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A social recommender mechanism for location-based group commerce

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A B S T R A C T

With the rapid growth of social media platforms, numerous group commerce websites, which exploit both the advantages of price discounts and experience value, have emerged. Moreover, the popularity of sophisticated mobile devices brings great commercial opportunities for local store to gain publicity. In this research, considering user preference, geographic convenience, and friends' influence, a group-coupon recommender system is proposed for promoting location-sensitive products. The results of experiments conducted on Facebook indicate that the proposed mechanism could accurately recommend products and satisfactorily provide a companion list of to customers, significantly increasing willingness to purchase by taking advantage of the power of social influence.

1. Introduction

With the rapid growth of e-commerce markets, several on-line transaction platforms supporting customers have sprung up over recent years and transformed customers' shopping behaviors. In the traditional e-commerce operation pattern, traders exhibit the product on a high-popularity auction website such as e-Bay or Yahoo to attract customers to purchase. Recently, a new type of group commerce, utilizing the advantages of price discounts and social influence, has emerged. According to the general economic rule, the larger the volume of products bought, the lower the unit price. Hence, for e-commerce buyers, aggregating individuals to raise the purchase volume can increase their bargaining power and achieve a lower purchase price.

According to an e-commerce industry research report, the population of Internet users in China is estimated to reach more than 600 million, and the population of online shoppers is predicted to rise to more than 300 million, by 2015 [36]. Moreover, a German research company, yStats.com, reported that the number of online shoppers in the US is predicted to grow to more than 150 million in 2012, with almost 80% of US internet users engaging in shopping online [16]. With the huge business opportunities afforded by the e-commerce market, a substantial number of traders have entered into this e-commerce market and online shoppers are using their social capital to increase the purchase volume to get the lowest price possible. Hence, numerous online group-buying transactions have naturally arisen in this market.

The operational model of traditional online group buying is described briefly as follows. The traders publish products on online e-commerce platforms, such as auction websites, to attract customers to purchase. The group-buying commerce retailer provides products and services at significantly discounted prices on the condition that there exists a minimum number of buyers willing to buy the same item [50]. However, although customers are certainly attracted to products offered at a

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substantial discount, they may well not have the will or patience to put in the inevitable effort involved in forming a large-sized consumer group. As a result, traditional group-buying e-commerce is not particularly promising. Moreover, there is a need for some local shops to increase publicity to enhance their business. Under the above circumstances, a brand new business model exemplified by well-known group-coupon websites such as Groupon, Gomaji and Meituan, was developed to meet the above needs. As the originator of this new group-coupon market, Groupon launched its first market in Chicago in November 2008. There is a major difference between this new group-coupon business model and the traditional group-buying model. The group-coupon platforms play a role in matching traders and end customers. They seek shop-type traders in urgent need of increased publicity and then make an agreement assuring the traders of the sale of a fixed volume of products for an ultra-low price. These group-coupon websites sell the product featured as the "deal-of-the-day"; most products are in the form of a ticket package which needs a certain number of consumer companions to enjoy the product or service together. After purchasing the coupon product on a group-coupon website, the buyer prints off a voucher and claims their discount at the retail trader.

In other words, the effort of bargaining with traders migrates from the individual customer to the intermediary platform. However, because of the low entry barrier of these new group-coupon sites, numerous copycat competitors have rapidly emerged. Recently, CNN Money News reported on Groupon's precipitous stock decline on June 4, 2012, and the market cap fell below the $6 billion which Google offered as a buyout in late 2010. The phenomenon of the competitive group-coupon market not only affected the revenue of intermediary platforms but also brought customers the problem of spending more time finding desired products.

In the increasingly competitive environment, group-coupon platforms are currently facing numerous challenges and problems. The main problems faced by these group-coupon platforms are:

(1) How to develop personalized and value-added services for group-coupon customers.
(2) How to recommend accurately location-sensitive coupons to customers.
(3) How to utilize the power of social influence to increase the revenue of a group-coupon platform.

In this study, a group-coupon recommendation mechanism, analyzing the factors of individual preference, location sensitivity, and social influence, is proposed to solve the problem by finding a group of customers who are interested in the product and geographically close to the shop offering the product to assure the success of group-buying transactions by achieving the minimum numbers of buyers. Specifically, for each recommended buyer of package products, a consumer group list of a size equal to the suitable number of consumer companions for a certain coupon product is also suggested to increase their willingness to purchase. Moreover, for group-formed coupon products, a group member list is generated for all the customers in the same group to increase their willingness to purchase a typical product. By conducting experiments on Facebook and comparing with several benchmark recommendation strategies, we verified the superior effectiveness of our proposed group-coupon recommendation mechanism. From the perspective of online group-buying platforms, this customer-value-enhanced mechanism could raise both their popularity and profits simultaneously.

The remaining sections are organized as follows. The literature related to our work is reviewed in Section 2. Section 3 gives a detailed description of the proposed mechanism. In Section 4, the experiments conducted based on the proposed mechanism are delineated. The results and evaluation of the experiments are presented in Section 5. Finally, Section 6 highlights our research contributions and describes research limitations and corresponding directions for future studies.

2. Related literatures

2.1. Social and group commerce

Social commerce is an emerging new market in which individual sellers are linked over online social networks [46]. Both the quality and social support of the website could affect the user's intention to participate in social commerce and to continue using the service of social networking [30]. A key benefit of creating a social commerce network is to make stores more accessible to customers visiting the marketplace [10]. Significantly influenced by the preceding fast growth in social networking, social commerce is synonymous with next-generation electronic commerce [28]. Fundamentally different from traditional e-stores, online stores have created a new paradigm of business and sales models within the past several years.

While the phenomenon of group commerce is formed by consumer bundling as well as consumer flocking, the existence of such a grouping phenomenon has been strongly dependent on new information technologies and the global proliferation of the Internet over the last decade [22]. For example, Groupon, as the best known and largest daily-deals businesses vendor, which launched in November 2008, operates a local commerce marketplace that links merchant partners to consumers by providing goods and services at around 50% off the list price [8]; due to its rapid growth, Groupon boasted a $1.35 billion valuation in just 17 months [44].

The group commerce retailer operates by offering one group-coupon product daily in each of the metropolitan marketplaces it serves [12]. Each successful deal has a minimum number of buyers that must be reached for the deal to occur, and sellers may also set a maximum threshold to constrain the number of coupons sold [22]. The mechanism of time-limited purchase increases customers' sense of urgency and generates panic buying [35]. Essentially, the business model of group commerce is a three-win situation. For local traders, the effects of publicity and advertising could directly increase their revenue and advance consumption through heavily discounted prices. For the group commerce platform, the least effort possible is expended to get the biggest discount possible from traders to attract more and more customers to the platform. The platform sells the coupons to the end customers at a slightly higher price than it got them from the traders. For the end customers, a large discount can be obtained without the effort of bargaining.

However, the phenomenon of the competitive group-coupon market not only affected the revenue of intermediary platforms but also brought customers the problem of spending more time finding desired products. In this research, considering user preference, geographic convenience, and friends' influence, a group-coupon recommender system is proposed for promoting location-sensitive products.

2.2. Group recommendations

A recommender system [37] is a commonly used approach for providing suggestions to users for selecting a set of items, activities or any other kind of products. The suggestions involve different decision-making processes, such as what products to buy, what music to listen to, or what online news to read.

Recommender systems can be classified into three main categories [1,3]: (1) content-based recommender systems: the recommendation aims at taking advantage of customer's previously expressed preferences, (2) collaborative recommender systems [7]: the recommendations are made according to items chosen by other users who have similar preferences to the target user, and (3) hybrid recommender systems [34,31]: this mechanism combines the two previous methods.

