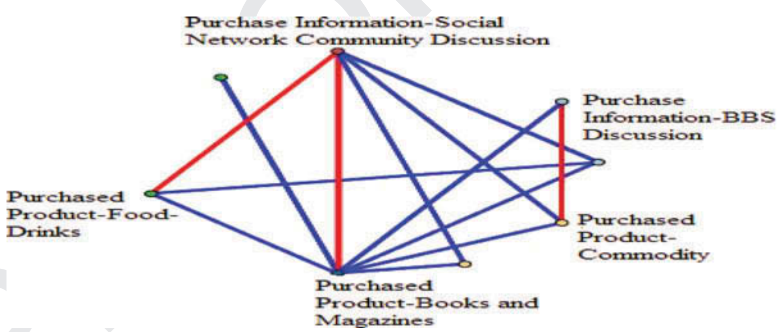

FIGURE 12 Lurker purchase and information behavior association diagram (Cluster 2).

Purchase and Brand Fan Page Reference Behavior

Many different categories of users referred to brand fan pages before making a purchase. Behaviors of these users were investigated using the consequent structural component such as the "Purchase Product" and the antecedent structural component such as "Brand Fan Page" to conduct association rules integration.

TABLE 7 Lurker Purchase-and-Information-Reference Behavior (Cluster 2)

Rule	Lift	Sup.	Conf.	Consequent	Antecedent
R1	1.087	48.333	57.241	Product-Commodity.	Purchase Information-BBS Discussion.
R2	1.068	59.5	57.143	Product-Food Drinks.	Purchase Information - Social Network Community Discussion.
R3	1.031	59.5	64.426	Product-Books and Magazine.	Purchase Information-Social Network Community Discussion.

Under the criterion for minimum antecedent support of 40% and minimum rule confidence of 40%, in accordance with Table 8, three significant association rules were derived. All the lift values were greater than 1, and the levels of associations are shown in the association diagram in Figure 13. According to the rules shown in Table 10, this research found that contributors referred to the Costco fan page for cosmetic product purchases. In addition, these contributors referred to the Eslite Book Store fan page for book purchases. They also referred to the 7-Eleven fan pages for food and drink purchases.

Under the criterion for minimum antecedent support of 40% and minimum rule confidence of 40%, in accordance with Table 9, three significant association rules were derived. All the lift values were greater than 1, and the levels of associations were shown in the spider web diagram in Figure 14.

TABLE 8 Contributor Purchase-and-Information Behavior—Brand Fan Pages (Cluster 1)

Rule	Lift	Sup.	Conf.	Consequent	Antecedent
R1	1.087	48.333	57.241	Product-Commodities	Purchase Information-BBS Discussion
R2	1.068	59.5	57.143	Product-Food and Drink	Purchase Information-Social Network Community Discussion
R3	1.031	59.5	64.426	Product-Books and Magazines	Purchase Information-Social Network Community Discussion

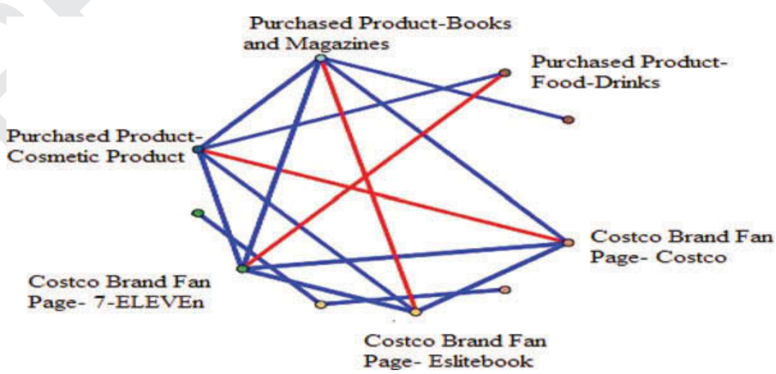

FIGURE 13 Contributor purchase-and-information behavior association diagram (Cluster 1).

