國立交通大學

資訊管理研究所

博 士 論 文

社群商務決策支援機制之設計

Designing Social Commerce Decision Support Mechanisms

研 究 生： 李易霖

指導教授： 李永銘 博士

中華民國 101 年 7 月

社 群 商 務 決 策 支 援 機 制 之 設 計
Designing Social Commerce Decision Support Mechanisms

研 究 生： 李易霖　　Student: Yi-Lin Lee

指導教授： 李永銘博士　　Advisor: Dr. Yung-Ming Li

國立交通大學

資訊管理研究所

博士論文

A Dissertation

Submitted to Institute of Information Management

College of Management

National Chiao Tung University

in Partial Fulfillment of the Requirements

for the Degree of

Doctor of Philosophy in Information Management

July 2012

Hsinchu, Taiwan, the Republic of China

中華民國 101 年 7 月

中文摘要

社群商務決策支援機制之設計

研 究 生： 李易霖　　　　　　　　　指導教授： 李永銘博士

國立交通大學資訊管理研究所博士班

摘要

隨著社群網站的蓬勃發展，以其為基礎的商業用途應用程式也越來越多。然而目前所知多數相關研究以及應用程式開發，其目的多在於建立品牌形象以及支援客戶互動。與前述情況相比，對於購買決策相關應用則較少論及。事實上，許多消費者在購買商品時，會聽取朋友的意見與建議，以作為選擇最終購買商品的參考依據。本研究之目的在於以消費者之線上社群網路為基礎，透過社會心理學以及消費者購買行為決策流程，建立社群商務購買決策支援機制。

現實生活中，互動頻繁的朋友較可能是親密的朋友，但在線上社群網站中此種情況是否仍然如此，在進行決策機制設計前必須先加以驗證。透過蒐集本研究所使用之實驗平台上的各項互動，以及實際調查所得到之社會關係指標，利用社群網路分析之 MRQAP 法對此推論進行驗證的結果，證實了此一關係的存在。此一關聯性被確認後，本研究接著針對三種常見的消費者購買決策情境，設計了不同的決策支援機制。

消費者進行購買決策時，通常會處於以下三種狀況其中之一。第一，消費者已經 找到數種符合需求的商品，需要在其中挑選一項作為最終購買商品。第二，消費者已經列出了某些評選商品的考量因素，但卻不知道有哪些商品符合所列條件。第三，消費者僅僅知道要購買某種商品，但卻不知道從何處開始著手。本研究針對以上情境，分別設計了相對應的決策支援機制。在第一種情境中，本研究設計了決策支援小組的篩選機制，以找出適當的參考團體。而改良過後的投票機制則被用來選出最終的建議購買產品。而在第二種情境中，決策支援小組以 QOC 表達方式，針對消費者所在乎之考量因素給予權重，而後形成最後建議。在形成最後建議的過程中，決策小組成員間彼此相互影響的程度也被納入考量。第三種情境裡，考量朋友之間的友誼會因時間產生變化，因此甄選決策小組的條件增加了時間因素。此外，決策小組發表的各項意見與建議，透過文字處理篩選出評選商品的考量因素，經由人工智慧的工具，做出最後的建議。除此之外，本研究也進行相關實驗以確認各機制之可行性。實驗結果確認本研究所提之機制，與其他決策方法比較後，能提供給消費者較佳的決策支援訊息。

關鍵字： 社群網路，決策支援，消費者決策行為，電子商務

ABSTRACT

Designing Social Commerce Decision Support Mechanisms

Student: Yi-Lin Lee Advisor: Dr. Yung-Ming Li

Institute of Information Management
National Chiao Tung University

Abstract

With the vigorous development of the social networking sites, many application systems have been developing for the purpose of branding and consumer service. In contrast, researches on consumer purchase decision making is relatively rare. In fact, many consumers collect advices and suggestions from friends as a reference for final decision. In this study, purchase decision support mechanisms were designed to support the operation of social commerce for different scenarios. In the first scenario, the consumer has found several products that meet requirements. For the second scenario, the consumer knows only selection criteria about the item required. In the third scenario, the consumer just wants to buy something, but has no idea about how and what to buy.

