國立交通大學

資訊管理與財務金融學系

資訊管理碩士論文

結合行動智慧之群體商務組構機制

Combining Mobile Intelligence with Formation Mechanism for Group Commerce

研究生：謝欣宸

指導教授：李永銘　博士

中華民國 103 年 6 月

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摘要

近年智慧型手機的崛起，造就行動商務的 Social、Local、Mobile 的整合概念(So-Lo-Mo)。目前的 So-Lo-Mo 服務只著重於個體使用者，而較少考慮群體服務之商機，而團體商務的發展現況沒有辦法滿足即時性的團體購物需求，亦較少考量顧客之間的社群關係。本研究將行動智慧與群體商務結合，並且考量偏好（preference）、情境（context）與社會影響（social influence），讓顧客在現場欲購買商品或服務的瞬間，能透過行動裝置即時找到附近具有潛在相同購買興趣的人組構群體（group formation）並且進行群體購物，媒合供需兩端的需求，使得行動商務與團體商務的價值獲得突破性的提升。

關鍵詞：團體構成、團體商務、行動商務、So-Lo-Mo、社會影響

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ABSTRACT

The rise of smartphones brings new concept So-Lo-Mo (social-local-mobile) in mobile commerce area in recent years. However, current So-Lo-Mo services only focus on individual users but not a group of users, and the development of group commerce is not enough to satisfy the demand of real-time group buying and less to think about the social relationship between customers. In this research, we integrate mobile intelligence with group commerce and consider customers' preference, real-time context, and social influence as components in the mechanism. With the support of this mechanism, customers are able to gather near customers with the same potential purchase willingness through mobile devices when he/she wants to purchase products or services to have a real-time group-buying. By matching the demand and supply of mobile group-buying market, this research improves the business value of mobile commerce and group commerce further.

Keywords: Group formation, Group commerce, Mobile commerce, So-Lo-Mo, Social influence.

致謝

光陰荏苒，回首時，碩士班兩年已經成為過去。在這兩年，學習和成長了許多，尤其是最後的碩士論文，需要感謝許多人的幫忙，才能順利完成。

首先要感謝我的指導教授　李永銘老師的指導。李老師和我亦師亦友的關係，讓我不只是向他學習如何做研究，並且也學習到老師的人生體驗和哲學。李老師是一位良師，身懷理想抱負，並且努力付諸實踐、追求價值創造的個性，深深地影響我的思維方式，開始懂得凡事都要思考價值，並且在做事的過程中都要追求能製作精緻的作品，做人處事在各個面向追求盡善盡美，追求自我卓越成長。在學術研究的領域，李老師的教學風格，能夠同時保持好的論文方向和學生能夠自由發揮創意的特質，是老師在深思熟慮之後獨創的教學方式，讓我們學習獨立研究、獨立思考的能力，並且學習如何創新，以及將創新研究出真實具體可行的研究成果。我在 IEBI 實驗室的這兩年，在李老師專業的帶領之下，收穫豐收，順利畢業，並且能以自己具有交大資管碩士學歷與資質為傲。

實驗室的博士班學長姐們，也是幫助我非常多、需要致謝的人們。已經畢業的賴政揚（無尾熊）學長，在我一開始煩惱要如何實作這深具創新性質的論文研究的時候，給予我具體可行的建議，和我討論了兩個小時，讓我能夠初步的釐清論文的概念，縮短從抽象到實務的過程，可以在起跑點走的順暢，十分感謝！李易霖學長會主動找我們這一些碩二的同學們，親切地詢問有沒有任何問題，都可以請教他，雖然是上班族，也願意和我們討論論文，是一位熱心的學長！林聯發（發哥）學長從碩一上學期開始，就常常給予我們指導，在論文主題發想、系統架構與方法、實驗設計、驗證等等，只要是各種

論文的問題，都可以面對面的找他討論，很用心地幫我們思考論文的問題和解決辦法，真的是很謝謝發哥，也祝福發哥可以順利博士班畢業！白檸瑤學姐，數次在 Meeting 之後，和我留在實驗室討論論文的實驗，親切地給我一些建議，在和學姐的討論中，都會讓我更發想到有效的實驗設計，讓我的論文可以進展順利，非常謝謝她。劉智華學姐，常常會和我們聊天，互相討論想法，讓我們能夠放鬆心情，面對未來的挑戰，非常感謝。

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INDEX

List of Equations

List of Tables

List of Figures

Chapter 1 Introduction

1.1 Background

In recent years, group-buying market has been grown up for several years, making surprising revenues all around the world. In United States, The revenues of the largest group-buying website, Groupon, are $1.61 billion USD in 2011, $2.33 billion in 2012, and $2.573 billion in 2013, and it is still growing now [1]. In Austria, the group-buying market generated $504 million in 2012 and $115 million in Q1 2013 [2, 3]. In China, the turnover of group-buying industry reached to $3.52 billion USD in 2012 and $2.29 billion from Q1 to Q2 in 2013 [4], which is about to 66% of the annual turnover in 2012.

However, the development of group-buying market is restricted by some problems. Increasing competition is still continuous and make pressure on group-buying websites [5]. There are so many same products and services that customers can purchase through one group-buying websites or the other one. The current group-buying companies cannot provide real-time services. Consumers can browse the group-buying websites and apps for recreational or informational purposes, but cannot get the products and services at once after paying by credit cards or digital wallets. Group-buying companies cannot get the best use of impulse purchases through this non real-time business model, and about 22% customers have impulse purchases behavior over the Internet [6].

Mobile computing is a powerful solution to the problems of group-buying market. Many group-buying e-business companies provide mobile group-buying app services, such as Groupon, LivingSocial and taobao in China, to get the business trend of mobile commerce. Mobile transactions make the group-buying industry growing and increase customer satisfaction due to better service and customer confidence [5]. The number of mobile buyers is increasing now. In United States, there are 34 million mobile buyers in 2011, 57 million in

2012, and 79.4 million in 2013. By 2017, the number is predicted to rise to 138.8 million [7].

To combine mobile intelligence and group formation, customers can take the real-time group-buying services through the mobile devices in their hands, while they want to purchase big size products at a shopping mall, get group tickets to visit a museum and exhibition, have an afternoon tea, etc. With the mobile services, group-buying companies are able to provide real-time business model to make profits, vendors can have the benefit of selling wholesale commodities quickly and the customers also get benefit from reducing the cost of purchasing products and services.

1.2 Motivation and Research Problems

Group-buying websites face some problems. Due to the low entry barrier of the industry, numerous competitors in different countries have emerged rapidly and many sites are no longer active [8]. In June 2012, CNN Money News reported on Groupon's precipitous stock declined and sent Groupon's market cap below the $6 billion that Google offered as a buyout in late 2010 [9]. In August 2012, Forbes issued a report about Groupon's problems and indicated that Groupon has an unsustainable business model for two reasons. First, Groupon is selling other companies' products that have the upper hand in any deal negotiations. Second, Groupon have plenty of competitors. The business model also has a problem that if the minimum number of consumers signed up is not reached, then no one gets the Groupon offer [10]. Although some group buying sites introduce mobile app services into their service range, they cannot change the fact that customers are waiting for more customers to take part in the group-buying gathering, or the group-buying gathering will be closed if not reach the least threshold of the number of customers joined in the limited time period.

However, group-buying service with mobile computing can create an innovative service model that provides real-time group-buying services with higher willingness to impulse purchase. There are three mobile advantages in group buying: (1) the benefit from real-time service: consumers are able to from a group buying by themselves at any time when they want to buy something and have the products or services at once after they pay by cash. They do not need to wait for delivery and the time to reach the minimum number of customers for a specific coupon. Stores can also benefit from the real-time group buying due to increasing sales and do not require to pay commission to group-coupon websites. For example, when a consumer wants to buy something at a local store, he/she can use app in the mobile device to sense people nearby who also likes the product or service and they can meet each other quickly to purchase together and enjoy the lower price due to group buying. The mobile group buying service can also discover the potential customers from one person to more people around, (2) the benefit from context awareness: the group-coupon website only use the location to classify their coupons, but it is less effective on increasing consumers' purchase willingness. However, mobile devices provide the ability to context awareness, which can be used to detect who are around you by global positioning system and compute the travel time from one place to another, and (3) the benefit from social relations: customers are more likely to purchase products if there are friends in the group buying [11]. The synchronization between social media and mobile device brings a new opportunity to collect and analyze whether there are friends near the customer or not and utilize the like and check-in data on social media to analyze the purchase preference of customers. Customers can from a group-buying group with high cohesion by taking advantage of the power of social influence and we believe it can bring a new trend to mine nearby potential customers.

The proposed mechanism is going to utilize the three benefits from real time, context awareness, and social relations to conquer the problems which will be faced and listed below:

(1) How to improve group commerce from passively waiting for coupons to actively gathering nearby consumers to make a real-time group buying?

In the current circumstance, consumers need to wait for more people signing up the coupon. Using mobile technology, it is possible to gather more people actively and quickly by identifying the people nearby. So it is a problem that how to improve group commerce from passive to active real-time service.

(2) *How to form groups with location-sensitive customers and high cohesion?*

To identify the people nearby and invite them to join a group buying, we need to identify the locations of customers and their travel times to go together. After knew the nearby customers, it is important to select who are the suitable one to be the group members to form a group with high cohesion to have a better experience of the group buying service.

(3) *How to utilize the power of social influence to increase the willingness to purchase?*

In order to improve the motivation of nearby people to join a group, it is important to consider their preference and social relationships. People are more likely to purchase with friends than with strangers. It is a problem for this study that how to identify whether there are friends near the customer and how to increase the purchasing willingness for them to group buying.

1.3 Research Goals and Contributions

The objective of this study is to design a new contextual group formation mechanism to make everyone has the ability to enjoy real-time group buying at anywhere and anytime. A contextual group formation mechanism, analyzing the factors of context awareness, social influence and individual preference, is proposed to solve the problems by finding nearby consumers who are also interested in the product and geographically close to the customer who creates the group buy event to assure the success of real-time group-buying transactions by reaching the minimum number of buyers from people nearby. A group member list is generated for the customer who requires more people to join his/her group buy and the consumers in the group member list will be invited to participate in the group buying.

The usage opportune moment of this mechanism can be extended to be the circumstance when someone needs to gather people quickly to do something together. Using this mechanism, not only customers but also vendors and shopkeepers can gather several consumers nearby to sell wholesale commodities with group discount. That benefits vendors to save advertising and marketing cost and make revenues.

There are several studies focusing on social intelligence or context-aware service separately. In this study, we combine social intelligence and context-aware service into mobile intelligence, which is a new research trend with strong potential impacts.

1.4 Thesis Outline

The remaining sections are described as follows. The literatures related to this research are reviewed in Chapter 2. The detailed description of the proposed mechanism is in Chapter 3. Chapter 4 delineates the experiments conducted based on the proposed mechanism. The evaluation of the experiments are described in Chapter 5. Finally, Chapter 6 concludes our research contributions and describes research limitations and the future works.

Chapter 2 Related Literatures

2.1 Mobile and Group Commerce

Mobile commerce (M-commerce) is the next generation of electronic commerce (e-commerce) beginning in 1997 the WAP (wireless application protocol) introduced [12] and is driven by the rapid proliferation of mobile devices, including personal digital assistants (PDAs), smartphones, tablets and other handheld devices [13]. M-commerce can be defined as any transaction with a monetary value, either direct or indirect, that is conducted over a wireless network [14].