TABLE 9 Lurker Purchase-and-Information Behavior—Brand Fan Page (Cluster 2)

Rule	Lift	Sup.	Conf.	Consequent	Antecedent
R1	1.087	48.333	57.241	Product-Commodities	Purchase Information-BBS Discussion
R2	1.068	59.5	57.143	Product-Food and Drink	Purchase Information-Social Network Community Discussion
R3	1.031	59.5	64.426	Product-Books and Magazines	Purchase Information-Social Network Community Discussion

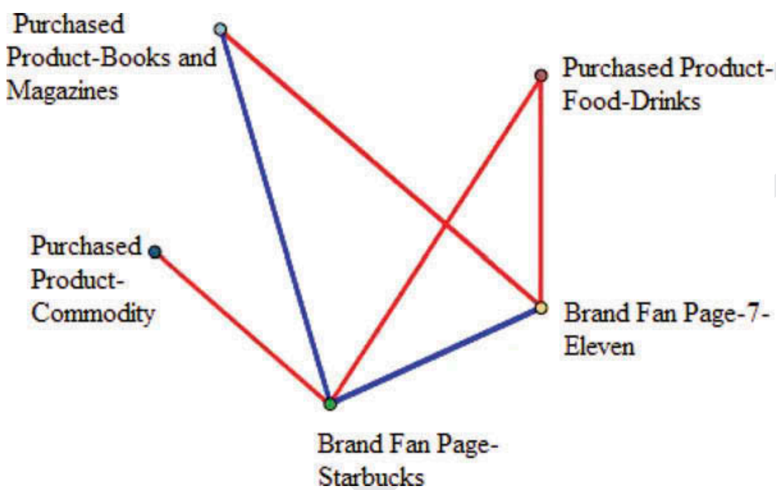

FIGURE 14 Lurker purchase-and-information behavior—brand association diagram (Cluster 2).

According to the rules shown in Table 11, this research found that lurkers referred to the 7-Eleven fan pages for books and magazines purchases. In addition, these lurkers referred to the 7-Eleven and Starbucks fan pages for food and drink purchases. They also referred to the Starbucks fan pages for commodities purchases.

IMPLICATIONS

During Facebook utilization, k-means clustering variable analysis showed users' preferences with particular social-networking tools. For cluster 1, user preferences included the wall, event invitation, shared link, status, and photo album. For cluster 2, their preferences included shared link, group, wall, event invitation, and fan page. The preferences of different user categories bolstered their reliance on the preferred tools and thus cohered and convened these interrelated social network communities. Any corporation interested in facilitating their product promotion through social network marketing should magnetize the information participation through inspired empowerment that attracts their target audiences.

TABLE 10 Marketing Strategy in Launching a Social Network Marketing Campaign

Cluster	Facebook Interactive Tools for Corporate Participation	Promotional Materials
Cluster 1	Wall.	Instant Message.
Contributor	Event Invitation.	Event Promotion.
	Shared Link.	Interactive Exchange.
	Status.	Invite Contributor to Share Experience.
	Photo Album.	Invite Contributor to hand out Product Samples.
Cluster 2	Wall.	Instant Message.
Lurker	Event Invitation.	Event Promotion.
	Shared Link.	Interactive Exchange.
	Fan Page.	Product Recommendation Post.
	Group.	Group Invitation.

Table 10 proposes relevant corporate marketing strategies for launching a social network marketing campaign. Corporations could collaborate with contributors and lurkers who engaged their dissemination affinity for the wall, status, photo album, and shared link in allured product interests derived from their posts. The product updates shared by the contributors and lurkers would facilitate interactions with other Facebook users.

Facebook Social Network Community Service Model

According to the findings derived from this research on the purchase-and-information-reference behaviors of the contributors and the lurkers, a service map was established, as shown in Figure 15.

In accordance with the findings derived from the association rules analyses in this research, the investigation gave insights into the behaviors of contributors and lurkers in association patterns. The findings that were highly significant with larger lift values were selected for further investigation where the uncovered association rules were aligned. Table 11 summarizes the selected association rules from each of the contributor and lurker categories to demonstrate the relevance of a Facebook social network service model.