A screening mechanism was designed for first scenario to identify appropriate friends as support group, and an improved majority voting mechanism was proposed. For the second scenario, a personalized and socialized recommendation tool was designed. During the consensus-making process, the degree of mutual influence among the members of the decision group was also taken into account. For third scenario, the time factor was included in the decision group screening mechanism. By using part-of-speech processing technique the possible selection criteria were identified, and artificial intelligence methods were used to propose product reference list. In addition, the experimental results confirmed that the proposed mechanisms can provide better support when compared with other benchmark methods.

Keywords: Social Network, Social Commerce, Decision Support, Consumer Behavior

致謝

鳳凰花開的季節，空氣裡滿是回憶的味道，重拾書本的博士班生活，終於畫下了句點。六年時間彷彿昨日，此刻的我沒有太多情緒起伏，只覺得完成了一個人生中重要的里程碑。這段不算輕鬆的過程，首先要感謝的是指導教授李永銘博士。桃李不言，下自成蹊。老師的言教，讓我知道人師之表；老師的身教，讓我看到經師之典。看著您的身影，如果有一天能執教鞭，我想我已經知道如何成為學生心目中的好老師。博士論文的完成，除了李永銘教授的指導外，也感謝論文指導委員會的清華大學服務科學研究所林福仁教授、中央大學資訊管理學系陳彥良教授、中正大學資訊管理學系古政元教授、交通大學資訊管理研究所羅濟群教授以及劉敦仁教授的提點。因為有您們的指導，讓本篇論文更嚴謹且完整。也謝謝您們的鼓勵，希望有一天我也能追隨您們的腳步，續窺學術殿堂的奧義。

博士班的生活中，那些曾經筆硯相親的夥伴，謝謝你們帶給我的一切。人生如渡一重汪洋，我何其幸運，與你們相聚在同一條狹船上。勇劭學長以及治華學長，謝謝你們的協助，讓我的論文能夠順利發表，那些星期三晚上一起度過的日子，都將會是未來每次相聚時聊不完的話題。建邦、嘉豪、敬文，還記得第一年暑假，在空蕩蕩的管二館裡報論文的日子嗎？乃儁，涵文以及子鳳，你們熬夜趕論文那蒼白的臉，我會永遠記得。宗穎以及雅玲，你們兩個勞來與哈台，即使在畢業後還是繼續帶給我歡樂。與我一起畢業的蕙如、宣銘、文翔、郁卉、佳林與詩雯，因為有你們，讓我在最後一年的學生生活，多了很多的回憶。蕙如，看妳順利畢業，我也鬆了一口氣，未來的路希望妳能靠自己的努力走下去。實驗室的清潔股長、勤務兵、設備組、補給官、五百里加急快遞員宣銘，感謝你默默的付出，讓研究室的所有人沒有後顧之憂。文翔提供的各式飲料，適時的緩解了遇到瓶頸時的壓力。沒有財務大臣郁卉，我們可能得喝西北風，妳帶來了故鄉的美味，也捎來鄉愁的滋味。因為佳林妳的祈禱，上帝賜給了我人生中最好的禮物，神會賜福予妳。入學時滑壘成功的詩雯，畢業時也維持妳一貫的風格撲回本壘，回首這段日子，妳跟宣銘帶給我們的笑料，相信會是大家永遠的歡樂。致緯、竣智和潘強三位小朋友，希望我們這群瘋狂的學長姐，沒有嚇著你們。跟我相處時間最久的革命戰友無尾熊政揚，那些年我們一起喝過的酒、聊過的事，留待未來相聚再繼續。還在奮鬥的博士班學弟妹們，繼續堅持下去就會成功。

在我背後默默支持我的母親、弟弟一家人以及太太曉菱，沒有你們的支持，我無法在工作與學業兩頭燒的情況下走完這段路程。最後，謹以此篇論文獻給在天上的父親，我做到了!