Mobile devices provides a whole new set of service capabilities, including location-based service, context awareness, and push delivery [12]. The key benefit of mobile commerce is its ubiquitous access to information at anytime and anywhere [15], and vendors are more accessible to customers. Mobile commerce has generated interest in industry and enormous opportunities for business model innovation [12, 13]. Both the mobility and broad reach are the two major characteristics of mobile commerce: mobility is synonymous with portability, e.g., customers can conduct real-time business via mobile devices, and broad reach is implies that customers can be reached at any time and place via mobile devices [16].

Mobile commerce is also significantly influenced by the fast growth in social networking. Various social media have emerged and the research on how to combine mobile commerce and social commerce to generate new knowledge, business model and social implications is likely to be the near future of mobile commerce [12].

The phenomenon of group commerce is formed by consumer bundling that the existence of group forming strongly depends on new information technologies and the global proliferation of the Internet [17]. A well-known example of group commerce is Groupon launched in 2008. Groupon operates a group commerce market that connects merchants to consumers by offering products and services at about 50% discount off the price [9, 18]. Every deal has to reach the minimum threshold size and the merchants may limit the maximum number of coupons sold [19]. Groupon provides a time-limited mechanism that increases customer's sense of urgency and make a phenomena of panic buying [20, 21].

Group commerce is a popular business model with three-win situation which benefits sellers by lower marketing cost [22]. It also benefits customers by lower costs with large discount. Group commerce platforms get the largest discount from sellers to attract more customers and sells coupons at a price higher than it got from sellers [11].

However, the business model of group commerce is not sustainable enough, which has been described in section 1.2. In this research, considering geographic convenience, social influence and customer preference, we propose a contextual group formation mechanism to promote real-time group buying to improve the business model of mobile and group commerce.

2.2 Context Awareness

Context is any information that can be used to characterize the situation of an entity, where entity is a person, place, or object that is relevant to the interaction between a user and an application, including the user and the application themselves [23, 24]. Ryan et al. proposed that the types of context are location, environment, identity and time [25]. Schilit et al. defined the aspects of concept as where you are (location), who you are with (identity) and what resources are nearby (environment) [26]. This study adopts the categories of context are location, identity, activity and time which is suggested by Dey and Abowd because activity is about what is occurring in the situation and these four context types are primary for characterizing the situation of an specific entity [23].

Context awareness is to use context to provide relevant information and/or services to the user, where relevancy depends on the user's task [23], which is first introduced by Want et al.

in 1992 [27]. Context awareness is well-known in ubiquitous computing, and context is the key to provide suitable services that are appropriate to the location, identity, activity and time [28]. Location is one kind of context that is most widely used for context-aware services [29].

The study considers (1) locations of users, (2) nearby people and (3) the circumstances of group buying as the contextual information to build a contextual group formation mechanism, which has the ability to gather nearby people at anytime and anywhere to enjoy real-time group buying.

2.3 Social Influence

Social influence has been widely used to explain collective and group behavior [30] and is defined as a process which individuals change and adapt their decisions and behaviors as a result of interactions with other group members [31]. Social influence is also defined as the degree to which people believe that important others in the same group would approve or disapprove of their behavior [32, 33]. Social influence is driven by social norms which define the acceptable and approved behaviors for the society or group which the individual belongs [34].

Social influence theory concentrates on the roles of social culture and social norms which is involved in interaction and communication within groups. Individuals in a group will adapt their behavior, attitudes and beliefs to the social context and to the reality of their own behavior and situation [35].

Social influence can be classified into three modes, including (1) compliance, (2) internalization and (3) identification [36]. Compliance is particular important in the initial decision making because the user has no relative usage experience and thus tends to depend more on second-hand information, which is particular from family or friends. Internalization is more important in deciding continuous group behavior, which is about the adoption of a decision based on the similarity of the values of one group member with the values of other group members. A person will form an intention to participate in a group if realize that he/she is sharing common values or goals with other group members. Identification can be referred to cognition of self-awareness of one's membership in the group, as well as the evaluation of self-worth and emotional involvement within the group [36-38].

In this study, we consider compliance and internalization modes of social influence, because it affects customers' thoughts, behaviors and willingness to participate in a group buying. We analyze social trust and social closeness between users, who are the candidate group members, to arouse the motivation of users to use the mechanism and group buy with others.

Chapter 3 System Frameworks

The proposed contextual group formation mechanism is an innovative service model that customers can gather other nearby customers with certain social relations and similar preference at anywhere and anytime when they want to enjoy group buying, as illustrated in Figure 1, where the smile face is the group leader, who needs this mechanism to gather people nearby and thus creates a group buying event.

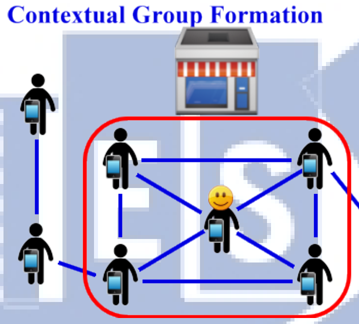


Figure 1. An Illustration of Contextual Group Formation

As a user uses this mechanism to create a group buying event to purchase something, he/she is the group leader. This mechanism will start to detect who are near the group leader and compute their degree of social influence and individual preference to the target product. Each user has three criteria of willingness to join a group or not: (1) group context, (2) social influence and (3) individual preference, and each criterion has its own weight for the user in a particular circumstance. Measuring the willingness-to-join of every person near the group leader, this mechanism takes top-k people with higher willingness as candidate group member to form several candidate groups. By computing the cohesion of each candidate groups, this mechanism selects a group with highest cohesion to provide the group member list to the group leader and invite all the group members to join the group buying.

The system architecture is shown as Figure 2.

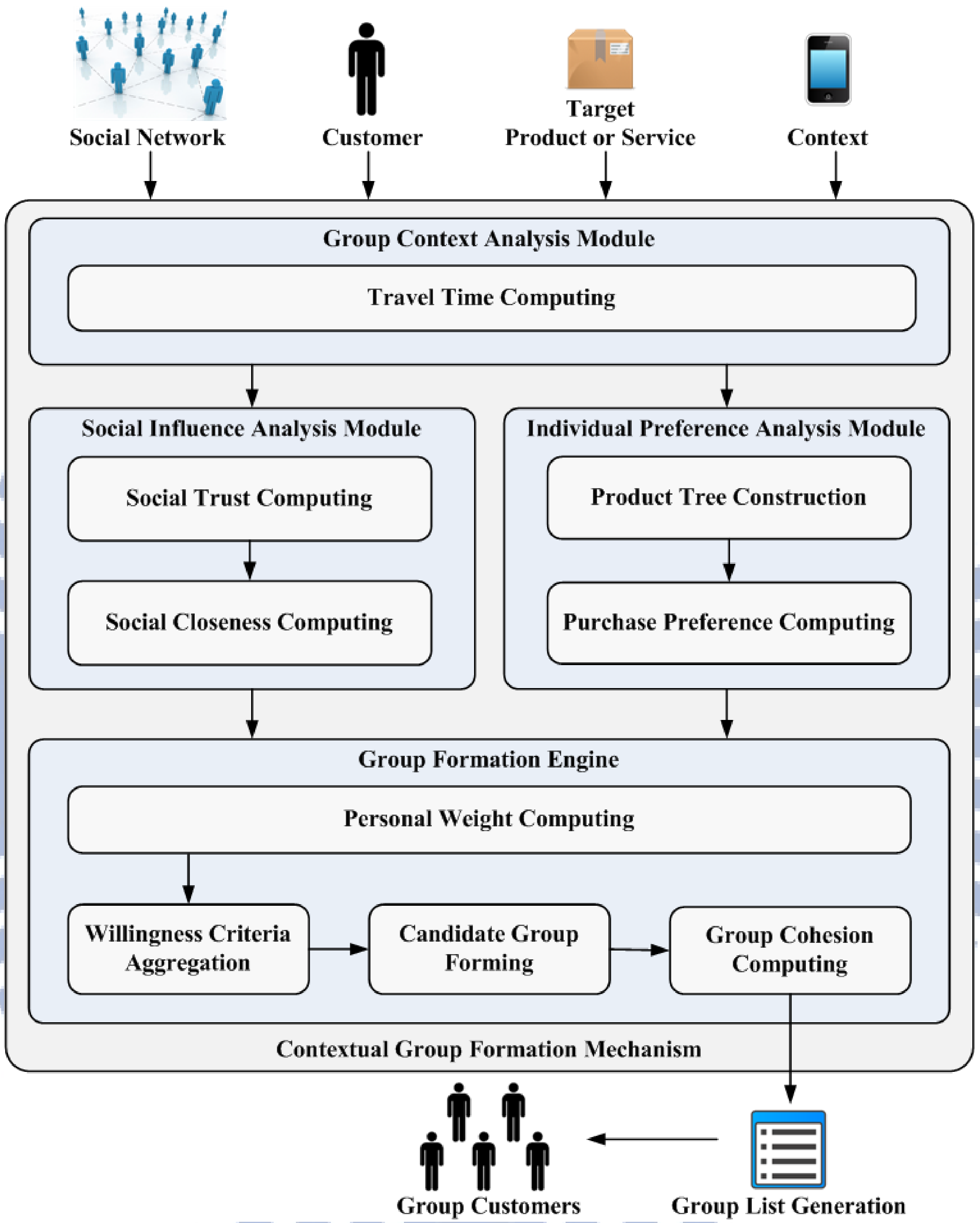


Figure 2. The System Architecture of Contextual Group Formation Mechanism

The main four modules in the system architecture are as follows:

(1) Group Context Analysis Module: The module is to detect who are nearby, which is measured by travel time, and then grade them with a value. It is the first module because

we only need to focus on nearby users in the other modules.

(2) Social Influence Analysis Module: The module utilizes social data to compute trust and closeness between nearby users to analyze who are trustable and close to the group leader, and then computes a value to every user nearby.

(3) Individual Preference Analysis Module: The module utilizes fan pages liked and check-ins on social media to analyze user purchase preference and then compute the similarity between user preference and the target product as a value to represent the degree how the user are interested in the target product.

(4) Group Formation Engine: The module combines the values of above three modules as group formation criteria, depending on personal weight of each user, to compute his/her willingness in joining the group buying. After we knowing the willingness of each user, the module generates several different candidate groups and computes the degree of cohesion of each candidate group to provide a group member list with highest cohesion to the group leader.

3.1 Group Context Analysis Module

The proposed mechanism provides a real-time service to gather people nearby with similar interest and certain social relations, so it is important to utilize the context data to be aware of the people around. If this mechanism invites someone far away from the group leader to participate in the group, he/she may not want to join the group due to far distance, even with a strong preference to the target product, on the other hand, if he/she is near the group leader, then he/she can go to there at once. In this group context analysis module, we take (1) user location and (2) nearby people as the context. The module uses the locations of users detected by mobile devices to find who are near the group leader.

3.1.1 Travel Time Computing

To get locations of mobile users, we use GPS (Global Positioning System) in mobile devices to receive longitude and latitude data of users. We consider the travel time but not distance between locations because distance cannot represent the real time spent that users may move by walking, driving or other methods.

