World Academy of Science, Engineering and Technology
International Journal of Economics and Management Engineering
Vol:10, No:8, 2016

A Social Decision Support Mechanism for Group Purchasing

Lien-Fa Lin, Yung-Ming Li, Fu-Shun Hsieh

***Abstract*—**With the advancement of information technology and development of group commerce, people have obviously changed in their lifestyle. However, group commerce faces some challenging problems. The products or services provided by vendors do not satisfactorily reflect customers' opinions, so that the sale and revenue of group commerce gradually become lower. On the other hand, the process for a formed customer group to reach group-purchasing consensus is time-consuming and the final decision is not the best choice for each group members. In this paper, we design a social decision support mechanism, by using group discussion message to recommend suitable options for group members and we consider social influence and personal preference to generate option ranking list. The proposed mechanism can enhance the group purchasing decision making efficiently and effectively and venders can provide group products or services according to the group option ranking list.

***Keywords*—**Social network, group decision, text mining, group commerce.

I. Introduction

WITH advancement of information technology and development of Web 2.0, there are a large variety of e-commerce applications, such as social commerce applications, mobile commerce applications and group commerce development etc.

The main factor of creating social commerce network is letting customers easily browse the marketplace, according to survey by Consumer Electronics Association [1], 24% of social network users browse social media before making a product decision, and 38% are referring to the comments from user who has goods or service experience. 84% people use reviews from opinion leaders to make business decision and 51% are used to share their product or service experience on social media. Additionally, for creating suitable products or services, most enterprises collect knowledge from customers [2]. According to a survey [3], 71% of products or services recommendation information provided by consumers are valuable to the companies. That is to say using product suggestions from customers can attract more customers to purchase.

Recently, group commerce has become an appealing electronic commerce. The group commerce venders provide products or services on the on-line websites, and they offer significantly discount price for customers who buy large quantity goods. In other words, when customers are aggregated to reach a required group size, they can enjoy discounted group price. According to research report from Institute for Information Industry, the group commerce market value increases from 7.2 billion dollars in 2010 to 9 billion dollars in 2011 [4] and the group commerce market value will up to a trillion in 2015. With the popularity of social media, the customer grouping phenomena is emerging and many emerging applications consider the role of social interactions in group commerce [5]. According to a report from TechCrunch [6], group commerce companies attempt to integrate with social platforms, such as Facebook, to allow consumers to post or discuss about the products or services they purchased.

In order to increase the quantity of products or services, group commerce vendors recommend coupons, advertisements or restaurants to the customers' based on their personal preference, such as staying time of browsing goods website or the types of goods previously purchased. However, many purchasing or consuming activities are likely group-driven, such as watch movie, travel, etc. Personalized decision method cannot meet requirements from group members because individual preference cannot represent group preference. In addition to the preference of each group member, the social influence and comments from opinion leaders are also the key factors affecting the group recommendation performance.

According to a report from Institute for Information Industry [7], the development of group commerce gradually slows down because customers cannot find the goods which conform to their needs. In order to enhance group consumption, enterprises have to provide differentiation or customization of goods. Although group commerce provides differentiation and customization of goods for customers, these kinds of promotions are mainly manipulated by the vender.

Recently, many group commerce enterprises use feedbacks from groups or organizations to learn customers' needs. For example, Groupon collaborates with CafePress, which sells group customization products, to build a platform to let groups of customers set group product types or factors which customers want to [8].

Group commerce enterprises provide a group decision platform and let customers organize groups to discuss their goods needs to produce more suitable product. However, this current approach has some drawbacks: first, group members have to take a lot of time to reach the consensus during the discussion; second, the final decision result may not be satisfactory to all group members. In this study, we aim to propose a social decision support mechanism grounded on social media for group purchasing commerce. The proposed mechanism can extract the customers' need and enhance the

Lien-Fa Lin is with the Information Communication Department, Kao Yuan University, Taiwan (corresponding author to provide phone: +886-7-607-7260; fax: +886-7-607-7260; e-mail: lienfa0704@ gmail.com).

Yung-Ming Li and Fu-Shun Hsieh are with Institute of Information Management, National Chiao Tung University, Taiwan (e-mail: yml@mail.nctu.edu.tw, a0912pudding@hotmail.com).

efficiency (time reduction) and effectiveness (consensus satisfaction) of group decision-making. Three main research questions are studied in this paper:

(1) How to exploit social media to generate proposals for group purchasing? Before group discussion, we build up options databank from the comments expressed on social media, such as Facebook fans page, blogger, or e-commerce websites etc. And considering different option criteria, a list of options are generated for support the discussion of group members. If the group members cannot reach consensus on the options, the system can discover and extend the options databank to recommend new options according to group discussion message.

(2) How to find the opinion leader within a group during the discussion process? The definition of opinion leader is someone who has a lot of accurate product or service information and whose opinions will influence people to make a decision. It is difficult for us to know who the opinion leader is. But we can utilize their interest or preference to identify the opinion leader. On social media, we can analyze personal interest by the set of fans pages a user clicked "like" button.

(3) How to optimize group member's satisfaction when they reach group consensus? Before making decisions, group members will express their individual opinions on the options. Their discussion messages could be segmented and separated into important nouns and adjectives. Each group members' social influence and personal expertise influence should be considered when the opinions of group members are evaluated.