Recently, several extended works on recommender systems have been proposed, such as focusing on fuzzy linguistic modeling [42] or utilizing multi-criteria ratings [20], and providing group recommendations [37]. The majority of recommendation systems provide personalized recommendations for individual users. However, there are some circumstances in which the items to be suggested are not intended for individual usage but for a group of users: for example, a group of friends or a family planning to attend a surfing course, to watch a movie, to have a lunch or dinner, or to select a holiday tour destination. For this reason, some recent works have addressed the problem of identifying recommendations for a group of users, trying to satisfy the preferences of all the group members (e.g., [2,5,6]). Generally, group recommendations use simple aggregation of group members' preferences when generating recommendations. Consequently, the preferences of partial members, especially the less active ones, are ignored.

Kim et al. [21] proposed a new group recommendation mechanism focusing on the improvement of not only the group recommendation quality but also individual members' satisfaction [21]. Chen et al. [10] presented a novel group recommendation mechanism which combines the collaborative filtering methodology and the genetic algorithm to learn the possible interactions among group members to estimate the rating that a group of members might give to an item.

In general, customers tend to choose a few companions who have similar interests and frequent interactions with them concerning product purchasing, since inherent pleasure and satisfaction can be derived from a group of close friends participating in the same activities. Moreover, because of the power of social influence, social networks are an excellent way to influence the behavior of an individual buyer [13]. A marketer can increase the volume of sales of a product by means of finding appropriate consumer companions who are also willing to buy the product along with the targeted consumer who has high willingness to purchase. For this reason, discovering the appropriate companions for each potential customer is an effective way to enhance the purchase intention of customers.

In this research, a group-formed recommendation mechanism is proposed to provide a consumer companion list for a targeted customer, utilizing the power of social influence to increase the willingness to purchase location-sensitive group coupons.

2.3. Context-Aware Recommendation Systems (CARS)

Dey and Abowd define the term "context" as any information that can be utilized to characterize the situation of an entity [11]. Most existing recommender systems only consider two types of entities: users and items, and do not take into consideration any contextual information, such as location, time, weather, and companions. Context-aware recommender systems, on the contrary, focus on providing users with relevant information based on their current physical contexts [41].

Recently, researchers have studied the helpfulness of using contextual information in the recommendation system. Adomavicius and Tuzhilin [1] indicated that there exist three different algorithmic paradigms for incorporating context information into the recommendation process: (1) Contextual pre-filtering: data selection or data construction is based on specific context. Ratings can then use any traditional recommendation model on the selected items. (2) Contextual post-filtering: initially, contextual information is ignored, and a list of items is generated using any traditional recommendation model on entire data. The recommendation results are then adjusted for each user based on the contextual information. (3) Contextual modeling: contextual information is used directly in the modeling process. Adomavicius and Tuzhilin [1] also demonstrated that contextual information is important for increasing the quality of recommendations. In the same way, Baltrunas et al. [4] showed that users gain more effective and satisfactory recommendations from a context-aware recommendation system than a standard recommendation system with the same user interface.

The proliferation of smartphones creates many opportunities for mobile commerce. Mobile commerce has attracted e-commerce scholars ever since mobile and portable devices became a convenient and effective means of executing business transactions and business practices [23]. Knowledge of the end user's location context could be utilized to deliver instant, relevant, and engaging content and information. Location-related information is popularly applied in the domain of geographic-related recommendation systems. For example, a map-based personalized recommender system which predicts users' preferences was developed by Bayesian networks [32]. Noguera et al. [31] proposed a mobile recommender system which allows tourists to benefit from features such as a 3D map-based interface and real-time location-sensitive recommendation. In another study, GPS-based data and users' comments from various locations were analyzed to discover interesting locations and possible activities related to those locations to inform recommendations. Moreover, historical location information can be used to develop a location related recommendation service for empty taxis [26]. In addition, some mobile commerce issues have been researched by proposing a new mechanism to secure and monitor group-buying transactions [24,25].

To ameliorate the above weaknesses, we propose a new recommender mechanism to enhance group-buying transactions. In this research, the online location-aware data were analyzed and incorporated this contextual information into the recommendation modeling process to measure geographic convenience in relation to certain physical stores.

2.4. Preference analysis and recommendation

User preference modeling is critical in the area of recommendation and personalization services. User preference involves a user's evolving long-term commitment to specific types of service, as well as a user's instantaneous service requirements, depending on the context of use [33]. Some studies have indicated that recommendations for a user may be made solely according to their similarities to other users, for example GroupLens [38], the Bellcore video recommender [18], and Ringo [43]. Other research has combined social network analysis and semantic concept analysis to improve recommendation effectiveness [47]. Furthermore, a user's browsing profile could be used to develop an Internet recommendation system via the semantic-expansion approach [29]. The hierarchical tree modeling approach is one category of personalized service system in user modeling approaches [17].

To estimate the similarity between a product and a users' preference, a tree-like structure is adopted in this study. We use the distance-based approach, which is proved to outperform other keyword-based similarity evaluation approaches [48], to estimate the similarity between a product and a target user's preference. Hence in this study we would also like to adopt the idea of distance-based approach to implement our preference analysis module.

2.5. Social psychology theory

Focusing on the motivations behind consumers' participation in group buying, some findings indicate that, apart from the price discount, the "flock-of-sheep" effect is also an important factor [9]. The flock-of-sheep effect is also named "herd behavior", which describes how members in a group can act collectively without any planned direction. The Groupon website displays the daily-deal coupon product with the additional information of the number of the people who have already joined in the buying group, in order to push customers into panic purchasing without applying rationality. This is similar to the phenomenon of information cascading, which is where an individual's decision may be influenced according to information obtained from others [19,40].

Several studies have shown that social influence plays an important role in group commerce and social commerce. Social influence takes place when a person adapts his or her behavior, attitudes, or beliefs to those of others in the social system [27]. Social influence theory has generally been referred to as conformity and regarded as the relatively simple act of following or agreeing with a visible majority [22]. Some research claims that influence does not necessarily need face-to-face interaction but rather is generated based on information about other people [15]. In this research, the power of social influence is exploited to increase customers' intention to purchase by providing a list of high-cohesion consumer groups consisting of customers who also have considerable interest in the product.

3. System frameworks

In this study, a group-coupon recommendation mechanism is proposed to implement location-based social commerce in the following two different scenarios: recommendations for group package products (e.g., museum ticket packages, or restaurant voucher packages) and for group-formed products (e.g., travel tour groups).

(1) The first product type is denoted a group package product (GPP), such as "a meal voucher for ten people" or "a surfing course for four people". This kind of package-type product is not too expensive and only needs one person to pay the bill but allows several people to consume the product together. The buyer may invite his/her friends to enjoy the product or ask them to split the price to him/her. In this scenario, the object of the trader is to find the customer who is most willing to buy the package product.

(2) The second product type is denoted a group-formed product (GFP), such as a tour group. This GFP product needs a minimum number of group members to join and is generally expensive, with each group member paying for their share of the product personally. The trader can utilize the strong power of social influence by informing every group member who is also in the same consumer group. A customer may decide to purchase this product by being attracted to it by their friends who also want to buy this same product.

In the proposed mechanism, decision-making in relation to the location-sensitive group commerce products consists of three purchasing criteria: the similarity between user preference and product characteristics, the geographic convenience of the store, and the influence of friends' evaluations of the product. Therefore, in the proposed mechanism, we predict the willingness to purchase of a customer by considering these three main aspects: According to a customer's willingness-to-purchase score, the system identifies suitable group members to enhance the recommendation of product packages and group-formed product coupons. The architecture of this mechanism is depicted in Fig. 1.