We are able to get travel time and route between two locations of users by using Google Directions API [39]. We denote $TravelTime(i,j)$ be the travel time from the user j (origin location) to the group leader i (destination location) in particular travel mode. We get the value of travel time by sending request with origin location, destination location and travel mode including walking, driving, bicycling or transit as parameters to Google Directions API, which will return the travel time in seconds. The travel time between user and the group leader is dynamic because it is possible that they are still moving and changing their locations.

To decide who are nearby people, we set the default maximum constraint of travel time to be 10 minutes, because we think if the user requires more than 10 minutes to go to the place, that is too long to be the real-time group-buying service what we want to provide. Users can change the default limit of travel time if needed. After get the travel times of users and filter out users far away from the group leader, we denote a set of people near the group leader i, $J(i)$, as the Equation 1, where n is the number of nearby people.

Equation 1. The Set of Nearby People

$$J(i) = \{j_1(i), j_2(i), \dots, j_n(i)\} \qquad (1)$$

Every person j in set $J(i)$ has his/her own $TravelTime(i,j)$, and we rank $j_n(i)$ according to $TravelTime(i,j)$ in ascending order. We denote $Rank(j_n(i))$ as the rank of person $j_n(i)$ in $J(i)$ and then compute the score of this module for the group leader i and each nearby person j is measured by Equation 2.

Equation 2. Formula of Group Context

$$GroupContext(i,j) = \frac{n - Rank(j_n(i)) + 1}{n}, \forall j_n(i) \in J(i) \tag{2}$$

3.2 Social Influence Analysis Module

There are several situations of group buying, and customers want to enjoy group buying with various friends in different situations. For instance, if a customer wants to have a dinner at a restaurant with group discount, he/she may want to be with close friends but not strangers, on the other hand, if he/she wants to purchase large amount of commodities at a wholesale store, he/she may not care about with friends or not.

This module is to measure the degree of trust and closeness between two users. We denote $SocialInfluence(i,j)$ as the degree of social influence between the person j near the group leader i. We select Facebook to be the social data source because Facebook is one of the most popular social media in the world with 1.3 billion active users in Jan. 2014 [40].

3.2.1 Social Trust Computing

As a group leader uses this mechanism to gather nearby people to join his/her group buying, it is important to know whether the person is trustable or not. If users meet with malicious one and are harassed or cheated, we cannot control the situation but can avoid it to increase users' willingness to take a grouping invitation.

In this section, we denote $SocialTrust(i,j)$ as a value that represents how nearby person j is trustable to the group leader i. We use four kinds of social data to analyze it: (1) the number of successful transactions of nearby person j denotes as $STrans(j)$, (2) the number of reports of nearby person j denotes as $Reported(j)$, (3) the total number of transactions of nearby person j denotes as $Trans(j)$ and (4) the number of good reviews given by the group leader i and i's friends to the person j nearby denotes as $FriendsReviews(i,j)$. We consider the number of good reviews of nearby people base on friend referrals. That is to say, nearby candidate users who have received more good reviews will receive a higher score, and thus more likely to be recommended to a group leader for group formation.

All the transaction, report and review data are stored after a transaction is completed. In order to compute $FriendsReviews(i,j)$, we denote $Friends(i)$ as a set of all the friends $f_n(i)$ of user *i* as Equation 3, where *n* is the number of friends.

Equation 3. The Set of Friends of user *i*

$$Friends(i) = \{f_1(i), f_2(i), \dots, f_n(i)\} \tag{3}$$

Having Equation 3, $FriendsReviews(i,j)$ can be measured by Equation 4.

Equation 4. Formula of Fiends Reviews

$$FriendsReviews(i,j) = \sum_{f_n(i) \in Friends(i)} Reviews(i, f_n(i), j) \tag{4}$$

Where $Reviews(i, f_n(i), j)$ is the number of good reviews given by the group leader *i* and *i*'s friend $f_n(i)$ to the person *j*.

The value of $SocialTrust(i,j)$ is measured by Equation 5. If the candidate nearby user *j* has no transaction or review data, we set $Trans(j)$ or $FriendsReviews(i,j)$ as 1 to avoid to divide by or multiply with 0.

Equation 5. Formula of Social Trust

$$SocialTrust(i,j) = \frac{STrans(j) - Reported(j)}{Trans(j)} * FriendsReviews(i,j) \tag{5}$$

The $SocialTrust(i,j)$ value should be normalized before going to the next step. We adopt min-max normalization approach because min-max normalization has higher efficiency than other normalization approach, such as z-score normalization and normalization by decimal scaling, and is more appropriate in real-time group-buying. The equation of min-max normalization is shown as Equation 6 and the $SocialTrust(i,j)$ value will be normalized from 0 to 1.

Equation 6. Min-Max Normalization

$$V' = \frac{V - Min(Set_v)}{Max(Set_v) - Min(Set_v)} \qquad .(6)$$

Where *V'* is the new value after normalization, *V* is the original value, Set_v is a set which contains all the *V*s, $Min(Set_v)$ is the minimum value of Set_v and $Max(Set_v)$ is the maximum value of Set_v.

3.2.2 Social Closeness Computing

It is usual that customers want to purchase something together with friends more than with strangers, so we consider the social relations between two users into this mechanism. In this section, we compute the degree of closeness between two users by using their social data collected from Facebook. In some cases, it is possible that the person near the group leader is not a direct friend, but an indirect friend, in other words, the person is friend of friend of the group leader (two-degree-relationship) or more degrees. We illustrate the situation as Figure 3.

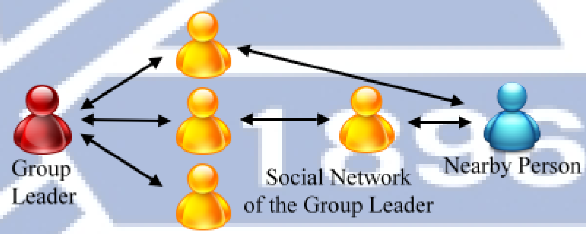


Figure 3. The Illustration of Social Relations in a Social Network

Red (left) user icon represents the group leader, yellow (middle) ones represents social network of the group leader (including friends of the group leader, friends of friends of the group leader, and so on), and blue (right) one is the person near the group leader. The black solid arrow represents the friendship between two people. The size of the social network does not need to be too large, because it represents the group leader almost has no relation with the person. To define the maximum size of the network, we consider "six degrees of separation" theory to set the limit to six. Six degrees of separation is a theory that two people are able to link each other less than or equal to six steps [41]. If the number of links between two people is larger than six, the value of social closeness between them is set to zero.

In order to compute the degree of closeness between the group leader to any person nearby, the interaction between users who are in the social network of the group leader is required on social media. The interaction between two users, who are denoted as u_1 and u_2 on social media is measured by (1) the number of the two users be tagged together in comments and posts, including statuses, check-ins and photos and we denote it as $Tag(u_1, u_2)$, (2) the number of comments written by the two users under a same post which is created by them and we denote it as $Comment(u_1, u_2)$ and (3) the number of likes given by the two users in comments and posts, including statuses, check-ins and photos which they own and we denote it as $Like(u_1, u_2)$. The interaction between two users, u_1 and u_2, is measured by Equation 7.

Equation 7. Computation of the Interaction on Social Media

$$Interaction(u_1, u_2) = Tag(u_1, u_2) + Comment(u_1, u_2) + Like(u_1, u_2) \quad (7)$$

The $Interaction(u_1, u_2)$ value should be normalized to be a value ranged from 0 to 1 before go to the next step. We also adopt min-max normalization approach to do it, which has been described as the Equation 6.

After described how to compute the interaction between two users, we are going to explain how to compute the social closeness value between the group leader and the person near the group leader.

We denote $Paths(i, j)$ as a set which contains all the social paths which are the routes to connect the group leader *i* with the nearby person *j* and each social path has a set of links, which connects two users in the particular social path and has its $Interaction(u_1, u_2)$ value, denoted as $Links(u_1, u_2)$. The length of a social path is denoted as $LenPath(Path_n(i, j))$, which is equal to the number of links in the social path. The two sets are shown as Equation 8 and 9, where *n* is the number of elements of the set.

Equation 8. The Set of Social Paths between Two People

$$Paths(i,j) = \{Path_1(i,j), Path_2(i,j), \dots, Path_n(i,j)\} \tag{8}$$

Equation 9. The Set of Links in a Social Path

$$Links(u_1,u_2) = \{Link_1(u_1,u_2), Link_2(u_1,u_2), \dots, Link_n(u_1,u_2)\} \tag{9}$$

The influence of $Interaction(u_1,u_2)$ value of two users who are not direct friends with the group leader should be reduced according to its social degree far from the group leader. We denote $Degree\big(i, Link_n(u_1,u_2)\big)$ as the social degree from the group leader *i* to the particular link $Link_n(u_1,u_2)$.

The social closeness between the group leader *i* and the nearby person *j* can be measured by Equation 10 below, which value is equal to a particular social path with maximal value. The $Max()$ function is to find the maximal value of its parameter.

Equation 10. Formula of Social Closeness

$$SocialCloseness(i,j) = Max\left(\frac{1}{LenPath\big(Path_n(i,j)\big)} * \sum \frac{Interaction(u_1,u_2)}{Degree\big(i, Link_n(u_1,u_2)\big)}\right), \tag{10}$$

$$\forall\, Link_n(u_1,u_2) \in Links(u_1,u_2) \in Path_n(i,j) \in Paths(i,j)$$

Finally, we have done social trust computing and social closeness computing, and then we combine them to calculate the social influence between the group leader *i* and nearby person *j* by using the Equation 11 below.

Equation 11. Formula of Social Influence

$$SocialInfluence(i,j) = SocialTrust(i,j) * SocialCloseness(i,j) \tag{11}$$

3.3 Individual Preference Analysis Module

This module is to analyze the degree how a user wants to purchase the target product with his/her preference. It is important to discover users' preference in a group buying event. When the group leader invites someone nearby to buy something together, if the person does not like it, then he/she may ignore the invitation. However, if the person also likes the product too, then he/she may join the group buying. To measure individual preference, we denote $IndividualPreference(j, p)$ to compute the similarity between the preference of person j near the group leader and the target product p, that is to say, the target product is sure ready for this module.

3.3.1 Product Tree Construction

Before computing the similarity between user preference and target product, we should identify the target product at first. To identify the target product, a tree structure is built to classify the target product. Products are hierarchical structures in the real world. For example, food can be divided into Chinese and American food, and restaurant can also be divided into Chinese and American restaurant. That is to say, each product can be related to a place where the product is sold.

In order to enhance the relationship and synchronization between products and places, we refer to the hierarchical categories of places on Facebook to construct a tree structure for the place tree and match the products to the categories which it belongs, see as Figure 4. We name the special tree "ProductPlace" tree and mark the index of each node to identify each category. The index is the number shown in each node. A product can belong to many categories in some cases. For example, people can buy burgers at American restaurant, burger restaurant and fast food restaurant.