Facebook Social Network Community Marketing Model

Corporations with official corporate websites could first launch advertisement efforts on Facebook with a fan page created with promotional events. The virtual interactions should be materialized by convening events such as seminars and meetings where the brand meets its clients, where clients have a chance to develop relationships with others who share the same

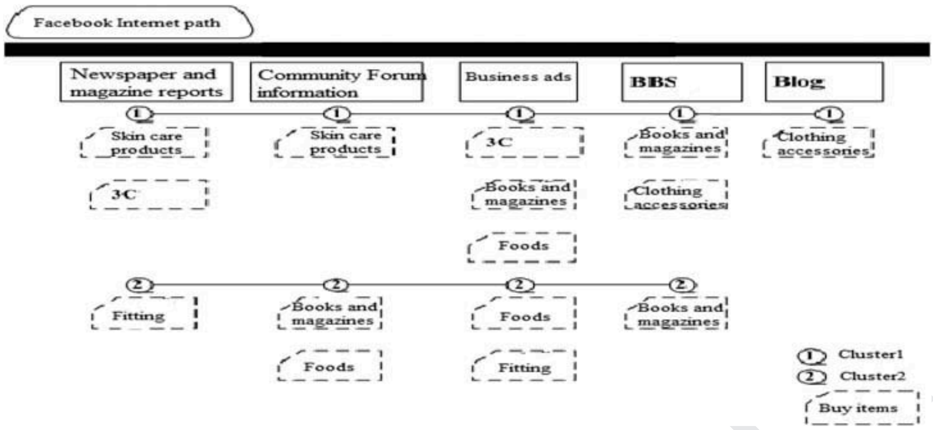

FIGURE 15 Service map: information source and purchase product–Facebook channel.

TABLE 11 Social Network Service Model

Alignment	Contributor	Lurker
Information Collection	Consuming Information	Experience Sharing
Receiving Information	Group Shared Information	Shared Link
Information Attitude	Aggressively Participated	Just Browsing
Sharing Tools	Wall	Shared Link
Sharing Audiences	Colleague	Classmate
Sharing Purposes	Brand Tracking	Brand Tracking
Purchase Information Source	Corporate Advertisement	Social Network Community Discussion
Brand Fan Page	Apple	7-Eleven
Purchased Product Category	3C Products	Food

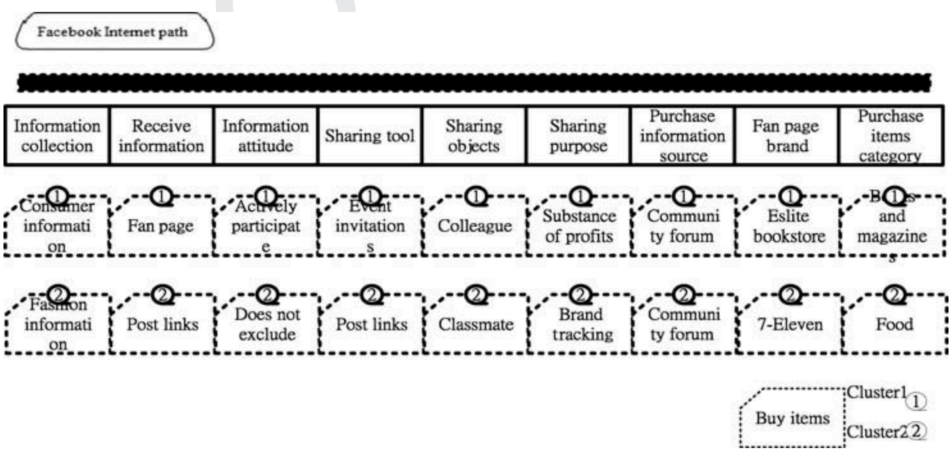

FIGURE 16 Marketing map: social network community marketing model.

interests and preference. A reputation is thus built for the brand itself and the corporation behind it (Figure 16).

Furthermore, integrating Facebook's social network service and marketing model, this study illustrates a whole picture of the Facebook business model on Figure 17. Based on user profile and segment, this study investigates Facebook-user purchase behavior on user preference and group recommendation. Accordingly, Facebook-user online purchase recommendation is thus provided for marketing. However, this is not to say that using Facebook ensures absolute marketing success. Similar to other online