李易霖 2010/07/01

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Background

Social networks are the grouping of individuals, and online social network platforms are now one of the most popular online communities. Most online social network services are used for sharing what you've done or what you're doing, but this may not be the only thing they can do. Companies have been devoting their efforts to explore the opportunities of social network over the past years. The increased popularity of social network has opened opportunities for electronic commerce, often referred to as social commerce. Social network not only provides a new platform for pioneers to innovate, but also raise a variety of new research problems for electronic commerce researchers.

There's more evidence that online social network can be a conduit to social commerce [24]. Social network provide an open platform for social commerce consumers and vendors to search, share and advertise product information. From a survey conducted by Gartner [7], 40% of consumers regularly search products information on social media, 34% are more likely to share product information on social media with their friends than in e-commerce sites, and 77% of online shoppers use reviews. The survey also showed that 75% trust personal recommendations, and 75% are more likely to purchase if a friend endorses. This open up the gate to provide product information meeting consumer's personal preference based on social relation. At the same time, 81% of consumers receive advice from friends. The result implies that a social support mechanism for product selection would be helpful to consumers. In this study, the phenomena were addressed based on consumer purchase behavior. According to OTX's purchase intention survey [65], 70% of consumers visit social media websites to collect information on a product. According to the Nielsen Global Online Consumer Survey of over 25,000 Internet consumers from 50 countries in 2009, 90% of consumers trust the opinions of personal acquaintances [18]. IBM's survey in 2011 found that 50% of 16-64 year olds who use online social networking sites such as Twitter and Facebook admit to using these online social networks to assist with shopping decisions while 35% stated they use online social networks to rank products and services. These respondents believe it is important to be able to use online social networks to assist with buying decisions [75].

1.2 Research Problem

Behind the visible action of making a purchase in social commerce lies a decision process that must be investigated. Consumer behavior involves study of how and why they buy. It blends the elements from psychology, sociology and economics. It also tries to assess the influence on the consumer from groups such as family, friends, reference groups and society in general. Consumer purchase decision is the processes undertaken by consumer in regard to a transaction during the purchase. A typical consumer purchase decision making process is depicted in Figure 1.1.

Figure 1.1 A typical consumer purchase behavior

Social commerce is a subset of electronic commerce (EC) that uses social network to supports social interaction, to assist in the online buying and selling of products and services. It includes tools that enable consumers to get advice from trusted individuals, find goods and services and then purchase them. Social commerce helps consumers make smart and savvy purchase, and consumers now are looking for ways to leverage each other's expertise, understand what they are purchasing, and make more informed and accurate purchase decisions.That is, they are increasingly influenced by online social networks when it comes to purchase decision making. Despite its growing interests, however, there are relatively few studies on social commerce support mechanism. For the purpose of helping consumer with making purchasing decision, it is desired to have proper social commerce support mechanisms based on online social networks. Moreover, as research suggests that customers value and respect personal sources more than other sources [29, 57], it would be ideal to construct decision support groups from their online social networks.

In real life, we are constantly influenced by other factors than just information, such as friends, social classes and psychological needs when making purchase decision. A consumer can obtain information from several sources:

- Personal experience: past purchase history, experience of similar products etc.
- Personal sources: family, friends, colleagues etc.
- Commercial sources: advertising, company websites, and salespeople.

In social commerce context, consumers also collect information from these sources. As social relation is the core of social commerce, in this study it was used to be the infrastructure of social commerce support mechanisms.

Consider three common scenarios of product purchasing (see Figure 1.2). Suppose that customer A wants to buy a digital camera,

Scenario 1: He/she has searched for various products, and at this point he is interested in several models. However, he/she is unable to make up his/her mind, so his/her friends or family are consulted to rank the products for him/her.