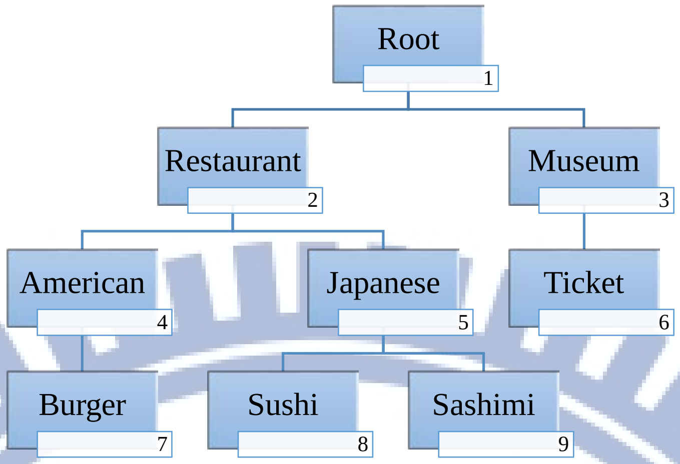


Figure 4. The Example of ProductPlace Tree

3.3.2 Purchase Preference Computing

This computing method is to calculate the similarity between user preference and the target product by using the ProductPlace tree. We measure the purchase preference of a user by two kinds of social data: (1) pages: the pages that user likes on social media and (2) check-ins: check-in is the process whereby a person posts his/her location on a social network service. Check-in data show the preference of the user. For example, if a person has many check-ins at different restaurants, we can know that he/she likes to enjoy delicacies. We should transform the data types of the two kinds of data above because all the data should match the ProductPlace tree. Pages on Facebook have its own categories, and we can use its categories to match the ProductPlace tree. For example, "Costco" page is classified into "Shopping & Retail" category on Facebook and "McDonald's" page is "Burger Restaurant" category. Check-ins on Facebook are tagged with a location, which is a page with its own categories too.

In order to know whether the user likes the target product or not, we calculate the similarity between the target product p and preference of user j. We take the target product p into the ProductPlace tree to identify and classify it clearly and create a new vector for the target product p which utilizes the index of nodes to represent the categories p belongs and denote the vector as $\vec{p}$ which the value of each dimension is 1 if the category matches the node or 0 if the category does not match the node. We take the place categories of the pages and check-ins data which the user j likes and posted to match the ProductPlace tree to identify and classify them and also denote a vector as $\vec{j}$ to represent all the categories related with the pages and check-ins data, which the value of each dimension in $\vec{j}$ is the number of appearance of the category and sub-categories in pages and check-ins. The dimensions of the two vectors are the same to compute the similarity correctly.

Here is an example to show how to make the two vectors about target product and user preference by using the ProductPlace tree. We take "Sushi" as the target product p and suppose the user j has 1 number of check-ins at an American restaurant, 2 number of that at a Japanese restaurant and 3 number of that at a museum. Then the two vectors $\overrightarrow{Sushi}$ and $\vec{j}$ with 9 dimensions (the order of dimensions depends on the index of nodes in ProductPlace tree) can be created as below. The nine dimensions are (1) Root, (2) Restaurant, (3) Museum, (4) American, (5) Japanese, (6) Ticket, (7) Burger, (8) Sushi and (9) Sashimi.

$$\overrightarrow{Sushi}(1, 1, 0, 0, 1, 0, 0, 1, 0)$$

$$\vec{j}(6, 3, 3, 1, 2, 0, 0, 0, 0)$$

After having the two vectors about target product and user preference, we are going to compute the similarity between these two vectors. We modify Cosine Similarity method to create a new similarity equation because Cosine Similarity method has two defects and cannot be used into this mechanism: (1) if a user has many check-ins of different categories, the value of similarity will be reduced because the denominator of Cosine Similarity will be larger and cause distortion and (2) the value of Cosine Similarity will be normalized and make the value between 0 and 1 because of it denominator, but this neglects the influence of many pages liked and check-ins posted on the same category. We retain the numerator of Cosine Similarity using dot product but delete the denominator to create our similarity as Equation 12, where $\vec{p}$ is the vector of target product p and $\vec{j}$ is the vector of preference of user j, to keep the features of many pages and check-ins in the same or different categories.

Equation 12. Similarity between Product and User

$$Similarity(\vec{p},\vec{j}) = \vec{p} \cdot \vec{j} = \sum_{i=1}^{n} \vec{p}_i * \vec{j}_i \qquad (12)$$

We explain how the Equation 12 works by using the same example above.

$$Similarity\left(\overrightarrow{Sushi},\vec{j}\right) = 6 + 3 + 2 = 11$$

If we add a user k into this example, the user k has 2 number of check-ins at an American restaurant, 1 number of that at a Japanese restaurant and 3 number of that at a museum, then the vector and similarity between target product and user k is:

$$\vec{k}(6, 3, 3, 2, 1, 0, 0, 0, 0)$$

$$Similarity\left(\overrightarrow{Sushi},\vec{k}\right) = 6 + 3 + 1 = 10$$

The result shows that the similarity is able to discriminate the difference of preference of different users and keep the features of many pages and check-ins data.

In the end of this section, we need to adopt the min-max normalization method which has described in Equation 6 to normalize the value of similarity after computed all the values of similarity of the candidate group members. We denote $Similarity'(\vec{p},\vec{j})$ as the normalized value and return it to be the value of individual preference analysis module as the Equation 13 below.

Equation 13. Formula of Individual Preference

$$IndividualPreference(j,p) = Similarity'(\vec{p},\vec{j}) \qquad (13)$$

3.4 Group Formation Engine

The group formation engine is to generate candidate groups and find the group with highest cohesion, which is appropriate to the circumstance of particular group buying, to the group leader. There are four parts in this module: (1) Personal Weight Computing is to compute the weight values of three group formation criteria, including group context, social influence and individual preference, of a user in a particular circumstance, (2) Willingness Criteria Aggregation is to multiply the weight values of three criteria with its values to be the willingness of a user to join a group buying, (3) Candidate Group Forming is to generate several candidate groups according to the willingness of users and (4) Group Cohesion Computing is to compute the cohesion of candidate groups to find the one with highest cohesion.

The circumstances of group buying should be taken into consideration, because it may affect the willingness of users to join a group buying. For example, purchasing a plenty of products at a wholesale store, such as Costco, the group leader will dismiss the group after the transaction is completed. However, having a dinner gathering with friends at a restaurant with group discount, the group members will interact with each other for long time after the transaction is completed, which implies demand of social relations.

3.4.1 Personal Weight Computing

Each user has his/her own weights of criteria which affect the willingness to participate in a group or not. The measurement of willingness to join a group is various due to different circumstances. In this section, we compute the personal weights of three criteria which influence the willingness of a user to join a group in a specific situation.

We adopt the analytic hierarchy process (AHP) theory, a well-known structured technique for organizing and analyzing complex decision-making problems with multi criteria, which is proposed by Thomas L. Saaty in 1971 [42, 43], to compute the weights of the three willingness criteria: group context, social influence and individual preference towards a particular circumstance. We explain the detailed description as follows.

To apply AHP theory, we first define the problem to “whether to join a group or not” and then construct the hierarchy structure as the Figure 5.

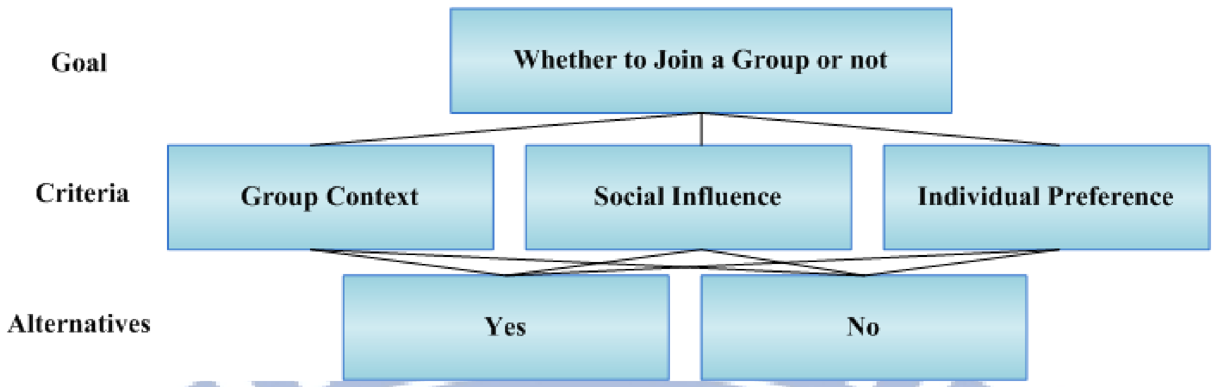


Figure 5. The Hierarchy Decision Structure of Personal Weight Computing

There are three criteria in the hierarchy structure, which requires $C_2^3 = 3$ comparisons and builds a pairwise matrix denoted as M_{CSP} shown as Equation 14, where C implies group context, S implies social influence and P implies individual preference. The results of three comparisons between each criterion are on the upper triangle of the matrix and the values of the lower triangle are the reciprocal of the relative position on the upper triangle. The values on the diagonal line are 1 because they compare with themselves.

Equation 14. The Pairwise Matrix of Analytic Hierarchy Process

$$M_{CSP} = \begin{bmatrix} 1 & A_{CS} & A_{CP} \\ \frac{1}{A_{CS}} & 1 & A_{SP} \\ \frac{1}{A_{CP}} & \frac{1}{A_{SP}} & 1 \end{bmatrix} \tag{14}$$

Where A_{CS} represents the relative decision weight of group context similarity to social influence, A_{CP} represents the relative decision weight of group context similarity to individual preference, and A_{SP} represents the relative decision weight of social influence similarity to individual preference. These data has been collected from questionnaires in users' first usage and its value may be affected by the circumstance. We define a set of this relative decision weights in a specific circumstance of a user j as $A_{CSP}(j)$ and this set can be indicated as Equation 15.

Equation 15. The Set of Relative Weights of Criteria

$$A_{CSP}(j) = \{A_{CS}(j), A_{CP}(j), A_{SP}(j)\} \tag{15}$$

We can compute the eigenvectors to obtain the weights of criteria by the eigenvalues after construct the pairwise matrix. We adopt average of normalized columns (ANC) method to get the eigenvectors because the pairwise matrix is not usually consistency matrix and use this ANC method can have higher accuracy of computing results then other methods when encounter non-consistency matrix [43]. We define a set containing the three weight values of the user j on the three criteria (group context, social influence and individual preference) as $W_{CSP}(j)$ and this set can be indicated as Equation 16.

Equation 16. The Set of Personal Weights of Criteria

$$W_{CSP}(j) = \{W_C(j), W_S(j), W_P(j)\} \tag{16}$$

The weights of three criteria can be calculated by using the Equation 17.

Equation 17. Formula of Personal Weight Computing

$$W_\alpha(j) = \frac{1}{3}\sum_{\gamma=1}^{3}\frac{A_{\beta\gamma}(j)}{\sum_{\beta=1}^{3} A_{\beta\gamma}(j)}, \forall[W_\alpha(j) \in W_{CSP}(j)]\ \&\ [A_{\beta\gamma}(j) \in A_{CSP}(j)] \tag{17}$$

These three weights of three criteria imply how the user *j* makes decision to whether to join a group buying with the invitation from the group leader or not.

3.4.2 Willingness Criteria Aggregation

Using the weight values of three criteria, this mechanism can have the ability to measure the willingness-to-join that the person *j* who is near the group leader *i* will want to join the group to purchase target product p together in a specific circumstance. We denote the willingness-to-join of person *j* as $JoinWillingness(i, j, p)$ and its value is calculated as the aggregation of the weight value of each criterion with the corresponding score of the criterion which calculated by the group context, social influence and individual preference analysis module. The value of $JoinWillingness(i, j, p)$ is measured as the Equation 18.