The main modules included in the proposed system framework are as follows:

(1) *Preference analysis module:* By means of comparing the similarity between product characteristics and the preferences of each customer, the goal of this module is to find customers who are interested in the target product.
(2) *Location analysis module:* This module is used to filter customers who are in closer proximity to the store by analyzing the geographic-related information accessed from the self-disclosure behaviors on online social networking platforms.

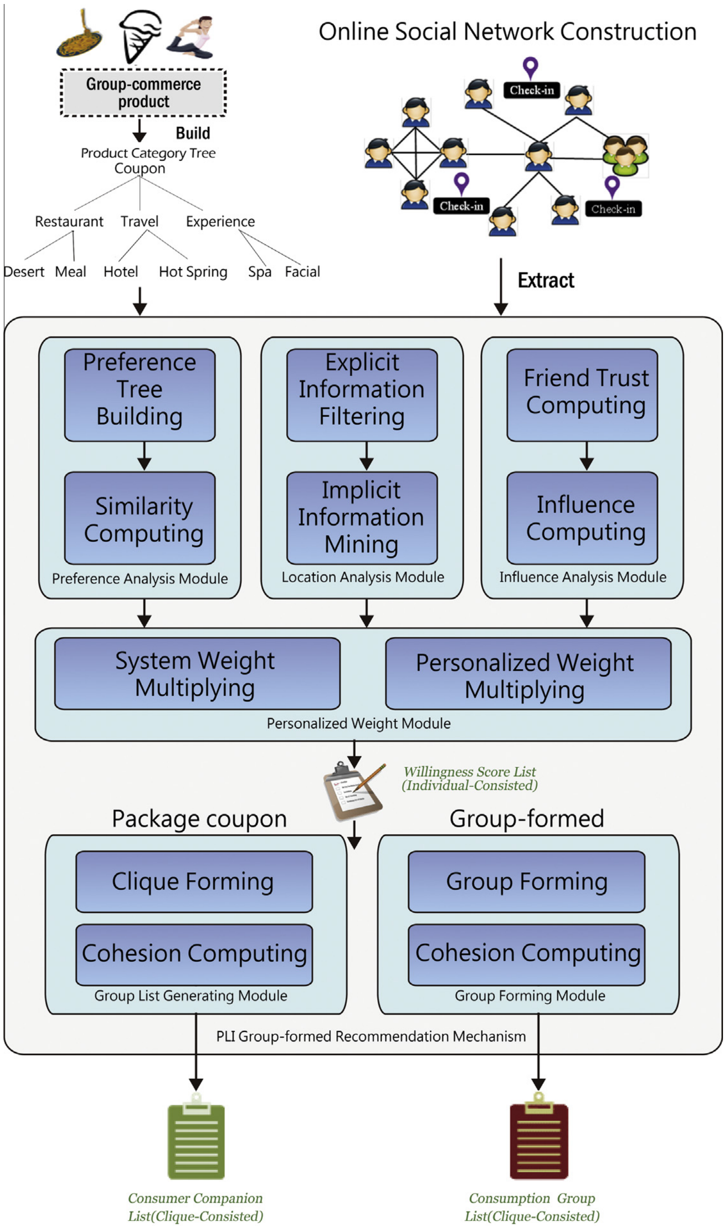

Fig. 1. The system framework of the group-coupon recommender mechanism.

(3) *Influence analysis module:* This module examines the degree of influence of a friend's evaluation of the product. We could speculate that a customer is more likely to be influenced by a friend who shows a greater liking for the product and is highly trusted by the customer.
(4) *Personalized weighting module:* A customer's willingness to purchase is measured by aggregating the above three corresponding scores (preference score, location score and influence score) by utilizing different personal combinations of decision weighting derived using the analysis hierarchy process (AHP) method.
(5) *GPP coupon recommendation module:* For GPP, this module generates companions for customers who are identified as highly willing to buy the product. Specifically, for each targeted customer, the module examines the cohesion score of each group formed and identifies the higher scores, namely the groups in which the members are more likely to enjoy the product together.
(6) *GFP coupon recommendation module:* For GFP, the module analyzes and identifies a candidate customer group whose members have the highest willingness-to-purchase score towards the target product. The products are recommended to each member of those groups with higher cohesion scores. Moreover, each customer to whom recommendations are made is informed of the list of group members.

In Section 3.1, we detail the processes of the modules.

3.1. Preference analysis module

The purpose of this module is to identify customers whose preference is in accordance with the features of the target product. Through this module, the preference analysis score is obtained to represent the degree of preference of customer i regarding the target product. The measurement of this module is denoted as the *PA* score. The similarity score between the characteristics of the target product and user's preference is measured through preference tree building and computing similarity.

3.1.1. Preference tree building

Before calculating the similarity between the target product and a customer, a product category tree first has to be built by referencing a certain classification index. Each node of the product category tree represents a single category. Every product is classified into only one category node. According to the name of each category, a category-extended term (CET) set is developed to cover the more comprehensive concept of this category. The CET set for a category c, $\Theta_{CET}(c)$, is established by searching all of the original category names on the experiment platform or website and retrieving the extended terms which are related to the original category name. For example, to construct the CET of category node "swim", we could search using the keyword "swim" and retrieve the related search results.

If the product category tree contains n nodes, all target products will be classified into n categories and n CET sets are established.

3.1.2. Computing similarity

In order to discover the potential customers most likely to purchase the target product, the similarity between a single customer and the target product has to be calculated. The preference information of each customer has to be mapped onto positions in the product category tree. Customer preference information refers to attributes or terms which could represent the interests of a customer.

The raw data of customer profiles or behavior recorded on online social networking platforms could be retrieved as the customer preference. By transforming the raw data into several terms, the customer interest term set for customer u_i, denoted as $\Theta_{CIT}(u_i)$, is built to describe the preference of each customer. For example, on Facebook, the "fan page" mechanism is similar to a web page and can help a local business, company, brand or community to build a closer relationship with customers. If a user is interested in a certain fan page, he/she can press the "Like" button to subscribe. Therefore, the names of liked fan pages can be used to express a user's preferences. The CIT set of a user can be built by incorporating the names of all the fan pages subscribed to by this user. The preference degree of a typical customer i in a category node c is computed using the Jaccard similarity measure.

$$SC_c^i = \frac{|\Theta_{CIT}(u_i) \cap \Theta_{CET}(c)|}{|\Theta_{CIT}(u_i) \cup \Theta_{CET}(c)|}. \tag{1}$$

For example, if there are 15 category nodes in the product category tree, a total of 15 scores will be generated to represent a customer's degrees of preference with respect to these different category nodes. In order to compute the similarity of two category nodes in the tree structure, a distance-based similarity computing approach is adopted. According to the proposed method, the similarity between two concepts is quantified by measuring how closely they are related in the hierarchy. This approach has been proven empirically to achieve a better performance than other keyword similarity computing approaches. The preference score of a customer in relation to the target product is aggregated by the weight-multiplied score of each category and the category of the target product, denoted as C_{tp}. The weighted score of customer u_i in category c, denoted as α_c^i, is computed by formula (2):

$$\alpha_c^i = \frac{SC_c^i}{\sum_{k=1}^{N_c} SC_k^i}, \tag{2}$$

where N_c represents the total number of category nodes.