In this paper, we aim to enhance the decision-making performance (efficiency and effectiveness) in group purchasing by the utilizing the social media platform. We incorporate social context with group collaboration systems to help the group easily make decisions. According to the experimental results, the proposed system can support group members to make a decision on selecting group purchasing opinion efficiently and satisfactorily. Group commerce venders can also benefit from providing more appropriate group products/services according to the option with consensus.

The remaining sections are organized as follows: Section II discusses the related literature. In Section III, the research model will be demonstrated, and the experiments will be presented in Section IV. The experiment results and evaluation are discussed in Section V. Finally, Section VI concludes this study and presents the directions of future research

II. Related Work

A. Social and Group Commerce

Social commerce is a form of commerce which integrates both online and offline environments by social media platform and social commerce utilizes social network sites for social interactions and user information to promote the online buying and selling of various products and services [9]. Significantly affected by fast development of social networks, social commerce has become a synonym for the next generation online commerce [10]. Moreover, electronic commerce venders build social platforms to provide goods or advertisement recommendation services.

Group commerce is a specific type of social commerce. While the concept of group commerce is a group of customers bundling together for bargaining goods price [11] and reason of fast group commerce development is dependent on new information technologies and the global proliferation of the Internet. Moreover, group commerce websites, where buyers with similar purchase interests congregate online to obtain group discounts, have metamorphosed into several variants. The most popular variant is the deal-of-the-day group-buying website. With the feature of fast-growing, group commerce market value increases from 7.2 billion dollars in 2010 to 9 billion dollars in 2011 [4], and the group commerce market value will up to a trillion in 2015.

In this research, we present the social decision mechanism customer purchasing decision making, which is implemented in social network platforms, such as Facebook, for support group purchasing with option proposing and opinion evaluation.

B. Purchasing Decision Making

According to [12], before making purchase decisions, individual or group consumers will ask the opinions of someone who have information about products they will want to buy. When they want to make a decision, they will be often influenced by the people who have similar decision experiences. Several individual or group consumer behavior decision models were proposed. In consumer decision-making models, utility model theory suggests that consumers make a purchasing decision by usefulness of products; consumers are seen as rational actors who will estimate the product utility scores. However, in the real world, consumers are not entirely rational. Conversely, Simon proposed a concept of decision-making process [13]. In this process, a decision maker can evaluate and compare all options with others. There are three phases: intelligence, design, and choice. Intelligence means thinking and finding all problems that will be encountered when someone proposes the alternatives. Design refers to a process that creates, develops, and analyzes all available alternatives. Choice means selecting an alternative from the possible options.

When consumers need to make decisions on something, they begin to search some information and ask someone who has the past experience. Then, in the stage of alternatives evaluation, consumers will evaluate all alternatives with some established criteria that are might be derived from past experience and friends who have given advises. Finally in purchase decision stage, consumers will stop searching and evaluating information and make their final purchase decisions.

In this research, we use group members' interaction messages to analyze each group members' preference on each option. Then according to their opinion view to identify what kind of option criteria is the most people prefer.

C. Purchase Decision Making

Individual decision making is to maximize decision effectiveness in the condition of being given limited resources. However, there are three factors influencing people when making a decision: influential people, utility improvement from the options, and people's social network [14].

Social influence is the process that individuals will change their feelings, thinking or behavior when interacting with someone with similar experience or expert [15]. In the past, traditional social behavior is realized through physical interactions, such as face-to-face communication. But now there have a lot of powerful social network platforms which allow us to interact with each other on the Internet. As the quick development of social media, consumers can much easily get information (people's preference and relationship) from on-line sources and make a decision with the support of their social network. It is an ideal approach to build up a decision support system by utilizing online social information which can extract much valuable data sources [16].

In this research, we present a social decision support mechanism according to human behaviors on and information extracted from the social networks.

D.Multi-criteria Decision Making and Adjective Analysis

It is a common decision-making process that people solicit some opinions from their friend social network before they makes a decision. However, the feedbacks are likely to be vague as we usually use nature language to express our opinions. So, when people make decisions, they will encounter some problems, such as getting completely unknown or incompletely known information, time pressure, lack of knowledge and limited expertise [17].

Recently, intuitionistic fuzzy sets have been used for dealing with information vagueness in the semantic web [18]. Conceptually, intuitionistic fuzzy sets have feasible presentations for the degree of membership and non-membership, and degree of uncertainty [19]. It is difficult to level and classify users' options. TOPSIS ("the technique for order preference by similarity to the ideal solution") a powerful tool to classify the adjective level of the opinions. This technique is proved to be effective in solving multiple-adjective classification problems [20]. The concept of the technique for ordering preference by similarity to the ideal solution uses positive and negative aspects to level adjective degree [21]. For example, an adjective that is closer to the positive aspect also indicates that it is farther from negative aspect in the meanwhile.

In this research, we use vague information method to analyze vague words extracted from the interaction messages and apply the TOPSIS method to classify the positive and negative adjective sentiment of the opinion.