Scenario 2: He/she has identified price, megapixels and LCD size as selection criteria and needs someone to recommend products based on them.

Scenario 3: He/she has no idea about digital camera and just asks his/her friends or family to tell him/her what factors should be considered and what to buy.

Naturally, the following research problems arise when designing social commerce support mechanisms:

- For scenario 1, how to find adequate group with similar taste or preference so that consumer can get advice from the group and the group can rank the products for consumer.
- For scenario 2, how to design the recommendation mechanism so as to utilize friend network to recommend items based on consumer's selection criteria, that is, how to design a personalized while socialized recommendation results.
- For scenario 3, how to build up functionalities so that consumers can discover product information based on personal and/or commercial sources.

To address these scenarios and meet the requirements of social commerce, in this study the corresponding mechanisms were designed. For more vivid picture of the study, Figure 1.2 serves as the research paradigm.

Figure 1.2 Scenarios of this study and corresponding support mechanisms

1.3 Research Contributions

While there are on-going researches on social network and its effects on business, there is relatively little solid research on social commerce support. The contributions of this study are listed as follow.

- Social Support Mechanism for scenario 1:

  This work designed a mechanism to find the most fit group for consumer, and an adaptive majority voting method was used to rank items.

  1. Regarding support group selection, other than selecting group members based on some predefined measures, in this study the agglomerative hierarchical clustering method was used to find the proper home group for consumer.
  2. Concerning improved voting method, social power was used to weight each voting and suggest the ranking of items.

- Social Recommendation Mechanism for scenario 2:

  This study proposed a system framework for personalized (personal preference) recommendation results based on socialized information sources (friend networks)

1. For personalized recommendation, an assistant tool based on QOC schema was designed to recommend proper items based on consumer's preference. And a recommendation conflict resolution was also proposed to solve the recommendation inconsistency on certain product.
2. As for socialized recommendation, by introducing social impact theory of social psychology into social network analysis process, a new decision group recruiting method was designed to select friends with higher impact power.

- Social Intelligence Mechanism for scenario 3:

This research suggested a set of functions to collect information from personal or commercial channel based on trustworthy sources.

1. With regard to sources selecting function, source credibility including friendship, social similarity, network centrality and expertise was used to recruit proper members. A PageRank-like index based on post-reply was proposed to measure expertise on products.
2. As to information collecting function, artificial intelligence techniques were used to reduce human's intervention.

1.4 Outline of the Study

The remaining part of this paper is organized as follows. In chapter 2, existing literatures related to this study were reviewed. The corresponding support mechanisms were demonstrated in chapter 3, 4 and 5 respectively. The system framework, experiment and discussions are also included in each chapter. Finally, chapter 6 concludes research contributions and presents future research directions.

1.5 Chapter Summary

In this chapter, the applications of social network in electronic commerce environment were introduced and pointed out the imperious demands of support mechanisms. In addition, the research questions this study tried to address were also highlighted, and the important contributions were also spotlighted in this chapter.

CHAPTER 2

LITERATURE REVIEW

In this chapter, a consumer purchase decision support system framework was built based on the following theories. First, consumer purchase decision-making process was studied to understand the decision-making stages. Second, social psychology was investigated to understand the characteristics a friend should have so as to be selected as a reference group member. Third, in order to identify the decision reference group social network analysis was used to analyse the members within social network. The complete theoretical foundation related to this research is shown in Figure 2.1.

Figure 2.1 Theoretical foundation

2.1 Consumer Purchase Decision Making

Human decision making process has been characterized as relatively sequential, and it becomes more complex with distributed source of information and the quantity of information available through networked sources. The way people make decisions varies considerably. Early research has focused on the way people are observed to make decisions and the way in which people should theoretically make decisions. Depending on their methodological foundation, these models can be classified as: descriptive, prescriptive or normative. A simple way of distinguishing between these modes of decision making is [26]:

- Descriptive: What people actually do;
- Prescriptive: What people should and can do;
- Normative: What people should do.