D_{tp} denotes the path distance between the category of the target product C_{tp} and the first common parent (FCP) category node. D_j is the distance from the product category j to the FCP category node. D_{FR} is the distance from the FCP category node to the root node. The similarity between the target product and a typical category j is formulated as:

$$Sim(C_{tp}, C_j) = \frac{2D_{FR}}{D_{tp} + D_j + 2D_{FR}}. \tag{3}$$

The preference analysis score (*PA* score) of customer i with the target product is computed by formula (4):

$$PA(C_{tp}, C_j) = \sum_{j=1}^{N_c} \alpha_j^i * Sim(C_{tp}, C_j). \tag{4}$$

An example of similarity calculation is illustrated in Fig. 2. There are three leaf nodes (“Cake”, “Spaghetti”, “Sushi”) on the category tree. The target product belongs to the “Sushi” category node (C_{tp} = “Sushi”). The final *PA* score is aggregated by the weight-multiplied *PA* s (C_1 and C_{tp}) and (C_2 and C_{tp}). If the score of category C_1 is 2 ($SC_1 = 2$) and the score of category C_2 is 3 ($SC_2 = 3$) and the score of target product category is 1 ($SC_{tp} = 1$), then $\sum_{k=1}^{N_c} SC_k^i = 2 + 3 + 1 = 6$. The *PA* score is calculated as $\frac{2}{6} \times \left(\frac{2\times2}{2+2+2\times2}\right) + \frac{2}{6} \times \left(\frac{2\times2}{2+2+2\times2}\right) + \frac{1}{6} \times (0) = \frac{5}{12}$.

3.2. Location analysis module

Location analysis (LA) is used to evaluate the convenience of transportation for the customer to go to a store selling the target product which he/she wants to consume. Customers are more willing to go to a store if it is close and convenient to reach. In general, transportation convenience is one of the factors influencing the customers’ purchase intention. In this module, both explicit and implicit types of geographic-related information are retrieved to depict the area in which the customer is typically to be found. The purpose of this module is to find the customers who live near the store or feel the store is easy to visit. The measurement of this module is denoted as the *LA* score which represents the degree of geographic fit between a customer and a store. The processes of location-related information collection are filtering explicit information and computing implicit information.

3.2.1. Filtering explicit information

We analyze the geographic-related data obtained directly from the user profile recorded in the social networking platform to find the customers who live or have ever lived in the city where the store is located. The location information of a customer, such as his/her home town and city in which he/she lives currently, can be obtained from his/her profile. The explicit location vector of customer i is represented as $ELV(u_i) = [hometown(u_i), current\_city(u_i)]$. If store S_j which provides the target product is located in city $L(s_j)$, the explicit location score for customer i with respect to store j is measured by formula (5):

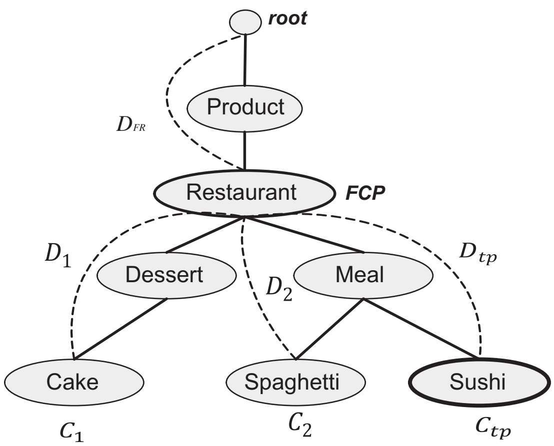

Fig. 2. Distance-based computation of similarity.

$$Explicit\_LA(u_i, s_j) = \begin{cases} 1 & \text{if } hometown(u_i) = L(s_j) \text{ and } current\_city(u_i) = L(s_j); \\ \alpha & \text{if } hometown(u_i) = L(s_j) \text{ and } current\_city(u_i) \neq L(s_j); \\ \beta & \text{if } hometown(u_i) \neq L(s_j) \text{ and } current\_city(u_i) = L(s_j); \\ 0 & \text{if } hometown(u_i) \neq L(s_j) \text{ and } current\_city(u_i) \neq L(s_j), \end{cases} \quad (5)$$

where $0 < \alpha \leqslant \beta < 1$.

3.2.2. Computing implicit information

In addition to explicit profile information, some implicit information from customer activities on the online social networking platform can also be collected. Many social networking services, such as Foursquare, Facebook and Google+, allow users to "check in" at a physical place and share with their friends the information of their geographic location [38]. Users can deliver a message of check-in information by using a mobile app on a smartphone—the app will utilize the phone's GPS to identify the current location [14]. In this research, check-in information is used to analyze a user's implicit location information. Generally, check-in information contains the coordinates of a physical check-in position and the tagged friends who are with the check-in user. According to the address (with coordinate X and coordinate Y) of the store, we can compute the distance between the check-in position and store address and use it to sort the candidate customers in ascending order. For a store S_j, a distance score of check-in information is used to express the distance from the position of check-in to store S_j. T denotes the total number of tag-ins contained in all check-in information. The ranking of check-in information CI_i toward store S_j is represented by $rank_{CI_i}^{S_j}$. If the ranking of the check-in information CI_i is the nearest one to store S_j, the ranking of check-in CI_i is denoted as $rank_{CI_i}^{S_j} = 1$. The distance score of check-in information CI_i toward store S_j is normalized as in formula (6):

$$d\_rank(u_i, s_j) = \frac{(T+1) - rank_{CI_i}^{s_j}}{T}. \quad (6)$$

For store S_j, the *Implicit_LA score* of customer i is measured by averaging all the distance scores of each piece of check-in information which customer i publishes or is tagged in. The explicit location score for customer u_i with respect to store s_j is measured by aggregating all the check-in rankings of user i who is tagged, and is formulated as:

$$Implcit\_LA(u_i, s_j) = \frac{\sum_{t \in \Theta_{Tag}(u_i)} d\_rank_t(u_i, s_j)}{|\Theta_{Tag}(u_i)|}, \quad (7)$$

where $d\_rank_t(u_i, s_j)$ stands for the distance ranking of user u_i related to store s_j in a check-in t and $\Theta_{Tag}(u_i)$ is the set of check-ins in which user u_i is tagged.

Finally, the final $LA(u_i, s_j)$ is obtained by aggregating the *Implicit_LA* and *Emplicit_LA* scores and is expressed as:

$$LA(u_i, s_j) = Implcit\_LA(u_i, s_j) + Explcit\_LA(u_i, s_j). \quad (8)$$

3.3. Influence analysis module

Influence analysis (*IA*) is used to measure the extent to which a customer is likely to be influenced by his/her friends' evaluation of the target product. The more trusted friends who give a positive evaluation of the target product, the greater the possibility that the customer will also like the product, due to the effect of social influence [50]. The purpose of this module is to measure the extent to which a customer is likely to be influenced by his/her friends' evaluation of the target product. The measurement of this module is denoted as the *IA* score, which represents the degree of influence of a friend's evaluation. The procedures in this module are computing trust in friends and computing influence.

3.3.1. Computing trust in friends

In order to measure the degree of influence of a friend's preference, the trust levels between a customer and his/her friends have to be computed since social influence is formed based on trust [50]. Ziegler and Golbeck indicate that the strongest connection exists between users with mutual similarity and trust [50]. Ziegler and Lausen [49] claim that trust is associated with user similarity and can be derived. According to these studies, we compute the similarity between a typical customer and each of his/her friends as a proxy for the customer's trust in each of his/her friends. The trust between customer u_i and his/her friend f_j is computed as:

$$Trust(u_i, f_j) = \frac{|\Theta_{CIT}(u_i) \cap \Theta_{CIT}(f_j)|}{|\Theta_{CIT}(u_i) \cup \Theta_{CIT}(f_j)|}. \quad (9)$$

3.3.2. Computing influence

The greater trust the customer has in his/her friends, the more likely it is that the customer will be influenced by them. If trusted friends evaluate a product highly, the customer will also have a positive view of the same product. Therefore, the score of a friend's influence on a customer is computed as the average of the customer's trust values between him/her and each of his/her friends multiplied by the corresponding friend's degree of preference for the target product. $F(u_i)$ denotes the set of customer u_i's friends. The influence score IA of customer i with the target product is computed as:

$$IA(u_i, tp) = \frac{\sum_{f_j \in F(i)} Trust(u_i, f_j) \times PA\_score(C_{tp}, C_{f_j})}{|F(u_i)|}. \tag{10}$$

to each customer included in the same group.