III.The Model

In the proposed mechanism, we use a social media platform to analyze group interaction messages which could help us know the preference of group members. Besides, we use social relationship to compute the closeness and interaction between the group members for finding the opinion leader, the most influential people. In the meanwhile, we use personal expertise score to understand the product professionalism of each group member. Finally, this mechanism would utilize these expertise, social relationship and closeness, and criteria evaluation information to get the alternatives ranking list. Fig. 1 outlines the architecture of our proposed mechanism.

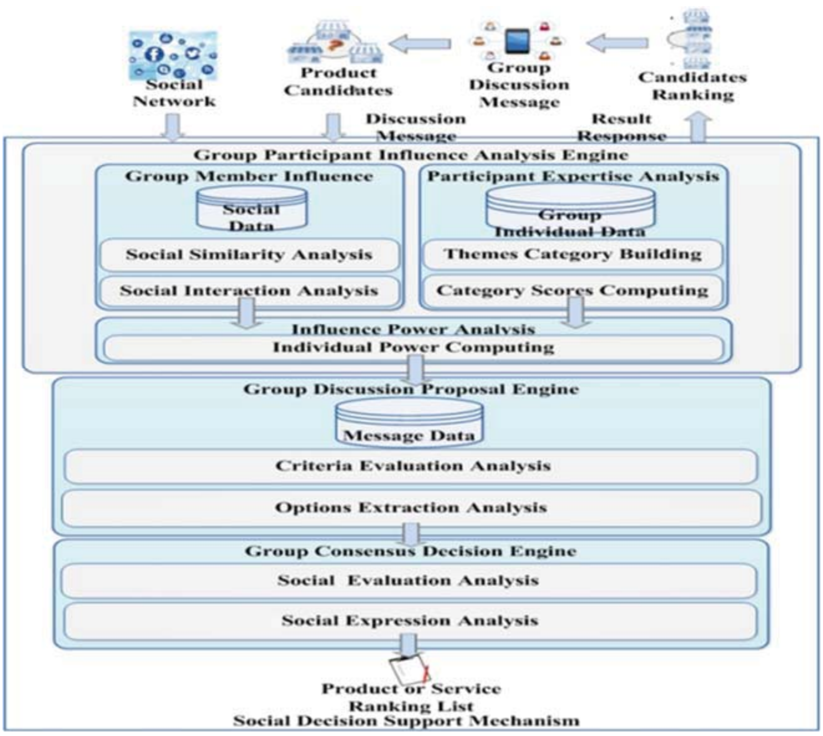

Fig. 1 Group Decision Support Mechanism Framework

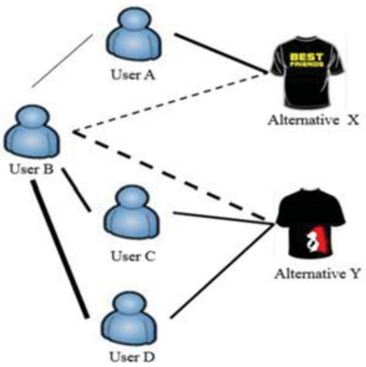

Fig. 2 The Social-Affiliation Network

A. Group Member Influence Analysis

1) Group Formation

When people, with same topic or target, make a group purchasing decision, such as go to restaurant, planning a travel tour, or purchasing group souvenir, they will organize a group to discuss.

2) Social Influence Analysis

The purpose of Social Influence Analysis module is to identify the all member similarity and the social tie strength in the group according to social information collected from social media. We use social-affiliation network to find what alternatives the member have interest. The social-affiliation network can be built up based on a group user's social network relationship. As shown in Fig. 2, if member A likes alternative X and share it (line AX) on his or her social platform to his/her friend B, the social influence will affect the friend B and arouse his/her friend's interest about alternatives X (line BX). However, the social influence power is not the same for all group users. For example user A, C and D are the user B's friends. Compared with A, users C and D have closer relationship (represented by a border line) with user B. User A, C and D are interested in different alternatives (A interested line is AX, C is CY, D is DY), because user B is closer relationship with user C and D, compared with alternative X (dotted line BX), he/she will be interested in alternative Y (border dotted line BY). Moreover, people join the same club because of the same interest. The more number of mutual clubs two people joined, the higher influence between them. In this research, we consider the number of mutual clubs on Facebook between each group members. Therefore, we should consider the relationship closeness to evaluate the social influence degree. If there are more common friends and clubs on Facebook between two people, their social tie will be stronger. Denote *Club* (m_i) as the set of clubs group member m_i attended in and *Club* (gm_i) is set of clubs group member gm_i attended. $AllClubs(m_i, gm_i)$ represents the total number of clubs group member m_i and gm_i participate in. And $Club(m_i) \cap Club(gm_i)$ denotes m_i and gm_i mutual joined clubs (both of they attended). *Friends* (m_i) as the set of group member m_i's friends and *Friends* (gm_i) is set of group member gm_i's total friends. $AllFriends(m_i, gm_i)$ is total number of member m_i's or gm_i's friends. The social similarity degree between group members m_i and gm_i is measured as:

$$GSS(m_i, gm_i) = a * \frac{|Club(m_i) \cap Club(gm_i)|}{AllClubs(m_i, gm_i) - |Club(m_i) \cap Club(gm_i)|} +$$

$$(1-a) * \frac{|Friends(m_i) \cap Friends(gm_i)|}{AllFriends(m_i, gm_i) - |Friends(m_i) \cap Friends(gm_i)|}$$