From a psychological perspective, it is necessary to examine individual decisions in the context of needs, preferences and values. From a normative perspective, the analysis of individual decisions is concerned with the logic of decision making and rationality. The rationality is ensured if the process of decision making is carried out systematically.

As purchasing decisions are often influenced by people who the consumer knows [44], this study focused on what consumers actually do when making purchasing decisions, that is, the descriptive mode was discussed. In consumer decision-making models, Utility theory proposes that consumers make decisions based on the expected outcomes of their decisions. However, in this model consumers are viewed as rational actors who were able to estimate the probabilistic outcomes [83]. As one might expect, consumers are typically not completely rational [69]. In contrast with this view, Simon was interested in the mechanics of the decision-making process [74], in that he considered how a decision maker evaluates all the consequences and compares them with each other. He proposed three principal phases:

- Intelligence: think of the problem and find out what the alternatives to the given problem;
- Design: determine all the possible consequences of these alternatives;
- Choice: evaluate all the possible consequences.

In the consumer purchase decision-making process proposed by Kotler [45], the consumer passes through five stages: problem recognition, information search, evaluation and selection of alternatives, decision implementation, and post-purchase evaluation. This process is an extension of Simon's model as three stages are included in Kotler's model (see Figure 2.2).

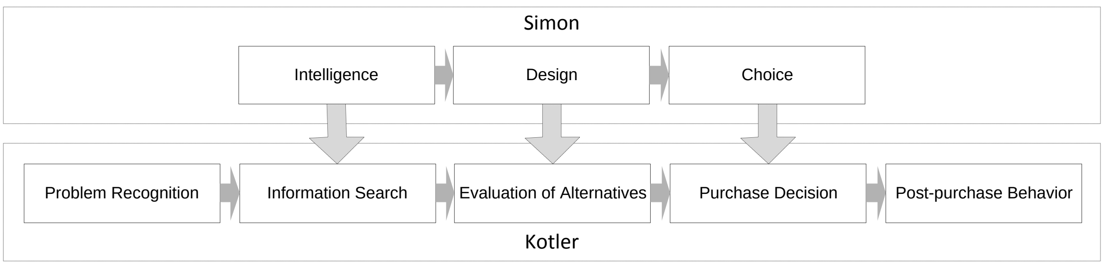

Figure 2.2 Mapping of Simon's and Kotler's decision process

Once consumers perceive a need, they begin to search for information needed to make a purchase decision. The initial search effort often consists of an attempt to recall past experiences. If the internal search does not collect enough information, the external sources are consulted. Empirical study found that consumers relied more heavily on personal sources of information for decisions [29, 57]. After acquiring information during the information search stage, the consumer proceeds to alternative evaluation. All the identified alternatives must be evaluated against some established criteria. These criteria might base on past experiences or the comments of friends. At purchase decision stage, the consumer stops searching for and evaluating information, and make purchase decision. From a consumer-behavior perspective, the products that consumers select can be influenced by their reference groups [5, 17]. Reference groups are people to whom an individual looks as a basis for self-appraisal or as a source of personal standards, and they have important influence on the purchase behavior. As dual process theory suggests, reference groups can be divided into normative and informational [25]. The former one is based on the desire to conform to the expectations of others, and the later one is based on the acceptance of information from others [40]. Essentially, the personal source is individual's online social network because it is constructed based on friends. Besides, online social network can be normative as well as reference group as friends can not only provide information but also influence each other.

2.2 Social Influence, Social Impact and Social Choice

In social network, social psychology, communication and information technology are essential in building meaningful relationships and influencing behavior. Today, the area of social commerce has been expanded to include the range of social network tools. Examples of these tools include consumer ratings and reviews, user recommendations and referrals, forums and communities, social network optimization and social applications. As the fast development of internet, together with the booming of online social network, it is much easier to collect information from personal sources. Many consumers are getting used to make decisions based on comments collected from their own online social networks. While conventional decision support system has been extensively investigated, little specific mechanism on social commerce is developed. For the purpose of helping consumer with making purchasing decision, it is desired to have proper social commerce support mechanism based on online social networks. Moreover, as research suggests that consumers value and respect personal sources more than other sources [29, 57], it would be ideal to construct decision support groups from their online social networks.