3.4. Personalized weighting analysis module

Each customer may have different decision criteria and corresponding weighted score in terms of preference even if purchasing the same product, because of the diversity of age, gender, income, etc. Further, even for the same customer, he/she many have different preference criteria in relation to various categories of product. A customer usually makes a decision whether to go to a store or not on the basis of several criteria including their own preference, geographic convenience and the influence of friends. The purpose of this module is to obtain the personalized weighted score based on the three decision criteria (preference, location and influence) in relation to each category of store providing the target product. The procedures in this module are computing personalized weighted score and calculating personalized willingness to purchase.

3.4.1. Computing personalized weighted score

We adopt the analysis hierarchy process (AHP), a popular and useful multi-criteria decision-making technique of practical application in cases dealing with several domains. AHP is an appropriate solution when the analysis involves the principles of decomposition, pair-wise comparisons, and priority vector generation and synthesis [39]. For the purpose of determining the personalized recommendation criteria, customers are requested to evaluate the relative significance of preference, location, and influence. M_{PLI} denotes the matrix of pair-wise weight ratios in which a row gives the ratio of the weight of each criterion. Element a_{kj} indicates the relative decision weighting of k criterion, in terms of the j criterion. M_{PLI} is calculated using formula (11):

$$M_{PLI} = [a_{jk}] = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} = \begin{bmatrix} 1 & A_{PL} & A_{PI} \\ 1/A_{PL} & 1 & A_{Li} \\ 1/A_{PI} & 1/A_{Li} & 1 \end{bmatrix}, \tag{11}$$

where A_{PL} is equal to a_{12} representing the relative weight of preference similarity to geographic convenience. A_{PI} is equal to a_{13} representing the relative weight of preference similarity to friends' influence. A_{LI} is equal to a_{23} representing the relative weight of geographic convenience to friends' influence. In order to determine the relative weight of a separate criterion from the comparison matrix M_{PLI}, an arithmetic mean is used as in formula (12):

$$W_k = \frac{1}{3}\sum_{j=1}^{3} \frac{a_{kj}}{\sum_{k=1}^{3} a_{kj}}, \tag{12}$$

where W_k is the relative weighted value of criterion k. The weighted score of user u_i on the three criteria (preference similarity, geographic convenience and friend's influence) can be represented as:

$$W_{PLI}(u_i) = [W_P(u_i), W_L(u_i), W_I(u_i)]. \tag{13}$$

3.4.2. Calculating personalized willingness to purchase

For a typical target product, a customer's willingness to buy the product may be influenced by the product's characteristics, the geographic convenience of the store, and their friends' evaluation of the product. Everyone has different weight distribution in relation to the above three criteria because everyone has an individual decision-making pattern. Therefore, a customer's willingness to buy a product is computed by aggregating the weight of each criterion multiplied by the corresponding criteria score. The willingness-to-purchase of user u_i regarding the target product is measured as:

$$Willingness(u_i, tp) = PA(C_{tp}, C_i) \times W_P(u_i) + LA(u_i, S_p) \times W_L(u_i) + IA(u_i, p) \times W_I(u_i). \tag{14}$$

3.5. Group package product (GPP) coupon recommendation module

We first consider the scenario in which traders sell location-sensitive group package coupons. In general, customers tend to choose a few companions who have similar interests and frequent interactions with them concerning product purchasing since inherent pleasure and satisfaction can be derived from a group of close friends participating in the same activities [22]. For this reason, discovering the appropriate companions for potential customers is an effective way to enhance their purchase intention. Therefore, for the GPP coupons, the proposed mechanism will discover the customers who have high willingness to buy the product and identify the close companions from their friends who also have high willingness to buy the product. By comparing the cohesion score of each group, we can find the groups with higher cohesion scores as the candidate companions. The main procedures in this module are clique formation and computing cohesion.

3.5.1. Clique formation

A clique is a group in which every member has a tie of strength above a certain minimum with each other member in the same group. In this research, the cliques are formed by recruiting those customers with a higher willingness-to-purchase score concerning the target product. The clique formation processes are as follows:

- Step 1: The customers with a top-k willingness score in terms of purchasing a target product are selected as the starting nodes during the process of clique formation. The clique scale, denoted N, is dependent on the consumption number of the target product.
- Step 2: The ego-centric networks are built from each starting node by including other neighbor nodes which have direct links to the starting node.
- Step 3: H nodes are selected which have a higher willingness to purchase score to form the companion set for each starting node with a clique scale of N. In total, a starting node could generate C_{N-1}^{H} number of clique combinations.
- Step 4: The tightness of all clique combinations is compared. Network density is measured by the degree of interconnectedness between network members: high density reflects a network in which many members know one another, and low density reflects a network in which few know one another [12]. In this research, we used the concept of network density to analyze the extent of contact people had with their clique members. In order to discover tighter cliques, the density of each combinatorial clique is the proportion of linkages among clique members when all possible linkages are considered [12]. $E(g)$ denotes the set of links in clique g. The density of clique g is measured as:

$$\text{Density of clique } g = \frac{2 \times |E(g)|}{N \times (N-1)}. \tag{15}$$

A clique with higher density reflects the fact that its members are more willing to consume the product together. Therefore, the cliques with a higher density value are selected for further examination of their degree of cohesion.

3.5.2. Computing cohesion

The purpose of cohesion analysis is to seek out the cliques with higher cohesion from the clique pool generated. If a group has a higher average strength of linkage than others, we can reasonably speculate that the majority of its group members will have similar thoughts and are more easily influenced by other group members. Link strength is used to interpret the cohesion of a single clique. The strength of a link e_{ij} between customers u_i and u_j is measured by the number of check-ins that customers u_i and u_j are commonly tagged in. The formula is as follows:

$$Link\_ST(e_{ij}) = |\Theta_{Tag}(u_i) \cap \Theta_{Tag}(u_j)|. \tag{16}$$

For a certain clique g, the cohesion score is measured by aggregating the link strength of each link existing in clique g. The cohesion of clique g is measured as:

$$\text{Cohesion}(g) = \frac{\sum_{e \in E(g)} Link\_ST(e)}{|E(g)|}. \tag{17}$$

Finally, the cliques with the highest cohesion scores will be chosen as the companions for the target customer.

3.6. Group-formed product (GFP) coupon recommendation module

We next consider the scenario in which the retailer sells GFP to the individual customers. As being accompanied by friends or people with high similarity will bring additional pleasure value, it is beneficial to discover and form a group with high cohesion so as to recommend the coupons to all the members in the same group. To enhance the interest of a targeted customer, a list of identified group members can be recommended together with the coupon.

For a certain group product the consumption size of which is S, we first identify the set of candidate customers with a high willingness-to-purchase score, and then we list all combinations of possible groups with size S. For example, if the size of the set of the candidate customers is D, the number of all candidate groups to be compared will be C_S^D. For each candidate group, we compute its cohesion score. Finally, the top-k groups with the highest cohesion score will be selected as the groups to recommend. The product and the list of each group's members are recommended.