The social similarity scores between member m_i and other group member gm_i attending group discussion is represented as

$$GSS(m_i) = \{GSS(m_i, gm_1), GSS(m_i, gm_2), GSS(m_i, gm_3) \cdots GSS(m_i, gm_n)\}$$

We can use interactions on the social media to calculate the social tie strength between two participants. Social interactions can be taken from the online posts on the social platform. In the research, we use the number of replied messages to calculate the strength of social interactions. Denote *Post* (gm_i) as the set of group member gm_i ‘s posts and *Comment* (gm_i) is the set of group member gm_i*'s* comments. Social interaction strength between group member m_i and gm_i is denoted as *GSI* (m_i , gm_i) and formulated as:

$$GSI(m_i, gm_i) = \frac{|Post(m_i) \cap Comment(gm_i)|}{|Post(m_i)|}$$

The social interaction scores between group members m_i and other group members is represented as:

$$GSI(m_i) = \{GSI(m_i, gm_1), GSI(m_i, gm_2), GSI(m_i, gm_3), \cdots, GSI(m_i, gm_n)\}.$$

Then, we normalize the social similarity and interaction scores by min-max normalization as:

$$Value_{nor}(m_i) = \frac{Value(m_i) - Min(m_i)}{Max(m_i) - Min(m_i)}$$

Finally, we merge two scores as SP_{nor} to represent the social influence weight.

$$GSP_{nor}(m_i) = GSS_{nor}(m_i) + GSI_{nor}(m_i)$$

3) Participant Expertise Analysis

Customers choose various kinds of product with their preference. For finding the target products which customers are interested in, identifying preference from customers is an important marketing skill. If people have high interest in some products, they likely have high familiarity with and expertise on the product. The purpose of this analysis is to find the group members' preference and infer a member's expertise influence. The measurement of this analysis is donated as PE score which represents the expertise of group members in some products categories.

Social Supporters Discovering Module Before calculating the group participant expertise score, a product category has to be built by referencing certain classification index. Each product is classified into only one category. In this research, the products categories include entertainment, food, travel, and sport.

We can utilize Internet behavior to observe the group member's preference, for example if people are interested in shopping, they will pay a lot of attention to shopping website. So we can aggregate each group member preference to identify an expert. We use social media platform, Facebook, to analyze the social behavior of each group member. Therefore, we utilize Facebook fans pages on which group member click "Like" Button to identify group expert.

After Facebook fans pages were collected, we break down each Facebook fans pages post into separated terms by using the key terms identification technique TF-IDF (Term Frequency–Inverse Document Frequency). The concept of TF-IDF is to find important terms based on term frequency and the representative terms across documents. For example, for a term *t* contained in a document, the importance of the term can be measured by TF-IDF score as:

$$w_{i,j} = tf_{i,j} \times idf_i \, , tf_{i,p} = \frac{frequent_{i,p}}{Max_l(frequent_{l,p})}$$

$$idf_i = \log \frac{TNM}{n_i} \, ,$$

Before we collect Facebook fans pages "Like" button from each group member, we search 50 Facebook fans pages by each product category. So each group member have 4 *PE* scores (entertainment, food, travel and sport). According to these *PE* scores we can set each group member weight in different purchasing decision scenarios.

Denote $PE(m_i,c_i)$ as m_i's participant expertise score with respect to category c_i. $PE(m_i,c_i)$ is group member m_i's the number of "Like" of the Facebook fans pages clicked in category c_i, and NFG_{c_i} is the Facebook total fans pages number in category c_i.

$$PE(m_i,c_i) = \frac{CF(m_i,c_i)}{NFG_{c_i}} \, .$$

Then we normalize the participant expertise scores by min-max normalization as:

$$PP_{nor}(m_i,c_i) = \frac{PP(m_i,c_i) - Min\{PP(m_j,c_i)\}}{Max\{PP(m_j,c_i)\} - Min\{PP(m_j,c_i)\}} \, .$$

$$PP(m_i) = \{PP_{nor}(m_i,c_1), PP_{nor}(m_i,c_2), PP_{nor}(m_i,c_3), PP_{nor}(m_i,c_4)\}$$

4) Influence Power Analysis

In discussion and decision process, people will be influenced by close friends or experts. So, in influence power analysis, we combine each social influence score and participant expertise score from each group member. Each group member has different participant expertise scores with respect to different discussion scenarios. The group member gm_i's influence power in c_i category is measured as:

$$GIP(gm_i,c_i) = GSP_{nor}(gm_i) * PP_{nor}(gm_i,c_i) \, .$$

where $GSP_{nor}(gm_i)$ is group member gm_i's social influence power score in the group. $PSP_{nor}(gm_{i,},c_i)$is the set which puts group member gm_i's participant expertise score in category c_i. So we can utilize these individual influence power scores to set opinion weight of each group member in different category scenario.

B. Group Discussion Proposal Analysis

Recently, many people use social media to share and discuss experiences on purchasing decision making. So, we collect discussion messages from social media to analyze and to discover the topics and products the majority of people talked about. Therefore, in group proposal discussion analysis module, we have two objectives: First, according to group discuss topic, we aim to automatically detect new options, which are related with the topic. Second, according to group discussion context, we extract adjective of each option criteria and use these criteria to recommend new options which are similarly conform to option criteria in the discussion context. Before we analyze the discussion messages, the sentences are separated by using CKIP Chinese words segmentation system.