In real-world decision-making process, human can experience emotional intensity and information overload that may affect their choices. Better decision support system should address these issues and assist human decision making by developing systems that integrate capabilities from human and computational intelligence. Social influence is the process by which individuals make real changes to their feelings and behavior as a result of interaction with others who are perceived to be similar, desirable, or expert [51, 68]. Social influence does not necessarily require face-to-face interaction, but is based on information about other people [70]. Social impact theory is widely cited in the research literature in social psychology, it provides a useful framework for understanding how a person is affected by social environment [61].

Social impact theory states that social influence is proportional to a multiplicative function of the strength, immediacy and number of sources [49]:

- Strength: the importance of the reference group to the individual.
- Immediacy: the closeness of the influencing group to the individual (in space and time) at the time of the influence attempt.
- Number: how many people there are in the reference group.

Research on social influence demonstrates that one's attitude and judgment tend to conform to those held by the majority of others [59]. Conformity can be due to either social pressure or one's belief that the majority is likely to be correct [25]. When a large portion of a reference group holds a particular attitude, it is likely that the individual will adopt it as well [68]. Social choice theory is concerned with relationships between individuals' preferences and social choice [28, 73], and decision making and social choice theory are strong connected [4, 15]. The method of majority decisions has been widely discussed in the context of social choice theory. Voting-based procedures are entirely natural for some kinds of social choice problems [72]. Research on consumer decision involving multi-attribute options provides empirical evidence for use of the majority rule [71, 86]. A weighted voting system is one in which the preferences of some voters carry more weight than the preferences of other voters. However, in most of the social choice literature, all voters are treated equally. In fact, some voters are more important than others.

2.3 Social Network Analysis

An online social network is a social structure made of people who are tied by one or more specific types of interdependency. Research on online social network has captured the effect of social influence on consumers' purchase decisions across a variety of context [6, 38, 55]. Online social network analysis (SNA) refers to techniques used to analyse online social networks. Online social network can be analysed in node level and dyadic properties. The most popular metrics used are degree, betweenness and closeness centrality [31]. Degree centrality can be used to see if someone in an online social network is involved in large number of interactions. Betweenness centrality is a metric to verify if an individual is an important node who lies on a high proportion of paths between others. A user with higher betweenness centrality is often considered as an opinion leader [31], and a higher closeness centrality indicates that a user is highly related to all others [64]. At the dyadic level the two properties are dyadic cohesion and equivalence [9, 10]. Dyadic cohesion describes to the social closeness of a pair of nodes. Equivalence refers to the extent to which pairs of nodes is similar.

Social impact theory suggests that social status, power and credibility can impact on decision [50]. Social status can be the proxy to estimate strength [62]. In-degree centrality, betweenness centrality [30, 31], and Bonacich power centrality can be used to measure social status [8, 30, 62]. Moreover, a member with high cognitive centrality would acquire pivotal power in a group and exert more influence on decision making [39]. In social impact theory, immediacy is used to describe group structure. Group structure can be treated as a pattern of immediacies between group members, and immediacies is the distances between individuals [61]. Furthermore, closeness may increase the power of social influence by making a source of influence more immediate [49, 61], hence closeness centrality can be used as the proxy of immediacy.

The studies of social network have examined a diverse set of properties, and these properties are classified as relational properties and structural properties [76]. Relational properties focus on the content of the relationship between network members and on the form of these relationships, while structural properties describe the way members fit together to form social networks. Human relationships are maintained, renewed, or deteriorate over time [77], but time factor is missing from the above properties.