4. Experiments

To demonstrate the proposed group-coupon recommendation mechanism, several empirical experiments were conducted. The experiments were conducted using the currently most popular social networking website, Facebook, which had over 901 million active users as of May 2012. According to Alexa.com, Facebook is ranked as one of the top two websites globally. Facebook is also the top target for entrepreneurs just getting started with social media marketing activities (79%) [45]. Therefore, with the huge number of users, 92% of marketers are using Facebook and 72% plan on increasing their activities [45]. Facebook provides the fan page mechanism for marketers to create their own page to share product and quality content to their customers. Customers, denoted as fans, can subscribe to the latest news and exclusive content by pressing the “Like” button in the typical fan page. Marketers can promote activities and interact with customers by the Facebook fan page to strengthen the customer relationship and discover potential customers among the friends of fans.

4.1. Data source

4.1.1. User profile

A social network with 726 users aged from 18 to 55 was captured from Facebook. The gender distribution was 319 males and 407 females. Most of the users lived in Taipei and Hsinchu, Taiwan, and the remainder in other cities. The statistical data of the user network constructed are listed in Table 1. The number of total links was 14,430. The average degree of a user was about 40. The total number of fan page records was 42,933 and check-in information was 2285.

4.1.2. Product profile

The total number of the products to be recommended was 20 and most of them were chosen from the original online group-coupon website, Groupon, and other pattern-similar group-coupon websites such as Gomaji (buy.gomaji.com), Lashou (tw.lashou.com) and 17Life (17life.com). The coupon products were mainly located in Taipei and Hsinchu, in accordance with the location of the sample. The recommended products were classified into three major categories (catering, leisure and cosmetic/maintenance) which were mapped onto the constructed product category tree. The total of 20 recommended products were classified into 20 leaf node categories. Six products were in the “catering category”, nine products were in the “leisure category”, and five products were in the “cosmetic and maintenance category”.

The product category tree, as shown in Fig. 3, was constructed by referencing the classification of the above Groupon-like websites. The product category tree was a four-layer tree with three major category nodes and 20 leaf nodes. The category “catering” contained restaurants selling cuisine and some desserts. The category of “leisure” contained tickets for sports activities, discounted hotel stays and talent courses. The category of “cosmetic and maintenance” contained tickets for body spas, hair salon services, and nail art services.

Table 1
Statistics of the user network constructed.

Number of users	726
Total links in network	14,430
Average degree of users	39.75
Total fan page records	42,933
Total check-in information	2285

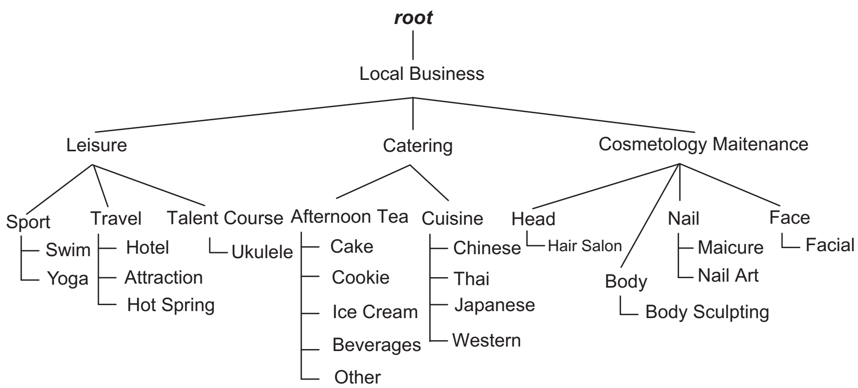

Fig. 3. Product category tree.

4.2. Experimental procedure

The procedures of the experiments were as follows:

(1) *Data collection*: The system would first construct the user network and collect users' behavior data from Facebook and the data of location-sensitive group products from the online group-coupon websites, such as Groupon Taiwan, Gomaji, and 17Life.
(2) *Data cleaning and processing*: The raw data captured from the above sites were processed. Based on the data collected, the system computed the scores of preference, location, and influence of customers in relation to the target product.
(3) Collection of personalized weighted scores: The system collected personalized purchasing weighted scores via an online questionnaire site, mysurvey.tw. A comparative seven-level scale was used in the questionnaire. The collected raw data were analyzed using AHP to obtain individuals' decision criteria preferences.
(4) *Calculation of willingness to purchase*: For each target product, the system calculated the willingness-to-purchase score according to the processed data and personalized decision criteria weights.
(5) *Coupon recommendation*: Two types of group coupon were used for the recommendation:
   - *GPP coupon recommendation*: Based on the willingness-to-purchase score calculated for each GPP coupon, the system generated the target customers and appropriate companions for each of them. The recommendation of the GPP coupon with a companion list was delivered to the target customer.
   - *GFP coupon recommendation*: Based on the willingness-to-purchase score calculated for each GFP coupon, the system generated the appropriate lists of consumption groups. The recommendation of the GFP coupon with a companion list was delivered to all the members in the same group.
(6) *Evaluation:* The evaluations were conducted and collected from the users who received the coupon recommendations.
   - For each GPP coupon, the target customers were asked to evaluate the recommended GPP coupon and the corresponding list of companions, using questionnaires.
   - For each GFP coupon, each member in the same group was asked to evaluate the recommended GFP coupon and the list of group members, using questionnaires.

4.3. Measurement computing

The scores of the measurement in different modules were computed as follows.

4.3.1. Criteria weight computation

The relative importance of the three purchasing criteria factors (preference, location and influence) were evaluated using a two-sided and four-level multiple choice questionnaire. Customers were asked which were the more important factors in their purchase decision-making and the degree of significance among the three pairs of factor combinations respectively for the three major product categories. The four-level evaluation values were 1, 3, 5 and 7, representing equal importance, weak importance, essential importance and extreme importance, respectively. The questionnaire was classified into three parts in which the product categories were "catering", "leisure" and "cosmetic and maintenance", respectively.

Utilizing the AHP method, the personal purchasing weighted score of the three factors (preference, location and influence) with respect to the three major product categories was generated. Through the statistical process of aggregating by product category and gender, the weight combinations derived could be used as the default weighted value for those customers who did not disclose their preferred weighted value. The following tables provide the derived weight combinations with respect to product category and gender to help the marketer plan its marketing strategy. Table 2 shows the values of importance of factors when customers made a purchase decision in different categories of product. We can observe that when customers considered whether to go to a local "catering" establishment, such as a restaurant or snack-bar, the characteristics of the catering establishment was the most important factor influencing the purchase decision and the influence of friends' evaluation of it was the second most important factor. For "leisure", the influence of friends' evaluation of the product was the most important factor; further, the characteristics of the leisure activity or of the scenery was the second most important factor. For "cosmetic and maintenance", the characteristics of the establishment where the service was provided was the most important factor, and the location was the second important factor.

Table 3 shows the values of the importance of factors in relation to different genders. For both male and female customers, "preference" was the most important factor and "influence" was the second factor in all cases. Female customers paid

Table 2
System weighted values of the three coupon categories.

Coupon category	Preference	Location	Influence
Catering	0.469	0.182	0.349
Leisure	0.389	0.177	0.434
Cosmetic and maintenance	0.416	0.302	0.282

Table 3
Weighted values of different genders.

Gender	Preference	Location	Influence
Male	0.419	0.223	0.358
Female	0.431	0.217	0.352

more attention to the characteristics of the product than male customers. Male customers, on the other hand, considered the "influence" and "location" factors to a greater degree than female customers.

4.3.2. Computation of willingness to purchase

In order to evaluate the accuracy of the willingness-to-purchase score calculated by the proposed mechanism, several approaches were used as benchmarks to compare the willingness-to-purchase score generated by the proposed mechanism (PLI). The approaches used in the experiments were as follows.