An option is group candidate or choice which they can select. The criteria are request or condition which group members care about. For example, customers select a restaurant, they will consider service quality, price and kind of dishes, therefore service quality, food price and kind of dishes are criteria in food selecting scenario. And criteria evaluation is group member can directly evaluate the options with respect to different criteria by using some adjectives, such as delicious, good, tasty, etc.

1) Criteria Evaluation Analysis

Adjectives are useful emotional indicators in the sentiment. Using sentiments of adjective, we can know personal subjective judgment from each group member. When people make a decision, they are more influenced by the opinions with positive or negative adjectives. We categorize the adjectives into two types: positive and negative and evaluate these adjective sentiments. Using the method proposed by Turney and Littman, an adjective graph with orientation identification, which is nondirective synonymous, is built up. With this graph, we can use the length of the shortest path between polar positive and polar negative aspect to measure adjective scores [21]. The adjective score $AS_{adj}(cr_i)$ is measured as: $AS_{adj}(cr_i) = ND_{adj}(cr_i) - PD_{adj}(cr_i)$, where $PD_{adj}(cr_i)$ is certain option criteria c_i of the path distance between adjective and polar positive and $ND_{adj}(cr_i)$ is certain option criteria c_i of the path distance between adjective and polar negative.

Fig. 3 Semantic Orientation Identification

Fig. 3 illustrates semantic orientation identification process. Suppose a discussion message has an adjective "Good" and we want to compute adjective Good AS_{adj} score. We need to calculate the distance from adjective "Good" to Polar Positive and Polar Negative. Adjective Good $PD_{adj}(cr_i)$ score is 1, $ND_{adj}(cr_i)$score is 3 and $OS_{adj}(cr_i)$ score is 3-1=2.

OS_{cr_i} is each group member's adjective score in certain option criteria cr_j |G| is total number of group members. The matrix is represented as:

$$OS_{cr_i} = \{OS_1, OS_2 \cdots OS_{|G|}\}\ .$$

$$OS_{nor}(gm_i, cr_j) = \frac{OS(gm_i, cr_j) - Min_k\{OS(gm_k, cr_j)\}}{Max_k\{OS(gm_k, cr_j)\} - Min_k\{OS(gm_k, cr_j)\}}\ .$$

We use semantic orientation identification method to score each criteria evaluation (adjective). Next, we aggregate and calculate evaluation average scores from each options criteria. Finally, we use average evaluation scores of each criteria to compare with the opinions in the option bank, and recommend the option have high similarity in the database.

In the discussion process, people will be influenced by close friends or experts. So, option generation module also considers social influence and participant expertise of each group member. According to different purchasing scenarios, group members have different influence power weights. So we can calculate each criteria evaluation score from each group member. The average option o_i's evaluation score from each group member is obtained as:

$$GDMAdjscores_{c_i, o_i, cr_i}(gm_i) = \frac{\sum_{i=1}^{N}[GIP_{c_i}(gm_i) * OS_{o_i, cr_i}(gm_i)]}{N}$$

2) Options Extraction Analysis

The objective of this analysis is to generate new options for group members, so we utilize group discussion message and evaluation from the public and unprejudiced third parties, such as blogger or forum, to generate the options. The first step is to compute the similarity between the discussion group's evaluation for option criteria and the evaluation in the option bank. The second step is to use TF to determine the term with highest frequency. This expresses that this term is a candidate option for the group.

Option Extraction from Outside Source

We have to build option bank by on-line information and classify the option by using product category, therefore option bank have four type product categories, and the four type categories are food, travel, sport and entertainment. There are a lot of evaluations on the Internet, so we use keyword to find several certain option comments from Facebook fans pages, blogger or forum post, and use CKIP system to separate each comment. Finally, according to option criteria, we extract evaluation of certain option criteria. For example, we want to find criteria evaluation of restaurant price, and then we get the evaluation such as cheap, reasonable or expensive. And we determine the evaluation of certain criteria with same adjective times which is certain option. For example, the times of food price criteria cheap 9 times, reasonable 4 times, expensive 1 time, we can judge that this food option price's criterion is cheap. After having option evaluation of each certain criterion, we transform each option criteria evaluation into scores. The option bank form is shown in Table I, and Table II is transforming each options criteria to scores.

TABLE I
OPTION BANK FORMAT

	option1	**option2**	**option3**	**option4**
Price	Cheap	Very Cheap	Expensive	Normal
Environment Quality	Good	Bad	Good	Normal
Food Quality	Normal	Normal	Very Good	Normal

TABLE II
TRANSFORM OPTIONS TO SCORES

	option1	**option2**	**option3**	**option4**
Price	2	4	-2	0
Environment Quality	2	-2	2	0
Food Quality	0	0	4	0

Option Expansion from Discussion Messages

We collect group discussion messages and use CKIP to separate words in the messages. Then, we use term frequency (TF) to find the words that occur frequently in the messages. Each term is assigned a score based on their frequency, and we use the term with the highest frequency as a candidate option. When people frequently mention a term, it likely means that it is the subject of discussion, and has a high probability of being a candidate option. So we extract the option associated with this term and criteria evaluation from each group member, finally store it in our options bank for further extraction.