Equation 18. Formula of Willingness-to-Join

$$JoinWillingness(i,j,p) = W_C(j) * GroupContext(i,j) + W_S(j) * SocialInfluence(i,j) + W_P(j) * IndividualPreference(j,p) \tag{18}$$

3.4.3 Candidate Group Forming

Now this mechanism has the ability to compute the willingness-to-join of everyone near the group leader who creates the group buying event in a specific circumstance. The number of people near the group leader may be very large, and it may be larger than the number of group members needed. For instance, the group leader needs 4 people to join his/her group buying, but the people nearby are about 20.

This mechanism requires this candidate group forming and next group cohesion computing approaches to solve the problem. We denote N_{re} as the number of people required to the group buying (not including the group leader) and choose top-k people with higher willingness-to-join to the group. The number of people chosen is *k* at most (i.e. range from 1 to *k*), where *k* is equal to N_{re} multiplies with a certain integer, because we need to consider the great diversity of the group members combination and its value of group cohesion and the higher ratio of willingness simultaneously, but we also need to limit the search range of people near the group leader. Therefore, a group leader can make about $C_{N_{re}}^{k}$ combinations for different groups. We denote $G(i, N_{re})$ as a set containing all the candidate groups as following Equation 19 and send it to the next approach, group cohesion computing, to compute which is the best group that the group leader *i* wants.

Equation 19. The Set of Candidate Groups

$$G(i, N_{re}) = \{G_1(i, N_{re}), G_2(i, N_{re}), \dots, G_n(i, N_{re})\} \tag{19}$$

3.4.4 Group Cohesion Computing

This group cohesion computing approach will run after receiving the $G(i, N_{re})$ set from the candidate group forming approach. The $G(i, N_{re})$ may have a great diversity of combinations. Examples of $N_{re} = 5$ are illustrated in Figure 6.

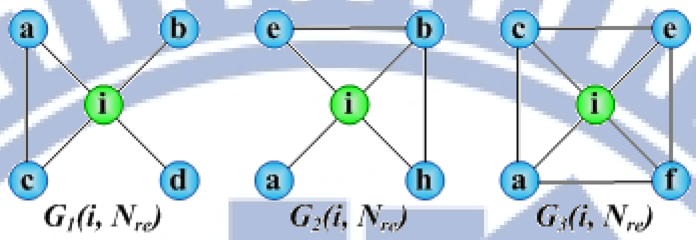


Figure 6. Example of Candidate Groups of Initial Forming

The central green node is the group leader *i* and other blue nodes are the people near the group leader. Every node represents a person, and the edge between two blue nodes represents the friendship between two people on social media. If there is no edge between two blue nodes, it means that they are not friends. The candidate groups are an undirected and non-reflexive graph (or network) structure.

We measure the cohesion of these groups by three steps: (1) the density of network, (2) the social closeness between group members and (3) the average score of willingness-to-join and social closeness in the network.

The density of network can be measured by Equation 20 [44], where *T* is the number of ties and N_{nd} is the number of nodes in the network.

Equation 20. Density of Groups

$$Density(G_n(i, N_{re})) = \frac{2 * T}{N_{nd} * (N_{nd} - 1)} \tag{20}$$

Measuring the density of each candidate group, this mechanism filters the top groups with highest density to do the next step. Because it is possible that there are several groups with equal highest density, we need to do advanced filtering. For example, the density of each candidate group shown in Figure 7 is 1.

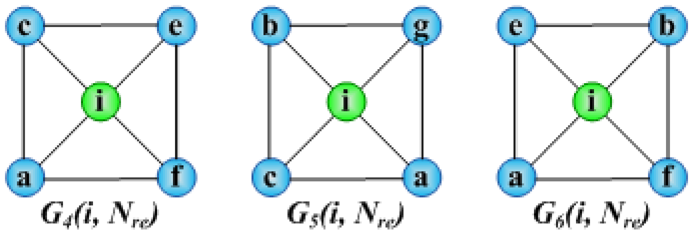


Figure 7. The Example of Candidate Groups after the First Step

The second step is to compute the social closeness between group members as the strength of each tie. The approach here only considers about social closeness because we have computed the preference and context before the candidate group forming, and thus we ensure that all the group members are near the group leader with certain degree of preference to the target product. What we care about now is the strength of social relationship between group members. Using the social closeness computing approach described in 3.1.2, we can compute the strength of each tie in the network. This approach requires to compute the strength of $C_2^{N_{nd}-1}$ ties in the network in the second step, where N_{nd} is the number of nodes in a network. The results of this step are illustrated in Figure 8, where the numbers shown on the edges is the score of social closeness between two blue nodes (two nearby people).

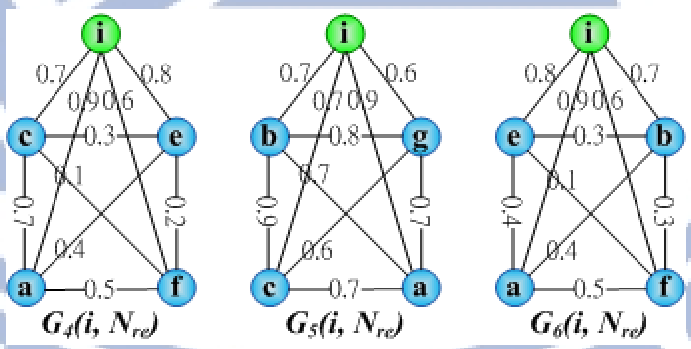


Figure 8. The Example of Candidate Groups of the Second Step

The third step is to compare which network is the best one to recommend to the group leader. We use the strength of ties to measure the group cohesion in this step. The type of ties are not all the same because the ties from nearby people (blue nodes) to the group leader *i* (central green node) are measured by willingness-to-join and the other ties between nearby people (blue nodes) are measured by social closeness. Due to the different types of ties, we need to calculate separately. We denote T_{jw} as a set of all the ties measured by willingness-to-join and denote T_{sc} as a set of all the ties measured by social closeness. The representations of the two sets are Equation 21 and 22, where *n* and *m* is the total number of ties of the specific type.

Equation 21. The Set of Ties between Group Leader and Group Members

$$T_{jw} = \{T_{jw}^1, T_{jw}^2, \dots, T_{jw}^n\} \tag{21}$$

Equation 22. The Set of Ties between Group Members

$$T_{sc} = \{T_{sc}^1, T_{sc}^2, \dots, T_{sc}^m\} \tag{22}$$

Next to compute the average values of T_{jw} and T_{sc} using the Equation 23 and 24 as following.

Equation 23. The Average of Ties between Group Leader and Group Members

$$Average(T_{jw}) = \frac{\sum_{i=1}^{n} T_{jw}^i}{n} \tag{23}$$

Equation 24. The Average of Ties between Group Members

$$Average(T_{sc}) = \frac{\sum_{i=1}^{m} T_{sc}^i}{m} \tag{24}$$

The average of strength of ties can represent the average cohesion of the network. After get the average values of T_{jw} and T_{sc}, we aggregate these two average values to compute the cohesion of the whole network by using the Equation 25. We decide to multiply these two average values because multiplying can make the higher value more higher, vice versa. It is useful to show the difference distinctly between each network.

Equation 25. Formula of Cohesion of Groups

$$Cohesion(G_\alpha(i, N_{re})) = Average(T_{jw}) * Average(T_{sc}), \quad \forall G_\alpha(i, N_{re}) \in G(i, N_{re}) \tag{25}$$

3.5 Group List Generation

The mechanism will provide a group list with highest group cohesion to the group leader and inform the group members to meet themselves. The group list provides five types of information: (1) name, (2) profile picture, (3) relationship with the group leader, (4) location and (5) travel time. The group leader can gather the appropriate and nearby people to enjoy group buying by the group list, and the group members also benefit from group discount. We expect it will change the purchase behavior of humans in the real world.

Chapter 4 Experiments

In this section of experiments, we will describe the process we experiment and evaluate the proposed mechanism. We develop a web-based mobile app using HTML5, CSS3, JavaScript and PHP to do the experiments because of four reasons: (1) this study requires to be implemented as mobile devices (2) worldwide smartphones with Android operating system garnered 78.4% of the market share and iOS operating system had 15.6% in 2013 [45]. Whether we develop a mobile app with Android or iOS operating system, we will lose the market of other mobile operating system. However we can develop a web-based mobile app to acquire all the mobile users no matter what the mobile operating system is. People can use the web-based app by web browsers such as Google Chrome, (3) HTML5 is able to get the location data by using Geolocation API to call the GPS in mobile devices and build full-duplex communications channels by using HTML5 Web Sockets, and (4) It is convenient to implement Facebook Login for web by using JavaScript. Due to the four reasons above, we decide to use a web-based app to do experiments. We select Facebook as the main social data source because it is one of the most popular social network platforms and provides FQL (Facebook Query Language) to collect data conveniently. The following sections will describe the procedures and discussion of the experiments.

4.1 Data Collection

We build a web-based app on an Apache HTTP server to collect data from mobile users and use MySQL to build the database. We adopt MySQL to construct the database because we can connect with database and access data by using PHP easily.

As user goes to the web-based app by using web browser of his/her mobile device, the user will be asked to log in Facebook to let us collect data or we cannot get his/her social data from Facebook because of the privacy policy. The current location of users will be received by

GPS in the mobile device at any time by using HTML5 Geolocation API. If the user is the first time to use the app, the app will request him/her to answer AHP questionnaires to compute personal weights of the three criteria. After the user inputs the target product and the number of people that he/she needs for the group buying, the mechanism will start to run and provide the user a group member list. The app will help the user to invite group members to make a group buying transaction. After a transaction is completed, the app will request the users to fill in questionnaires about our evaluation and their feedbacks.

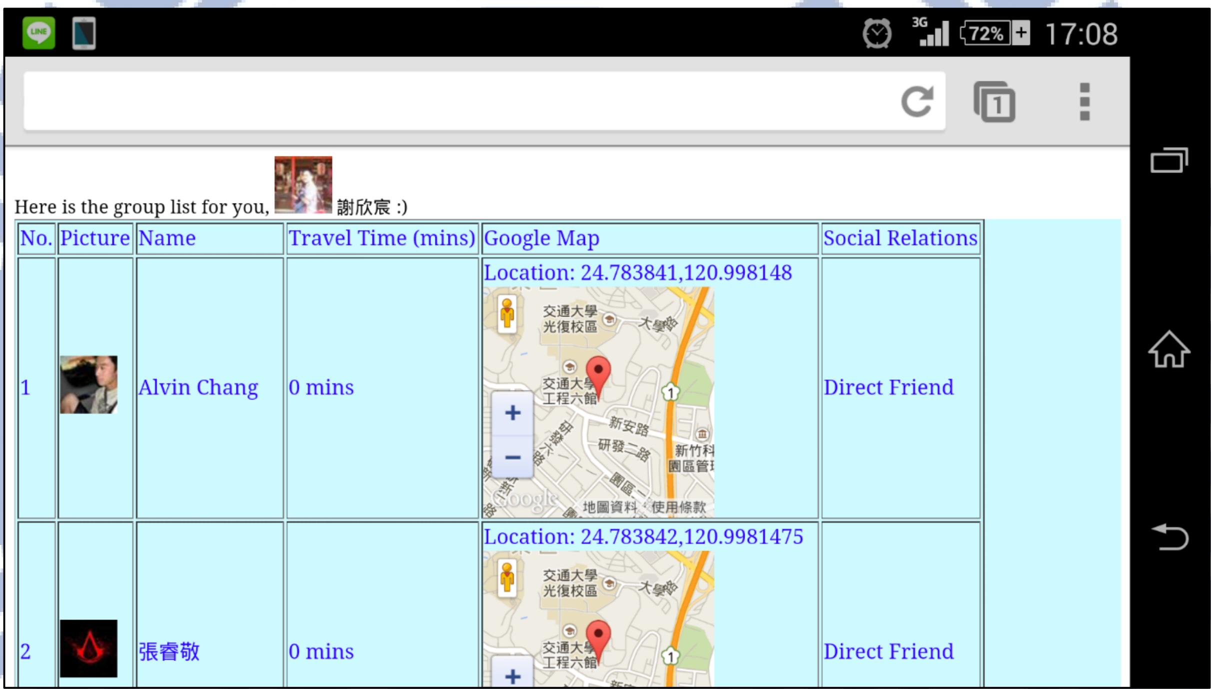


Figure 9. System Interface on an Android Smartphone

In a real condition, it is possible to compute the closeness between two nearby users who are not friends on the social media. To solve this problem, we store the required social data into the database to let the app has the capability to compute the social closeness between any two users because there are social data of all the users logged in the web-based app.