2.4 Multiple Regression Quadratic Assignment Procedure

Some data sets contain observations corresponding to pairs of entities (e.g., friends), and these data are not independent. The multiple regression quadratic assignment procedure (MRQAP) is commonly used in social network analysis. MRQAP is a nonparametric statistical algorithm regressing a dependent matrix on one or several independent matrixes. It is a standard technique to analyse social network data and to discover behavioral characteristics of friendship [85]. Therefore network regression measures are the most appropriate statistical method for testing them. However, these data are not independent and do not satisfy the assumptions of ordinary least squares regression, therefore requiring the use of the multiple regression quadratic assignment procedure (MRQAP) to test social network data [9].

MRQAP has been widely used in social network related research [27, 37, 48, 84]. However, in the development of social network applications, to my knowledge little effort has been devoted to test if the data collected from online social networks can be used to maintain online relationship. For example, some social network-based recommendation systems used interaction data such as comment, share, interests in common to measure online relationship [52, 53], but they are not empirically examined. To make this research more solid, this method was introduced to test if the interaction data on online social network can really reflection social relation.

2.5 Design Rationale and Representation Schema

Due to the complexity of decision problem and communication process between decision-making group members, there is a strong need in formatting the solution design process to help members record, access and assess design rationale. Design rationale is used to provide information about why certain decisions were made. A clear design rationale provides a medium for communicating between decision group members. A design rationale is an important tool in arriving at the initial decision alternatives in the first place, and a representation is needed for capturing design rationale. A good representation schema is vital to enabling effective design and discuss. A representation schema explicitly documents the reasoning and argumentation occurring in design. It determines the methods used to capture and retrieve the design rationale.

One design rationale representation schema known as Questions, Options and Criteria (QOC) developed by McLean et al. [54]. It focuses on three basic concepts indicated in its name. QOC represents the design space using three components:

- Questions(Requirements): identify key issues for structuring the space of alternatives
- Options(Alternatives): provide possible answers to the questions
- Criteria: provide the bases for evaluating and choosing from among the options.

A design rationale presented by QOC schema is depicted in Figure 2.3.

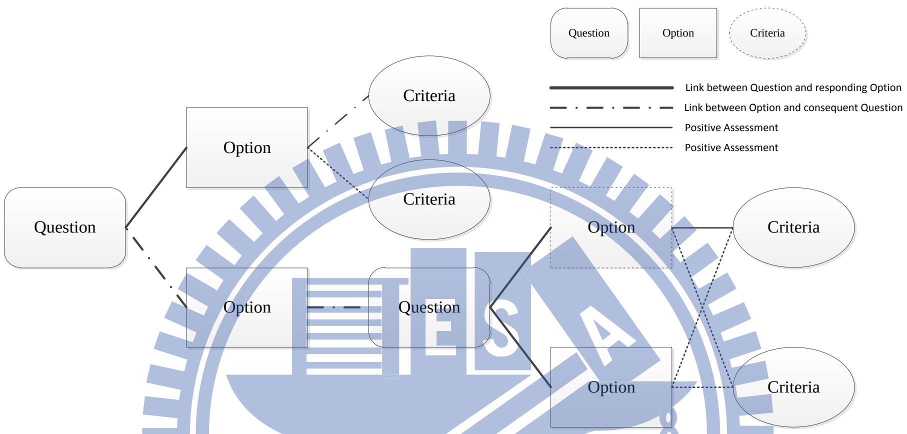

Figure 2.3 QOC representation schema for design rationale

2.6 Fuzzy Analytic Hierarchy Process and Fuzzy Delphi

The Delphi method is a group decision making technique. Murry et al. integrated the concept of traditional Delphi method and fuzzy theory to improve the vagueness of the Delphi method [58]. Fuzzy Delphi is a good method for group decision to solve the fuzziness of common understanding of experts' comments [60]. Analytic hierarchy process (AHP) is a structured, multi-criteria decision-making approach, and it is widely used for dealing with quantifiable and intangible criteria that can be applied to numerous areas such as decision theory [82]. Hsu and Chen [34] proposed a fuzzy similarity aggregation method, in which similarities between experts were collated and fuzzy numbers were assigned directly to each expert to determine the agreement degree between them. Fuzzy AHP (FAHP) translates the viewpoints of experts from definite values into fuzzy numbers and membership functions, and presents triangular fuzzy numbers in paired comparison of matrices to develop FAHP. Consequently, the comments of experts approach human thinking model, so as to achieve more reasonable evaluation criteria.