Discussion Category Initiation

In group discussion process, a hosted person will determine group discussion topic. Therefore, group member needs a hosted person to decide their discussion issue. The person who gathers group member can determine group discussion topic and our system recommends three options which are related to the setting topic for group discussion. For example, if a hosted person initiates that a topic is food category, our system will recommend three options from the food category option bank. Denote $CategorySim(GC, DB_{c_i})$ is category similarity between the hosted person of group and database category, GC is the category score from the hosted person, and DB_{c_i} is category score of c_i. We recommend the options by the minimum category score. Table III shows the category score format.

$$CategorySim(GC, DB_{c_i}) = Min\,|\,(GC - DB_{c_i})\,|$$

TABLE III
CATEGORY SCORE FORMAT

Category	Food	Travel	entertainment	Sport
Score	1	2	3	4

Discussion Option Selection

After determining the discussion category, we utilize the criteria evaluation from group discussion message and option bank to calculate criteria similarity between group discussion message and each option in option bank. The formula is shown as:

$$AdjSimilarity_{o_i}(GDM_{cr_i}, DB_{cr_i}) = \sum_{i=1}^{n} | GDMAdjscores(cr_i) - DBAdjscores_{o_i}(cr_i) |$$

where AdjSimilarity(.) is each criteria adjective similarity between group discussion messages and the option bank. GDM_{cr_i} is criteria cr_i which is discussed by a group, DB_{cr_i} is criteria cr_i from the option bank, and $GDMAdjscores(cr_i)$ is criteria cr_i evaluation score from group discussion messages, $DBAdjscores(cr_i)$ is criteria cr_i evaluation score from the option bank.

$$Recommend = Min_{o_i}(AdjSimilarity(GDM_{cr_i}, DB_{cr_i}))$$

C. Group Consensus Decision Engine

In the group consensus process, we observe each group member's group influence power scores and discussion messages, then we consider two kinds of evaluation scores (social evaluation and social endorse) to generate option ranking list. The social evaluation score is generated using each group member's evaluation on each option and the social endorse score is let group member endorse the options they want to purchase. Finally, we adjust each group member's voting and evaluation weight by group influence power scores, and produce product ranking list. If consensus scores don't exceed some threshold, the system will let group discussion continues again till scores exceed the threshold.

1) Criteria Evaluation Analysis

In social evaluation analysis, we observe each option criteria evaluation from each group member, and use their individual power score to generate social evaluation scores. We denote $SocialEvaScore_{c_i,o_i}(m_i, cr_k)$ as an option o_i 's score by aggregating each member's evaluation for each of the three criteria in category c_i. This scores also considers each member influence power, denoted by $GIP_{c_i}(m_i)$, $GIP_{c_i}(m_i)$ is group member's group influence power in category c_i scenario, $OS_{o_i}(m_i, cr_k)$ is group member m_i 's evaluation score for criteria k, cr_k , of option o_i and *J* is set of option o_i 's criteria.

$$SocialEvaScore_{c_i,o_i}(m_i, cr_k) = \sum_{i=1}^{|G|} \sum_{k=1}^{|J|} GIP_{c_i}(m_i) * OS_{o_i}(m_i, cr_k)$$

2) Criteria Evaluation Analysis

In this part, we use a social expression method to calculate rating score from all group members. In the traditional condition, most of the rating methods treat each group member equally, so the weight of rating is same. But in the real world, our social influence power is always not equal. So we consider different weights to compute each group member's rating score. Denoted $VS(o_i)$ as sum of all member rating scores with different social influence power, and $GIP(gm_i, c_i)$ is group influence power between each group member, $V(o_i)$ is a rating score by all group members. If a member does not vote for any option, then their rating score will be assigned 0.5.

$$VS(o_i) = \sum_{o_i=1}^{n} V(o_i) * GIP(gm_i, c_i), \text{ where } V(o_i) \in \{0, 0.5, 1\}.$$

Finally, we combine social evaluation score and expression score to generate option ranking list. Denote $OptionRankingScore(o_i)$ as option o_i 's final option score considering the social evaluation and expression scores.

$$OptionRankingScore(o_i) = \alpha SocialEvaScore(o_i) + (1-\alpha)VS(o_i) > \kappa$$

If $OptionRankingScore(o_i)$ is below a threshold, the mechanism will utilize ranking list to get first option criteria and use the criteria to match option bank, then find a new option for group member to discussion.

IV. Experimental Study

In this section, we execute an experimental study and verify the effectiveness of the proposed framework. The general idea of social decision mechanism is to generate a ranked options list according to the discussion of group members.

A. Experiment Design

We implemented the proposed mechanism on the most popular social network community, Facebook. According to a report form Statistic Brain, there are 1.8 billion active Facebook users. People commonly create a club to discuss or share information. A user is subscripted to averagely 80 groups. So Facebook provides one of the best platforms for implementing a social decision mechanism. Besides, Facebook provides a powerful application programming interface (API), so we can obtain social personal information, such as social relationship between two persons and personal preference from Facebook Pages.