The limitations of the experiment are that only the people who (1) have mobile device, (2) use the app to log in Facebook through wireless network and (3) stand nearby can help us experiment the proposed mechanism. In order to experiment this study on the limitations with enough representativeness, we went to real market places and invited strangers randomly to join our experiment. We choose the people who want to buy something in the market place with mobile device to be the app users, and share our mobile data network as a portable Wi-Fi hotspot with them to connect to the Internet. After the people became the app users, we create a group buying event to do this experiments.

4.1.1 User Profile

We collected 274 users with mobile devices aged from 10 to 60 to do the experiments. The gender distribution was 132 male and 142 female users. Most of the users lived in Taipei and Hsinchu, Taiwan, and the remainder in other cities. The number of tags was 129,538, comments was 196,334, likes was 335,922, check-ins was 6,210, and fan pages liked was 15,248. The average number of friends of users was 536.

Table 1. Statistics of the User Network Constructed

Number of users	274
Number of tags	129,538
Number of comments	196,334
Number of likes	335,922
Number of check-ins	6,210
Number of fan pages liked	15,248
Average number of friends of users	536

4.1.2 Transaction Profile and Scenarios

There are three scenarios of group buying with different characteristics: (1) buy products with very strong preference and dismiss after a transaction is completed, (2) buy products with essential preference and do something with group members together after a transaction is completed and (3) buy products with weak preference and do something with group members together with close interaction after a transaction is completed. We select “group buying at a wholesale store” as scenario 1, “buying group tickets” as scenario 2 and “eating at a restaurant together with group discounts” as scenario 3 because these three activities of group buying are closer to daily life and have the most of demands. The group leader can choose one of the three scenarios to be the target and then start group buying. After the user has created a group buying event, the app will run the proposed mechanism and invite the people who are appropriate to this group to join the group buying event. The standard of complete group formation is reaching the minimum number of people required and they are all ready to group buying.

There were several different places for different scenarios we did the experiments. The location, including latitude and longitude, was stored as a transaction occurred. We list some places as Table 2.

Table 2. Places for Experiments

Scenario 1	Costco Chungho Store, Costco Hsinchu Store, Costco Neihu Store, Carrefour Tianmu Store, Carrefour Sanmin Store, Carrefour Chongqing Store, Carrefour Yilan Store, RT-Mart Hsinchu Zhongxiao Store, RT-Mart Neihu I, A.mart Jingmei Store, A.mart Hsinchu Store
Scenario 2	National Palace Museum, Songshan Cultural and Creative Park, National Chiang Kai-Shek Memorial Hall, Taiwan Pavilion Expo, Taipei Fine Arts Museum, National Taiwan Science Education Center, Glass Museum of Hsinchu City, Vision Hall of Hsinchu City, National Center for Traditional Arts
Scenario 3	Hsinchu Tsinghua Night Market, Taipei Gongguan Night Market, Yilan Luodong Night Market, Mos Burger Tsinghua Store, Starbucks Qingda Store, McDonalds Zhongxiao Store II, McDonalds Chengda Store, Mister Donut Big City Store, Pizza Hut Hsinchu Gongdao Store

The number of transactions was 63. The location distribution was 28 transactions occurred in Taipei, 32 in Hsinchu and 3 in other cities in Taiwan. There were 21 transactions in scenario 1, 17 in scenario 2 and 25 in scenario 3 and the total people participated in scenario 1 were 92, that in scenario 2 were 73 and that in scenario 3 were 109. The statistics results are as Table 3 and Table 4 below.

Table 3. Statistics of the Transactions in Three Scenarios

	Scenario 1	Scenario 2	Scenario 3
Taipei, Taiwan	9	7	12
Hsinchu, Taiwan	11	9	12
Other cities	1	1	1
			Total: 63 transactions of group buying

Table 4. Statistics of the Users in Three Scenarios

	Scenario 1	Scenario 2	Scenario 3
Number of users	92	73	109
			Total: 274 users in 63 transactions in 3 scenarios

4.1.3 ProductPlace Profile

"ProductPlace" is the name of a tree structure constructed by combination with categories of products and places on Facebook, which has been described in section 3.2.1. The tree helps us link products to places where the products are sold to compute the individual preference by counting the number of check-ins and pages liked.

There were 6,210 check-ins and 15,248 fan paged liked of total 274 users we collected. The categories of pages on Facebook was 197 and the number of products which matched pages was 1,594.

The part of ProductPlace tree is as Figure 10 below. We only show a part of tree to be the example because of limited layout.

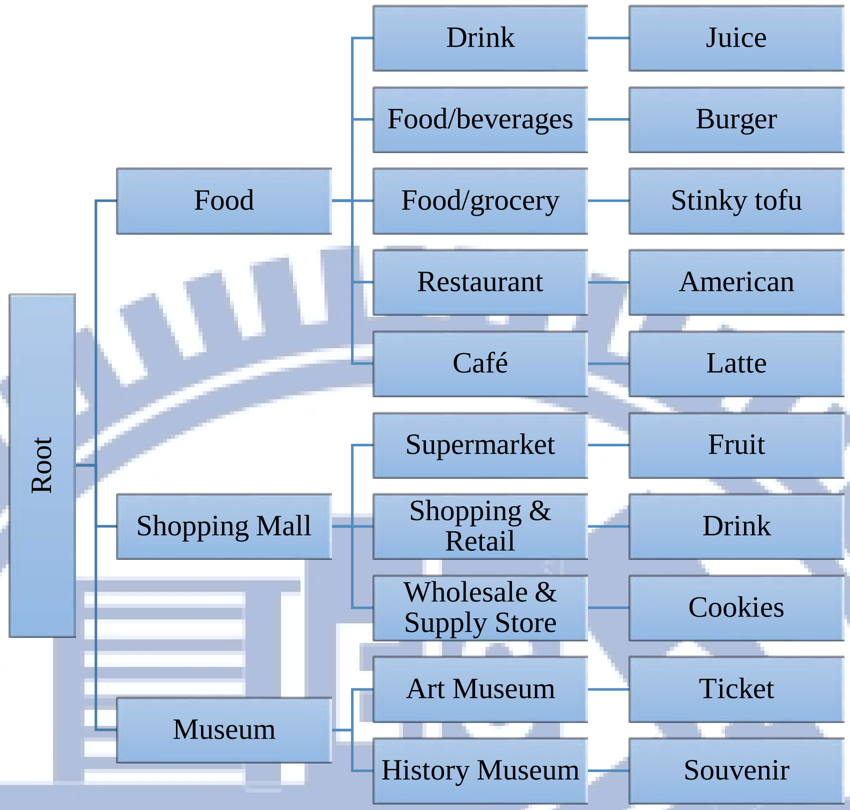


Figure 10. A Part of ProductPlace Tree

4.2 Experiment Process

The experiment process is described as following steps.

1. **Data Collection:** Collect users' contextual data from mobile devices and social data on Facebook.
2. **Data Process:** Process the raw data collected from above channels and compute the group context, social influence and individual preference analysis module.
3. **Personal Weight Collection:** Collect personal weight for the three different scenarios by online questionnaire using Google Drive. We use comparative 7-level scale to make the questionnaire and the raw data was calculated with AHP method.
4. **Willingness Score Calculation:** For each user to invite to join the group, calculate the willingness-to-join score with the processed values and group weight.
5. **Group Formation:** Based on the willingness-to-join score for each user, select top-k

candidate group members with highest willingness, where $k = 2 * N_{re}$, to generate the candidate group and filter the one which has the highest density and cohesion. The group list is delivered to every user in the group.

6. **Evaluation:** For every time a group buying completed, request the group members to fill in the questionnaires.

4.3 Measurement Computing

4.3.1 Criteria Weight Computation

The relative importance of the three criteria factors: group context, social influence and individual preference in the three scenarios were evaluated by a questionnaire with AHP method. People are asked to select which factor is more important and the degree of relative importance when in difference scenario in the two-side question. The four-level evaluation values are 1, 3, 5 and 7 represent “equal importance”, “weak importance”, “essential importance” and “very strong importance”. The questionnaire was classified into three parts which the scenario 1 is “shopping at wholesale together”, scenario 2 is “buying group tickets at a museum together” and scenario 3 is “having a dinner at restaurant together with group discounts”. The Table 5 below shows the questionnaire content of scenario 1 as example.

Table 5. Content of Questionnaire for Scenario 1

Scenario 1: Group Buying at a Wholesale Store								
Question 1	If you are at a wholesale store now, such as Costco, your smartphone shows that someone invites you to purchase something together with group discount to benefit for sharing the price and products. When you consider whether to join the group buying, which factor is relative more important to you?							
	7:1	5:1	3:1	1:1	1:3	1:5	1:7	
Group Context	○	○	○	○	○	○	○	Social Influence
Group Context	○	○	○	○	○	○	○	Individual Preference
Social Influence	○	○	○	○	○	○	○	Individual Preference

We invite people to do the questionnaire and use AHP method which described in the section 3.4.1 (Personal Weight Computing) to analyze this and calculate the weights of factors for the three scenarios. The analysis result is shown below as Table 6 and to be the default value of weight of each criterion in each scenario. If the user logged in does not fill in the AHP questionnaire, then we will use the default value to compute his/her willingness.

Table 6. System Default Weight Values for Three Scenarios

	Group Context	Social Influence	Individual Preference
Scenario 1	0.2457	0.1612	0.5931
Scenario 2	0.2042	0.3184	0.4774
Scenario 3	0.0671	0.4749	0.4580

The result shows that users care about their individual preference most in the scenario 1: shopping at wholesale together. In the scenario 2: visiting a museum together, the distribution of the scores are more balanced than scenario 1 and shows that user still consider that individual preference is the most important factor. However, in the scenario 3: having a dinner at restaurant together, the analysis result shows that users change their thought to change the most important factor from individual preference to social influence. We think that maybe it is because people are more care about who they having a dinner with and not so care about what they eat. We observe that the weight value of group context and individual preference is decreasing and that of social influence is increasing relatively from scenario 1 to scenario 3.