(1) *PLI model*: The willingness-to-purchase score was generated by aggregating the PA score, LA score and IA score multiplied by the personalized weight. If a certain customer's weighted score could not be acquired, the system category weighted value was used as a replacement.
(2) *PL model*: The willingness to purchase score was generated by aggregating the PA score and LA score multiplied by the relative weight derived from the personalized weighted value.
(3) *PI model*: The willingness to purchase score was generated by aggregating the PA score and IA score multiplied by the relative weight derived from the personalized weighted value.
(4) *LI model*: The willingness to purchase score was generated by aggregating the LA score and IA score multiplied by the relative weight derived from the personalized weighted value.
(5) *CF model*: The willingness to purchase score was generated by collaborate filtering rating multiplied by the relative weight derived from the personalized weighted value.
(6) *Random model*: In this strategy, the customers with high willingness-to-purchase scores are selected at random.

4.3.3. GPP coupon recommendation

Two recommendation strategies were used to generate companions. The two recommendation strategies in generation of companion lists were as follows:

(1) *Generating cohesive companions*: This method generated a companion list for each target customer by considering the cohesion of a group.
(2) *Generating untargeted companions*: For some products or situations, for example, heavily discounted take-out desserts or drinks, the choice of companions is relatively unimportant. In such a situation, if a customer has a discount coupon for cake which is take-out only, he/she may ask friends arbitrarily, instead of targeting friends according to the characteristics of the product. Hence, in this method of companion generation, the customers with higher willingness-to-purchase scores were chosen. Then for each customer, the companions were picked from his/her friends randomly.

The untargeted companion generation approach was used as the benchmark to compare the effectiveness of the proposed method. Each recommendation strategy recommended ten GPP coupons: three "catering" coupons, four "leisure" coupons, and three "cosmetic and maintenance" coupons. For each product, we recommended five target customers and five corresponding group lists each consisting of three companions. In total, 50 target customers received the recommended list of companions.

4.3.4. GFP coupon recommendation

In the experiments, two recommendation strategies were adopted to evaluate willingness to purchase the product promoted:

(1) Coupon recommendation with a group member list.
(2) Coupon recommendation without a group member list.

Each recommendation strategy recommended ten coupon products: three "catering" coupons, five "leisure" coupons and two "cosmetic and maintenance" coupons; for each product, we chose the groups with the highest three cohesion scores. The size of the consumption group was set at four. In total, 30 groups were recommended. Each group contained four people, so in total 120 people received the GFP coupon recommendation.

5. Results and evaluation

In order to evaluate the performance of the group coupons recommended, the experiments utilized online questionnaires to collect feedback on satisfaction with the recommendation. The evaluation of the GPP coupon recommendation is discussed in Section 5.1 and the evaluation of the GFP coupon recommendation is discussed in Section 5.2.

5.1. Accuracy of GPP coupon recommendation

In order to evaluate the effectiveness of the proposed mechanism in identifying the customers with high willingness-to-purchase scores, three other approaches, which considered only a subset of factors, were chosen as benchmark methods to compare accuracy. The evaluation included three parts: liking for the recommended product, satisfaction with the recommended companion list, and the elimination rate of the companion list. For each recommendation strategy, each target customer was asked to answer the following three questions in an online questionnaire:

- Question 1: *How much do you like this coupon?*
- Question 2: *Do you want to use this coupon with this group of friends?*
- Question 3: *If possible, how many recommended group members would you like to eliminate from the list?*

The scoring scale used to rate the liking for the recommended coupon was from 1 to 5, where 5 represented a higher degree of liking for the GPP coupon. The scoring scale used to rate the satisfaction of their recommended companion list was also from 1 to 5. The number of members to be removed from the recommended companion list ranged from 0 to 3.

Fig. 4 presents the evaluation results of different strategies for identifying target customers. The PLI model has the highest average product liking score. The random model has the lowest average liking score. The results show that the PLI model performs better in terms of recommendation than other benchmark approaches. The results also reveal that the preference factor plays a more important role in purchase decisions for package coupons. A paired sample t-test was used to verify the significance statistically of the difference of the liking score results (see Table 4). At the 95% significance level, all the test results showed that the strategy "PLI" was significantly different, at 0.05, in relation to the other strategies. Therefore, this proves that our proposed strategy outperforms other strategies.

Fig. 5 presents the results of satisfaction with companion lists for two different methods of generation of companion lists. The results show that our method of companion list generation had higher satisfaction in terms of the recommended companion list. Tables 5 and 6 show the statistical verification results which verify that our proposed mechanism outperforms other benchmark approaches at a significantly different level.

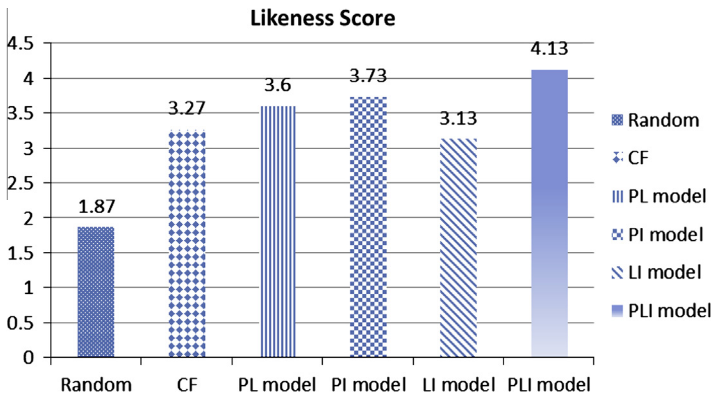

Fig. 4. Liking scores in relation to different customer identification strategies.

Table 4
Statistical verification results of PLI model on liking score.

Paired group	Mean	Std. deviation	Std. error mean	*T*	Sig. (2-tailed)
PLI					
PL	.54000	.33352	.08663	6.233	.000
PI	.40000	.22678	.05855	6.831	.000
LI	1.00000	.73095	.18873	5.299	.000
CF	.86000	.41713	.10770	7.985	.000
Random	2.26667	1.16292	.30026	7.549	.000

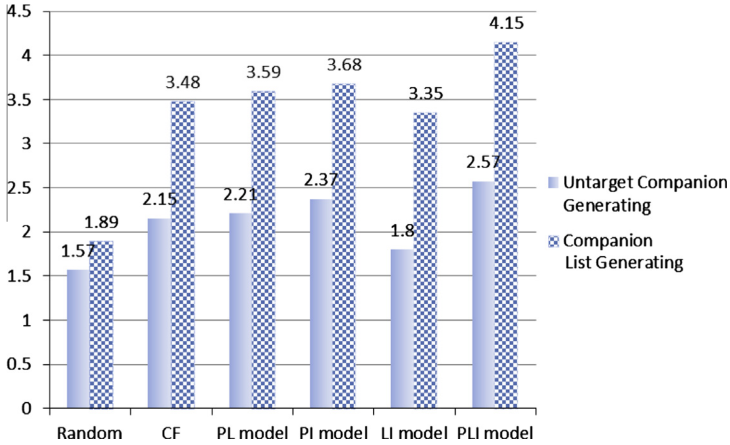

Fig. 5. Satisfaction scores for different companion list generation strategies.

Table 5
Statistical verification results of PLI model on satisfaction score using untargeted companion generating module.

Paired group	Mean	Std. deviation	Std. error mean	*T*	Sig. (2-tailed)
PLI					
PL	.33333	.29681	.07664	4.350	.001
PI	.28000	.18593	.04801	5.832	.000
LI	.73333	.56779	.14660	5.002	.000
CF	.39333	.28900	.07462	5.271	.000
Random	1.00000	.59881	.15461	6.468	.000

Table 6
Statistical verification results of PLI model on satisfaction score using companion list generating module.