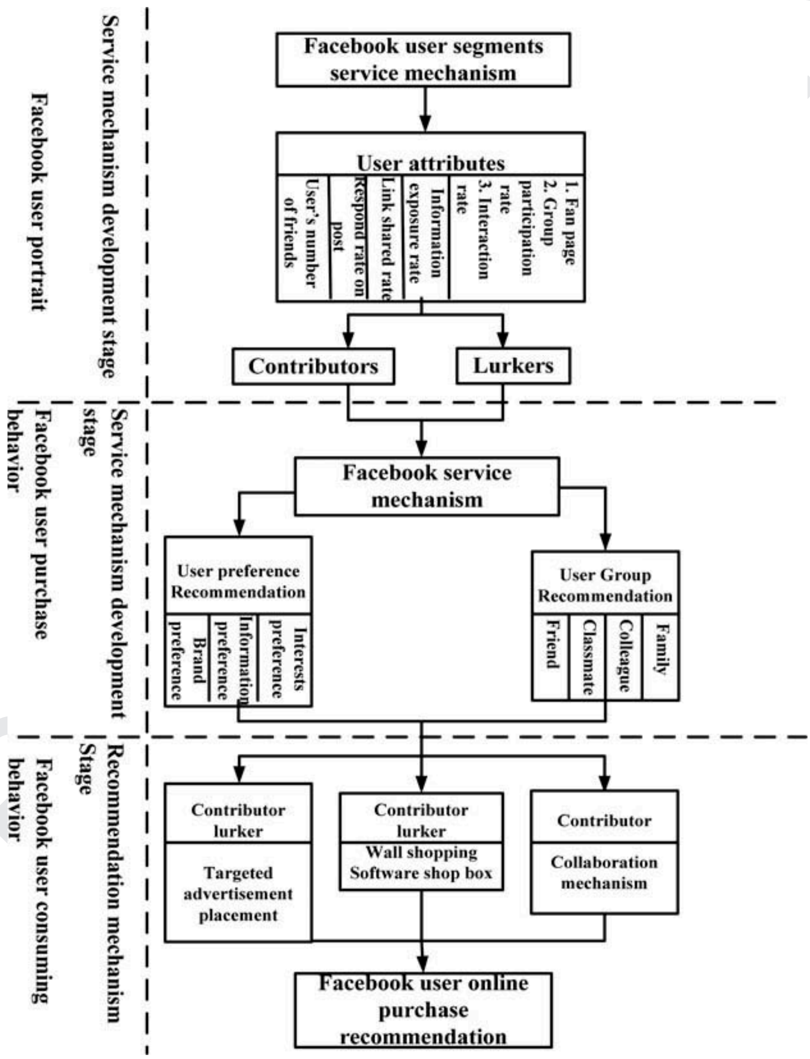

FIGURE 17 Facebook business models of service and marketing mechanism.

tools, implementation requires a strategic perspective to ensure the desired outcomes. Achieving results is a process involving preparation, resources, competencies, monitoring, and evaluation (Silk 2006). It is important to keep realistic expectations about the marketing outcomes of using Facebook (Treadaway and Smith 2010) because the results depend on how well business models utilize the website as a marketing tool.

Facebook offers a wide range of opportunities for international marketing. The perspective toward Facebook could explain the resources employed in using this SNS as a marketing tool and the manner of using Facebook to achieve marketing objectives. Perspectives of users/consumers toward the SNS could influence the outcomes for using Facebook as a marketing tool. It becomes important to learn if Facebook has changed the market to the extent of influencing Facebook users to utilize the site for successful business model developments.

CONCLUSION

There are two implications for Facebook. First, Facebook is a gathering place of a large pool of users/consumers. Second, this SNS is also a mine of consumer information and a means of spreading information to build market presence. In light of the operation and execution of Facebook's service mechanism, corporations that are interested in developing related marketing strategies should first promote the brand's visibility to the targeted demographic consumer groups. This visibility could be facilitated by the networking demand chain mechanism through Facebook, which could induce purchases by potential customers. Through the fan page and group interactive functions on Facebook, vital connections between the brand and its consumers could be realized and manifested. These users were connected by the social network community on Facebook. Facebook is more than a communicative medium. It closes the missing links between the corporation and its potential clients, so that the most loyal clients could be nurtured. In addition, this research shed light on how corporate decision-makers could reach understandings through both contributors and lurkers. Thus, a better product emerges and a competitive product results. A product has vital relationships that nurture its core consumers. In addition, a good product attracts customers, but the right clientele with close social network interactivities could bring the product to new levels of competitive innovations.

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