In the experiment, we collect the discussions of the users joining the same Facebook Groups. According to [18], when people join the same groups in the online community, they have higher probability to get together and do some activities together in their real lives. Moreover, as reported by EZprice [6], in the case of group commerce, such as Groupon, 17life, and GOMAJI, the most frequent purchased categories are food, travel and shopping. So in this research, we consider three scenarios for members who are in the same group on Facebook to (1) discuss about what kind of restaurants to eat at, (2) discuss about where they want to travel and (3) discuss about what group product they want to purchase.

We utilize SAS that is an analytical tool to analysis the data with a personal computer that has core i7-4770 GHz CPU and 8 GB memory. When conducting the experimental process, we implement API on Facebook.

World Academy of Science, Engineering and Technology
International Journal of Economics and Management Engineering
Vol:10, No:8, 2016

B. Data Collection and Preprocessing

Data collection includes two parts: group discussion messages collection and social information collection.

In the part of group discussion message collection, our experiments have three scenarios mentioned earlier. Then system will suggest some option criteria to support discussion. In the food scenario, group members will get three restaurant options to discuss, such as McDonald's, KFC and Pizza Hut. In the travel scenario, group members need to discuss with three option about sight. In the shopping scenario, group members discuss what kind of group product they want to purchasing. In the experiments, we collect 37 Facebook Club and there are 184 Facebook Club participants expressing comments on the options. The data was gathered from 2015/11/30 to 2015/12/15.

TABLE IV
THE DATASET SUMMARY AFTER DATA CLEANING

Title	Value
Duration of Experiment	2015/11/30 to 2015/12/15
The Number of Participants	166 participants
The Number of Groups	33 groups
Age	20-65
Gender	Male: 40% Female: 60%

In social information collection part, we collected the social information of each group member, such as their common friends, common Facebook Club, and their liked fans pages. In the real world, some people care about information security, so they locked their information if you are not their friend. Some of social information data can not completely be collected and we eliminate the incomplete data. After data cleanness, there are 33 groups and 166 participants' data we can use. The dataset summary after data cleanness is shown in Table IV.

V. RESULTS AND EVALUATIONS

In this section, we have two methods to evaluate and discuss the experiment performance of the proposed mechanism.

A. Hit Ratio

In the experiment, we evaluate the group member who will buy the products recommended by our mechanism. If the group discussion members feel satisfied with and the social support mechanism also recommends purchasing it. That is to say, we will evaluate our mechanism performance by comparing whether the decision made by the group members matches the first recommending option created by our proposed mechanism. A hit ratio means correct social decision is made.

$$hitratio = \frac{\#ofOptionThatHitTheUser'sSelection}{\#ofOption\,\mathrm{Re}\,commendToUser}$$

where $\#ofOption\,\mathrm{Re}\,commendToUser$ stands for the set of products recommended for purchasing. $\#ofOptionThatHitTheUser'sSelection$ stands for the set of satisfactory products group member purchased.

B. Factor Weighting Determination

In order to determine the weighting approach that brings better performance to the recommendation, we evaluate the weight of each factor by two different approaches: (1) equally weighting approach, (2) group weighting approach. Equally weighting approach assigns the weight equally as 33% for each factor, group weighting approach assigns the weight based on average weight of the each group member. Fig. 4 is performance of different weighting approaches, and Table V is statistical verification results of weighting approaches.

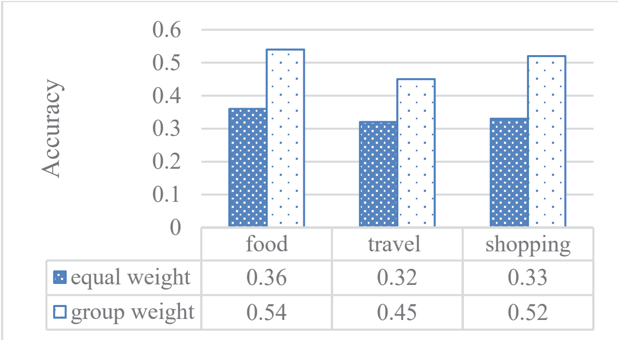

Fig. 4 Performance of Different Weighting Approaches

TABLE V
STATISTICAL VERIFICATION RESULTS OF WEIGHTING APPROACHES

Paired Group		Mean	Std Dev	t-Value	Sig(2-tailed)
Group Weigh	Equal Weigh	0.0384	0.01648	7.71	0

As shown in Fig. 4, because the average weight decided by the group members, so the performance of group weighting approach is better than equal weighting approach. So we utilize group weight approach to decide each factor weighting by the scores that we calculate in Section III.

C. Performance of Recommendation Factors

We compare three factors, social influence, and participant expertise and discussion message with different combinations in different scenarios (food, travel and shopping). Fig. 5 is the average of accuracy including all scenarios. As shown in the figure, we can find our proposed mechanism is higher than other six recommend approaches.