Paired group	Mean	Std. deviation	Std. error mean	*T*	Sig. (2-tailed)
PLI					
PL	.52667	34323	.08862	5.943	.000
PI	.45333	.35830	.09251	4.900	.000
LI	.80000	.41057	.10601	7.546	.000
CF	.60000	.29520	.07622	7.872	.000
Random	2.20000	.94415	.24378	9.025	.000

Fig. 6 shows that the companion list generated by the proposed PLI model had the highest hit ratio. The random model using the untargeted companion list generation approach had the lowest hit ratio. The results also verify that generating the companion list based on group cohesion analysis always results in better performance than the method of untargeted companion list generation. Tables 7 and 8 show the statistical verification results which verify that our proposed mechanism outperforms other benchmark approaches at a significantly different level.

5.2. Accuracy of GFP coupon recommendation

The target customers with higher willingness to purchase were identified using the proposed PLI model. The evaluation of customer satisfaction included two parts: willingness to purchase the recommended coupon and willingness to purchase the recommended coupon which is attached to a group member list.

Each group member in the recommended group was asked to answer the two questions in an online questionnaire.

- Question 1: *How willing are you to purchase this coupon?*
- Question 2: *How willing are you to purchase this coupon with the group member list?*

The scoring scale used to rate willingness to purchase for both questions was from 1 to 5.

Fig. 7 shows the willingness to purchase of the customers discovered by the top-10 and top-20 strategies. We can observe that a customer's "willingness-to-purchase" increased if a group member list was also recommended. In addition, the top-10

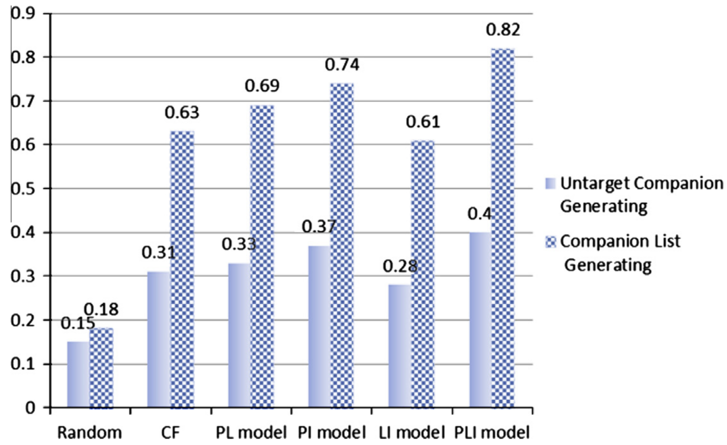

Fig. 6. Hit ratio of different companion list generation strategies.

Table 7
Statistical verification results of PLI model on hit ratio using untargeted companion generating module.

Paired group	Mean	Std. deviation	Std. error mean	*T*	Sig. (2-tailed)
PLI					
PL	.73333	.02845	.00735	9.982	.000
PI	.33333	.02225	.00575	5.801	.000
LI	0.12000	.06876	.01775	6.757	.000
CF	.09333	.03811	.00984	9.485	.000
Random	0.24667	.10601	.02737	9.012	.000

Table 8
Statistical verification results of PLI model on hit ratio using companion list generating module.

Paired group	Mean	Std. deviation	Std. error mean	*T*	Sig. (2-tailed)
PLI					
PL	.12667	.07575	.01956	6.476	.000
PI	.08000	.04690	.01211	6.606	.000
LI	.20667	.11159	.02881	7.173	.000
CF	.18667	.11721	.03026	6.168	.000
Random	.63333	.14960	.03863	16.396	.000

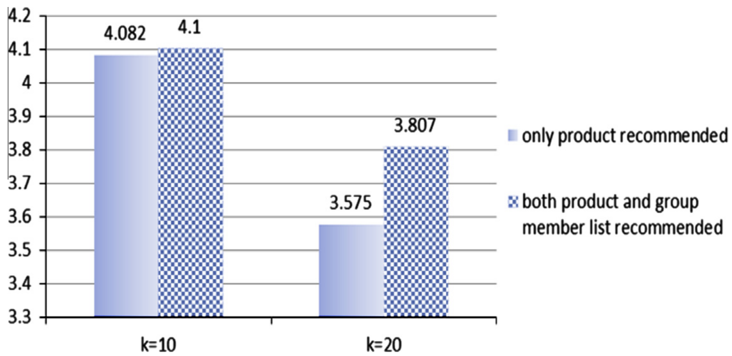

Fig. 7. Willingness to purchase for different top-*k* customer strategies.

recommendation strategy resulted in a higher average willingness-to-purchase score than the top-20 recommendation strategy, no matter whether a group member list was recommended or not. However, the enhanced level of willingness-to-purchase from a recommended group member list in the top-20 strategy was higher. This result is because the average relation of a recommended group discovered by top-20 strategies is stronger.

6. Conclusions

This paper proposes a group-coupon recommendation mechanism for location-sensitive products. Customers' decision making with regard to purchasing in a physical store was analyzed based on three main factors: the similarity between user preference and product characteristics, the geographic convenience of store position, and the influence of friends' evaluation of the product. For GPP coupons, we identified customers with a high willingness to purchase and suggested companions of high cohesion. For the GFP coupons, we identified the set of members with a high willingness to purchase and recommended the target product.

The results of the experiment showed that revealing the list of group members could significantly increase a customer's willingness to purchase due to the effect of social influence. Furthermore, the recommendation mechanism helped customers to discover products of interest to them by reducing the search cost of finding coupon products. The proposed group-coupon mechanism could effectively assist traders to increase their revenues by attracting the minimum number of group members through taking advantage of the power of individual preference, social influence, and location sensitivity.

6.1. Research contributions

This research provides several significant contributions. Firstly, from the methodological perspective, the proposed mechanism, which comprehensively considers multi-criteria factors (preference, location, and influence), can accurately identify customers with high willingness to purchase the products promoted. We also offer a mechanism for forming cohesive groups which can significantly augment the value derived from collective purchasing. Secondly, from the empirical perspective, the results of the experiments on the Facebook platform verify that suggesting and revealing companion names with the coupons can effectively increase the willingness to purchase on the part of the target customer. Furthermore, we also find that the effect of group members is particularly significant when the group size is small. Thirdly, from the practical perspective, the proposed mechanism can provide practical support for the group commerce provider in terms of recommending group package coupons and group-formed coupons with a list of companions or group members. The mechanism can significantly improve the benefits of group commerce, being advantageous both in cost reduction and revenue enhancement. It provides the group commerce providers with a powerful tool to promote location-sensitive products/services successfully.

6.2. Research limitations and future studies

While we have demonstrated the effectiveness of the proposed system, there are some limitations in the group-coupon recommendation mechanism. Firstly, the mechanism does not exclude the scenario that a customer may be included in more than one consumer group list concerning the same product. This could lead to the same customer being invited to visit the same store more than once; the repeated recommendation issue could be the subject of further work. Secondly, the mechanism also has the problem of cold start. To make an effective recommendation, the proposed mechanism needs a sufficient number of customers who already exist in the network and substantial data on customers' online behavior.

There are several related issues which could be further studied. Firstly, with the rapid development of mobile devices, group commerce recommendations could be applied to mobile devices to provide more immediate group lists with more accurate and timely location information. Secondly, the factors included in evaluating and identifying the target customers could be further extended or elaborated. For example, purchasing history and affiliation data could be considered in the analysis. Thirdly, in addition to cohesion analysis, group preference could be considered to evaluate further the value of the group formed. Fourthly, as well as the discovery of group members, there is the potential for more influential social content which could increase a customer's willingness to purchase to be discovered. Fifthly, in this study, customers were requested to evaluate the relative significance of preference, location and influence. Other alternative approaches, such as clustering methods, could be used for more systematic analysis. Finally, it would be interesting and desirable to compare in greater detail the effects of social influence in relation to various types of group product and different social commerce platforms.

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