4.3.2 Willingness Computation

In order to evaluate the accuracy of willingness-to-join in the proposed mechanism, we use the computations of several combinations of sub-module as the benchmarks to compare with the willingness-to-join calculated by the CSP model and group weight computing module. The sub-module of the willingness-to-join is described below.

1. CS model: CS model is to compute the willingness-to-join score by aggregating $GroupContext(i,j)$ and $SocialInfluence(i,j)$ multiplied with relative weight derived from the group weight computing module.
2. CP model: CP model is to compute the willingness-to-join score by aggregating

$GroupContext(i, j)$ and $IndividualPreference(j, p)$ multiplied with relative weight derived from the group weight computing module.

3. SP model: SP model is to compute the willingness-to-join score by aggregating $SocialInfluence(i, j)$ and $IndividualPreference(j, p)$ multiplied with relative weight derived from the group weight computing module.
4. CSP model: CSP model is to compute the willingness-to-join score by aggregating $GroupContext(i, j)$, $SocialInfluence(i, j)$ and $IndividualPreference(j, p)$ multiplied with relative weight derived from the group weight computing module.

Chapter 5 Results and Evaluation

In order to evaluate the proposed contextual group formation mechanism for likeness, satisfaction and willingness, we develop a web-based app to collect data and utilize online questionnaires to collect user feedback about the mechanism.

5.1 Accuracy of Contextual Group Formation

To evaluate the accuracy of the proposed contextual group formation mechanism in identifying the users with high willingness to participate in the group buying, six approaches of group formation including (1) random, (2) collaborative filtering (CF), (3) CS model (group context and social influence), (4) CP model (group context and individual preference), (5) SP model (social influence and individual preference) and (6) CSP model (group context, social influence and individual preference) were chosen to compare accuracy. The evaluation included three parts: (1) likeness for the group activity, (2) satisfaction with the group formation service and (3) willingness to join the group buying. After finished a transaction of group buying, each group member was requested to answer the following three questions in a questionnaire:

- Question 1: How much do you like this group activity?
- Question 2: How much do you feel satisfied with the real-time group buying service?
- Question 3: How much do you want to join the group buying?

The scale of the scores used to all the three questions was from 1 to 5.

5.1.1 The Evaluation of Likeness

Figure 11 shows the evaluation results of users about how much they like the target group activity in different models and scenarios. The value of each model is average score.

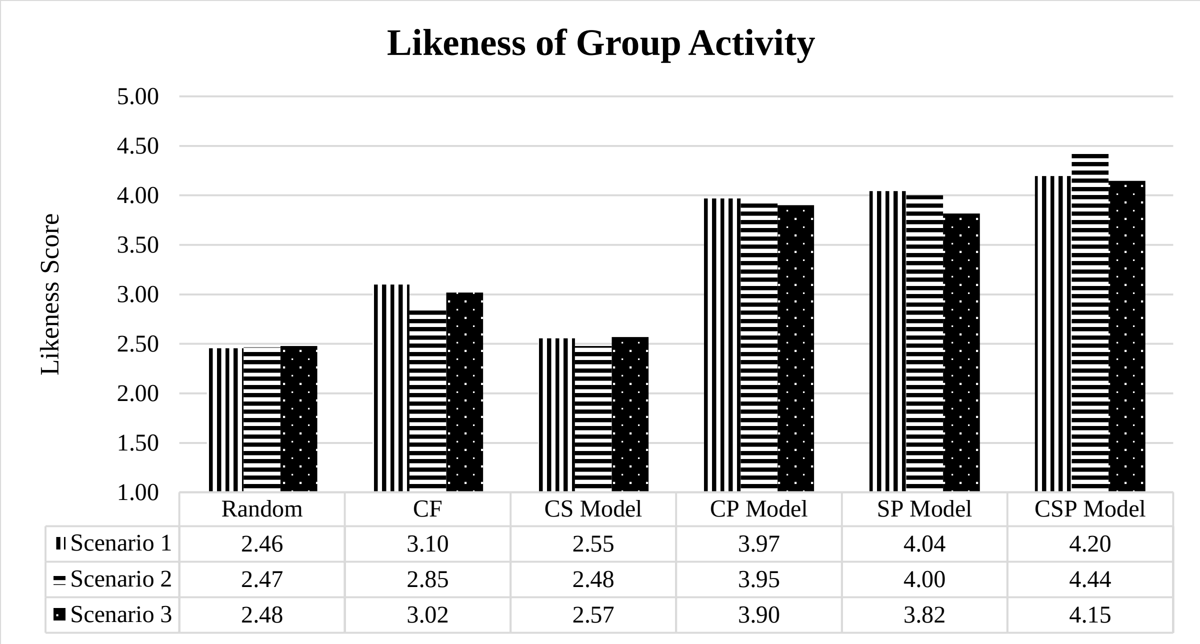


Figure 11. The Evaluation of Likeness of Group Activity

The random model has the lowest average score and the CSP model has the highest average score. The results show that the CSP model is better than the other benchmark approaches and the factor of individual preference is important in likeness.

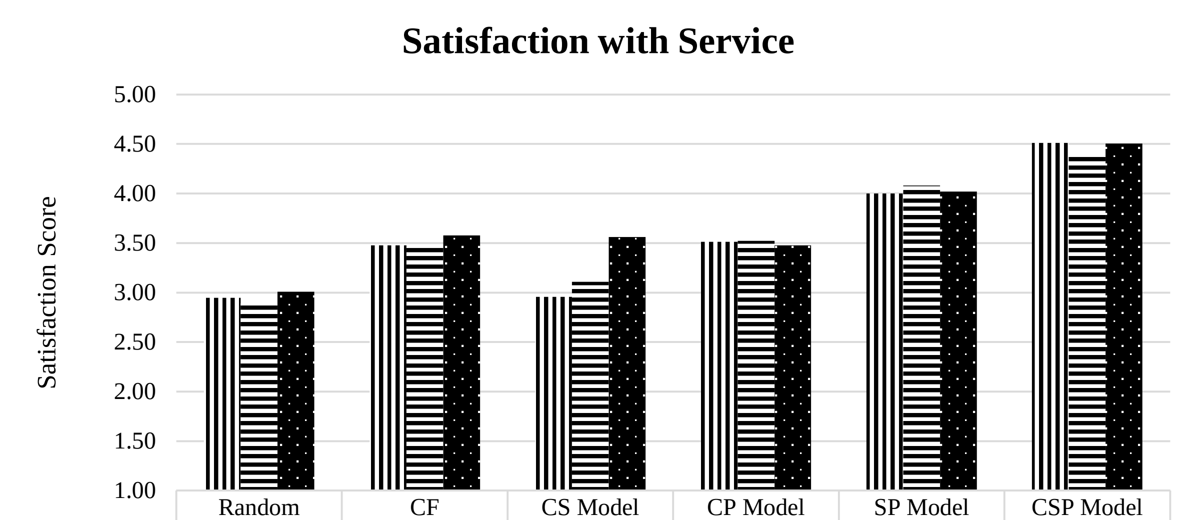
We adopt paired-samples T-test to verify the significance statistically of the difference of the likeness score, because it is normal population and the variance of population is unknown, as the Table 7 below. Using 95% confidence interval of the difference, all the test results show that CSP model is significantly different at 0.05 and prove that CSP model outperforms other models.

Table 7. Statistical Verification Results of CSP Model on Likeness Score

Paired Samples T Test							
	Paired Differences						
Paired Group	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval Lower	95% Confidence Interval Upper	t	Sig. (2-tailed)
CSP-Random	1.73	0.83	0.05	1.63	1.83	34.32	0.000
CSP-CF	1.24	1.03	0.06	1.12	1.36	19.86	0.000
CSP-CS	1.70	0.84	0.05	1.60	1.80	33.62	0.000
CSP-CP	0.31	1.07	0.06	0.18	0.43	4.75	0.000
CSP-SP	0.30	1.05	0.06	0.17	0.42	4.73	0.000

5.1.2 The Evaluation of Satisfaction

Figure 12 presents the evaluation results of users about how they are satisfied with this real-time group buying service in different models and scenarios. The value of each model is average score.



	Random	CF	CS Model	CP Model	SP Model	CSP Model
Scenario 1	2.95	3.48	2.96	3.51	4.00	4.51
Scenario 2	2.89	3.47	3.11	3.52	4.08	4.40
Scenario 3	3.01	3.58	3.56	3.48	4.02	4.50

Figure 12. The Evaluation of Satisfaction with Service

The results of satisfaction score show that the factor of social influence is more important than it is in the evaluation of likeness. We think that it is because group buying with friends is more joyful than with strangers. The score of CS model is lower than CP model may because consumers care about preference more than social influence where the context in the moment of group buying is the same. Due to the increasing importance of social influence, the satisfaction score of CS, SP and CSP models are higher than the likeness score of themselves, and the satisfaction score of CSP model is the highest, which is associated with the evaluation of likeness.

We use the same statistical setting as likeness score to verify the significance as Table 8. The statistical verification results show that our CSP model outperforms the other approaches at a significantly different level.

Table 8. Statistical Verification Results of CSP model on Satisfaction Score

Paired Samples T Test							
Paired Group	Paired Differences					t	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval			
				Lower	Upper		
CSP-Random	2.98	0.72	0.04	2.90	3.07	68.47	0.000
CSP-CF	0.96	0.73	0.04	0.88	1.05	21.92	0.000
CSP-CS	1.47	0.96	0.06	1.36	1.58	25.52	0.000
CSP-CP	0.98	0.70	0.04	0.90	1.06	23.21	0.000
CSP-SP	0.45	0.95	0.06	0.36	0.56	7.80	0.000

5.1.3 The Evaluation of Willingness

Figure 13 shows the evaluation results of users about how much they want to participate in the group buying in different models and scenarios. The value of each model is average score.