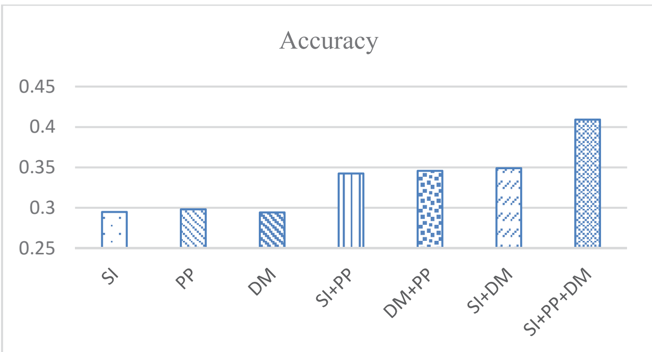

Fig. 5 The Average of Accuracy Including All Scenarios

VI. Conclusion

In this paper, we make some significant contributions described as follows. Firstly, from the practical aspect, most of decision support system mainly uses past data and expert opinions to determine the best option or strategy. None of these systems consider that group decision should integrate social influence between group members, participant expertise, and group discussion message information. The three types of information can provide more suitable option ranking list to group members. Moreover based on the dynamic discussion message analysis, the proposed system can extract and recommend the fittest options for group, then support them to reach common consensus fast.

Secondly, from the methodological aspect, this study integrate the techniques of mining and social network analysis, and MCDM techniques to identify important criteria from discussion context and discover influenced person who is opinion leader or close friends, and determine criteria weights to consolidate the group decision processes under social media environment.

Thirdly, from the empirical aspect, we discover that personal preference is a more important factor than two others in eating scenario, discussion message is a more important factor than two others in travel scenario, and personal preference is a more important factor than two others in purchasing scenario. According to the result of the experiment, the similarity will be significantly improved when system considers more factors.

References

[1] Taiwantrade, URL: http://www.taiwantrade.com.tw/CH/bizsearchdetail/42526/I, Accessed: 03/29/ 2014.

[2] Piller, F.T. and D. Walcher, Toolkits for idea competitions: a novel method to integrate users in new product development. r&D management, 36 (3) (2006) 307-318.

[3] OTX, The Impact of Social Media on Purchasing Behavior, 2008.

[4] Xuite.net, URL: http://blog.xuite.net/jin117/blog/54603029, Acessed: 10/26/2014.

[5] Tse-Ming Tsai,Ping-Che Yang, Wen-Nan Wang, Pilot Study toward Realizing Social Effect in O2O Commerce Services. Social Informatics Lecture Notes in Computer Science, 8238 (2013) 268-273.

[6] EZprice,URL:[http://news.ezprice.com.tw/3133/#.U3LkUvmSySo],Accessed:03/30/2015.

[7] Fodness, D., Murray, B., A Model of Tourist Information Search Behavior. Journal of Travel Research, 37 (3) (1999) 220-230.

[8] Anagnostopoulos. Sellers in e-marketplaces: A Fuzzy Logic based decision support system. Information Sciences, 278 (10) (2014) 267-284.

[9] Sanghyun Kim, Hyunsun Park, Effects of various characteristics of social commerce (s-commerce) on consumers's trust and trust performance, International Journal of Information Management, 33 (2) (2013) 318–332.

[10] Peter Leitner, Thomas Grechenig, Collaborative Shopping Networks: Sharing the Wisdom of Crowds in E-Commerce Environments, 21st Bled eConference eCollaboration: Overcoming Boundaries through Multi-Channel Interaction, June 15 - 18, 2008; Bled, Slovenia

[11] Liu Bao-zheng, Wang Ding-Wei, Research on the realization and the risk of group-buying pattern, Control and Decision Conference (CCDC), pp. 1248 – 1251, 2013.

[12] Peter, J.P. & Olson (1990), Consumer Behavior and Marketing Strategy. Richard D. Irwin Inc. pp.5-6.

[13] Simon, H. A. A Behavioral Model of Rational Choice. The Quarterly Journal of Economics, 69, 1(1955), 99-118.

[14] Alireza Abbasi, Rolf T. Wigand, Liaquat Hossain. Measuring social capital through network analysis and its influence on individual performance. Library & Information Science Research, 36 (1) (2014) 66-73.

[15] Ching-Yung Lin etc. Social Network Analysis in Enterprise, Proceedings of the IEEE (Volume:100 , Issue: 9), Sept. 2012, pp. 2759 – 2776.

[16] Ecommercetaiwanapp, URL: (http://ecommercetaiwanapp.blogspot.tw/2013/12/2013-o2o_8196.html), Accessed:12/15/2014.

[17] S.Y. Chou, Y.H. Chang, and C.Y. Shen, A fuzzy simple additive weighting system under group decision-making for facility location selection with objective/subjective attributes, European Journal of Operational Research 189 (1) (2008), 132-145.

[18] S. C. Alexander, J. L. Peterson, A. B.Hollingshead, Help is at your keyboard: Support groups and the internet. In L. R. Frey, editor, Group Communication in Context: Study of Bona Fide Groups, pp. 309–334, 2003.

[19] K.T. Atanassov, Intuitionistic fuzzy sets, Fuzzy Sets and Systems 20 (1) (1986), 87-96.

[20] Y.C. Hu, Classification performance evaluation of single-layer perceptron with Choquet integral-based TOPSIS, Applied Intelligence 29 (3) (2008) 204-215.

[21] J. Kamps, M. Marx, R.J. Mokken, M.D. Rijke, Using Wordnet to measure semantic orientation of adjectives, in: Proceedings of the LREC, 4th International Conference on Language Resources and Evaluation, 1115-1118, 2004.