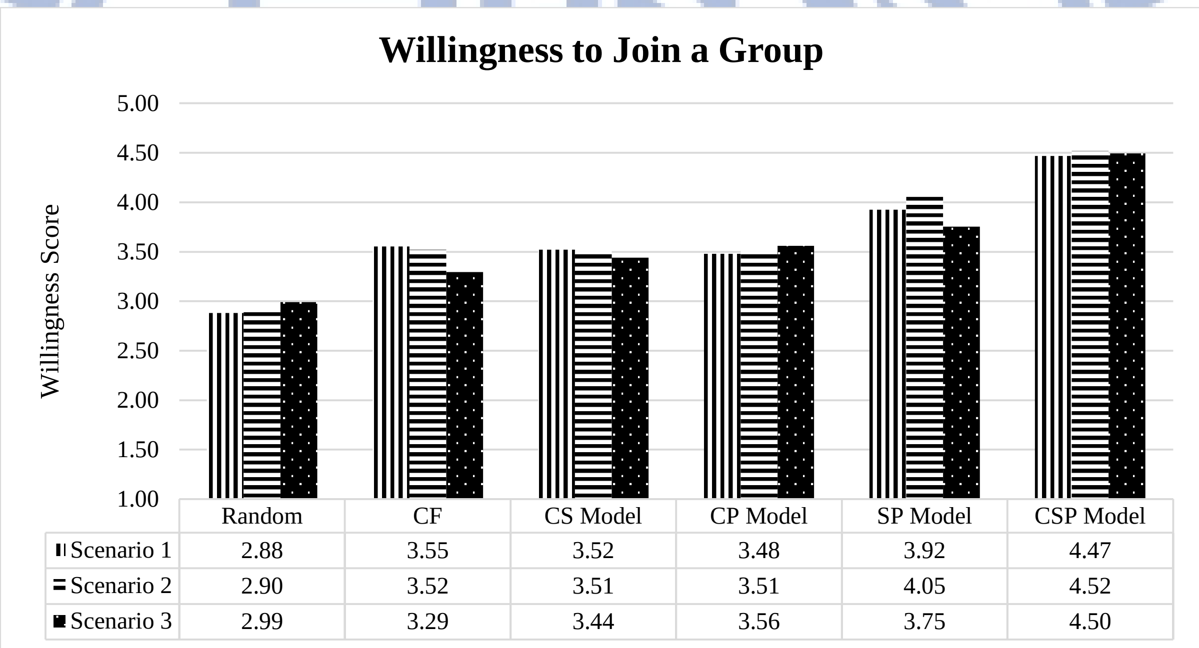


Figure 13. The Evaluation of Willingness to Join a Group

The evaluation results of willingness show that users care about individual preference and social influence almost equally. We can know that preference and social influence are the key criteria for users to decide whether to join the group buying or not, so the scores of SP and CSP models are higher than other models. Considering all the criteria, the willingness score of CSP model is the highest, because it is convenient to users to go to the place (group context), enjoy and interact with friends (social influence) and buy what they like or want (individual preference) in a group discount.

We use the same statistical setting as before to verify the significance as Table 9. The statistical verification results also show that CSP model outperforms the other models.

Table 9. Statistical Verification Results of CSP model on Satisfaction Score

Paired Samples T Test							
Paired Group	Paired Differences					t	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval Lower	Upper		
CSP-Random	3.01	0.70	0.42	2.93	3.09	70.88	0.000
CSP-CF	1.05	0.76	0.46	0.96	1.14	22.92	0.000
CSP-CS	1.01	0.71	0.43	0.92	1.09	23.45	0.000
CSP-CP	0.97	0.71	0.43	0.89	1.06	22.79	0.000
CSP-SP	0.60	0.98	0.06	0.49	0.72	10.14	0.000

After evaluated likeness, satisfaction and willingness in different six models, CSP model which combines group context, social influence and individual preference is the most suitable model for the proposed contextual group formation mechanism by considering all the aspects of the user experience of group buying.

5.2 Accuracy of Willingness Criteria Aggregation

According to the above evaluation results, CSP model is the most appropriate model for the contextual group formation mechanism. Now we evaluate the accuracy of willingness criteria aggregation, which has been described in section 3.4.2, to understand whether using the AHP method (described in section 3.4.1) to compute the personal weights of three criteria is better than average method or not, which each weight is equal to $\frac{1}{3}$.

We measure the willingness to join a group buying in this evaluation, because the weights of group context, social influence and individual preference is used to compute the willingness. We request users to answer the question in a questionnaire, where the value range of the answer is from 1 to 5. Figure 14 is the evaluation results in different weighting models and scenarios.

- Question: How much do you want to join the group buying in each model?

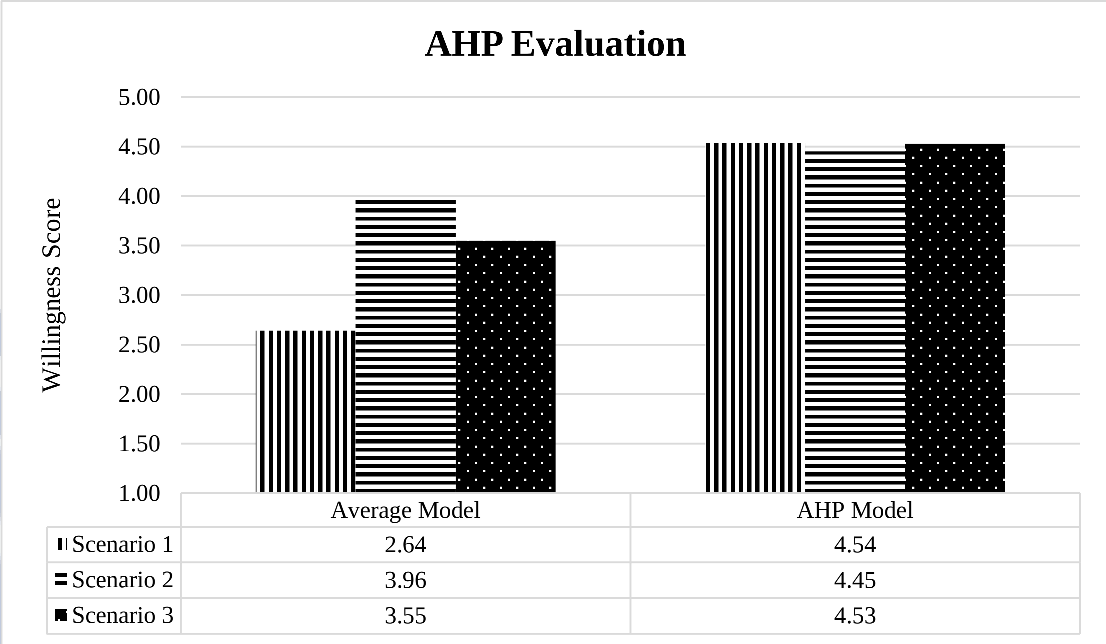


Figure 14. The Evaluation of Analytic Hierarchy Process

The results show that using AHP approach to compute the personal weights of the three criteria for decision making is better than average method, which just set the weights equally to the same. The willingness score of AHP model is almost equal and it represents that AHP method can make the user experience more stable and better in different scenarios. However, the willingness score of the average model is various. We think it is because average model sets all the weights to be equal and that will make the measurement of willingness unable to be appropriate to particular user and group buying circumstance.

We use the same statistical setting as before to verify the significance as Table 10. The statistical verification results show that AHP outperforms the average method.

Table 10. Statistical Verification Results of AHP Evaluation

Paired Group	Paired Samples T Test						
	Paired Differences					t	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval			
				Lower	Upper		
(Scenario 1) AHP–Average	1.90	1.23	0.07	1.76	2.05	25.55	0.000
(Scenario 2) AHP–Average	0.56	0.92	0.06	0.45	0.66	10.01	0.000
(Scenario 3) AHP–Average	0.99	1.20	0.07	0.84	1.13	13.58	0.000

After evaluated the computing approaches of weights of the three criteria, the AHP (analytic hierarchy process) technique outperform the average method. Using AHP to analyze the personal decision making about willingness to join a group buying in a particular circumstance, the proposed mechanism can provide a real-time group buying service which analyze the willingness of nearby people to join a group more accurately.

Chapter 6 Discussion and Conclusion

6.1 Research Summary

This research proposes a mobile intelligence mechanism for contextual group-buying formation. The criteria of recommending a custom to join a group buying is analyzed according to three factors: (1) group context: the geographic convenience between the group leader who creates the group buying event and the people nearby, (2) social influence: the degree of trust and interaction among group members measured by data collected on social media and (3) individual preference: the preference of nearby people that measured by pages liked and check-ins collected on social media. The willingness to join a group-buying event is measured by the values of above three factors multiplied with corresponding personal weights of criteria. The weight of each criteria is computed by using analytic hierarchy process method.

In order to select the best group, we introduce the group formation method. In the group formation engine, we identify the set of users with high willingness score and form candidate groups by combination. After combination, we compute the density of each group to execute the first filtering and then calculate the group cohesion measured by the willingness to join the group and their values of social closeness to execute the second filtering to generate the best group list to the group leader who starts the group buying event.

The evaluation results show that the proposed contextual group formation mechanism, which combines group context, social influence, and individual preference, has higher scores on the evaluation of likeness, satisfaction and willingness. In the measurement of multi-criteria, we found that group context is a fundamental criterion and social influence and individual preference are more important in the group buying service, which affect much on the likeness of product, user satisfaction and willingness to join a group buying.

The proposed CSP group formation mechanism could assist the local business to increase the revenue and help the consumers to gather nearby people actively who have similar preference and social interaction quickly and then enjoy the experience of group buying.

6.2 Research Contributions

We develop a new contextual group formation mechanism and its contributions are as follows.

(1) From the system development perspective, we design an efficient and effective group formation system for group buying. From the experimental results, we verify that the system can improve the user willingness to join a group buying.

(2) From the methodological perspective, we consider the multi-criteria factors of group context, social influence and individual preference in mobile environment and found that use the three criteria together can bring the most perfect user experience of real-time group buying service.

(3) From the practical perspective, the existing group-coupon platforms, such as Groupon, has not clearly recognized the importance of context awareness and social influence. The approach of using the users' contextual and social data to gather nearby and appropriate people to join a group buying is innovative.

(4) From the business perspective, the proposed mechanism provides more opportunities to group commerce. Not only group-coupon platform on the website can bring the group commerce but also make every consumer has the ability to gather nearby people to enjoy real-time group buying at anywhere and anytime, and vendors also benefit from selling large amounts of products at once.

6.3 Research Limitations

There are some limitations in this research listed below.

(1) The proposed mechanism has the problem of cold start. The mechanism requires enough

numbers of users in the database and maintain users' behavior and interaction on social media to provide group formation more appropriately.

(2) The proposed mechanism cannot help users to bargain with merchants how they can give discount to users. That is full of complicate personal factors but we can suggest merchants to cooperate with us to earn more popularity and profits because they are able to sell products at once but not wait for reach the minimum number of people to buy the group coupon.

(3) With the rapid development of mobile technology, there are certain risks that the versions of Android and Facebook SDK update usually. That cause some functions may be deleted in the future, so it is difficult to developers to maintain their works. There are several different kinds of mobile devices in the world, and each also has different kinds and versions of web browsers. Some web browsers with old versions do not support HTML5 and that will make problems that users cannot use this mechanism to enjoy our service.

(4) With the increasing consciousness of personal privacy protection, we think it will be more difficult to collect social data of users in the future, and that will affect the usage of this work. If this mechanism cannot collect personal data on social media, then it cannot identify who are nearby and their preference.

6.4 Future Works

There are some related issues could be research further.

First, in addition to location and the people nearby, perhaps there are some other contextual factors, such as weather and nearby events, which are useful to compute the willingness more accurately.

Second, in this study, we consider social influence to increase the willingness to join a group and use tags, comments and likes data to compute it. However, there are still several other social data which is possible to compute the social influence between two people, such as pokes and the frequency of messages sent.

Third, to compute the individual preference, we utilize the pages liked and check-ins data to analyze it, but it is possible to analyze purchase log or wish list of users that may provide the analysis result more precisely.

Fourth, in the future, not only smartphones or tablets can utilize the contextual group formation mechanism, but also mobile wearable equipment such as Google Glass and Sony SmartWatch can do it. Due to the rapid development of mobile technology, there are many opportunities to humans to enjoy more convenient group buying service.

Lastly, this study requires the social data of users heavily to identify the people nearby and measure their social relations and purchase preference. However that may drop the performance of the system when a user is first to use the system. This problem can be solved by using the clustering technics to match the new user to other similar existing user clusters and assign the initial personal preference to the new user, which may solve the cold start problem.

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