2.7 Chapter Summary

The primary objectives of this chapter were to provide a brief overview of related theories used in this study. By investigating Simon's human decision process and Kotler's consumer purchase decision-making process, their relationship was mapped. Furthermore, the key role of reference group in purchasing behavior was also pinpointed. Social impact, social influence and social choice drawn from social psychology were reviewed to understand how people influence each other within social context. For the purpose of representing the relation between selection criteria and possible candidates, design rationale representation scheme was also covered in literature review. Last but not the least, information technologies used in this study were also discussed- namely, social network analysis, Fuzzy Delphi and Fuzzy AHP.

CHAPTER 3

SOCIAL SUPPORT MECHANISM

In our daily life, we usually make purchasing decisions. Some can be easily made because we are familiar with the items we need, while others may be much more complex. In this chapter, a support mechanism is presented to help consumers with ranking desired products.

3.1 Scenario of Social Support Mechanism

For the consumer who is experienced in the product he/she wants to buy, there may have been a candidate list in mind after surveying available items. However, consumer may hesitate about which one to buy. Under the circumstances, advice from friends can be an important reference. In this chapter, a social support mechanism was designed to deal with this requirement. An illustration of this mechanism is depicted in Figure 3.1.

Figure 3.1 Scenario of social support mechanism

3.2 Empirical Analysis of Online Social Network Interaction

Basically, two types of data can be collected in online social network sites: social network structure characteristics and social interaction. Online social network analysis (SNA) is the measuring of relationships and flows between people. The nodes in the network are the people while the links show relationships or information flows. In summary, SNA provides a mathematical analysis of human relationships objectively.

In contrast, social interaction is more subjective. In famous social network sites such as Facebook, we can see mutual interactions like: comment, like, photo tag, share and join activity. Before proceeding further, it would be ideal to make sure these subjective data collected from online social network sites can be used to identify proper reference groups for the purpose of decision support. More precisely, can these data be used to be the proxies of identifying influential friends?

One of the issues facing researchers who analyse online social networks is that standard statistical tests may be inappropriate [42]. As social network interaction data do not satisfy assumptions of statistical inference in classical regression because the observations are not independent. Consequently, multiple regression quadratic assignment procedure (MRQAP) was used to run the multiple regressions [9, 46]. MRQAP tests are permutation tests for data organized in square matrices of relationships. Such a data structure is typical in social network studies, where variables indicate some type of relation between a given set of friends [23].

The social relationships index (SRI) was developed as a self-report version of the social support interview [11, 12, 66], and this scale has demonstrated good test–retest reliability and internal consistency [79]. It was designed to examine positivity and negativity in social relationships. Besides, the SRI can be used to assess specific individuals within one's social network and provides a summary within relationship categories. In this research, SRI was used to assess if the friends are supportive. Meanwhile, MRQAP was used to test the relationship between interactions and the usefulness of friends.

For the SRI, participants were instructed to rate how helpful they feel their friends are in a decision support context (i.e., when they need advice, understanding, or suggestion; 1 = not at all, 10 = very much). Thus, three items were used to measure friendship positivity [12]. At the end of this process, a $n \times n$ SRI matrix was constructed as the output. Next, the social interaction data including activity, comment, share, photo tag and like was collected, and five $n \times n$ matrices were constructed. Then the MRQAP was executed to test the relations between the friendship and social interactions. Five models were tested during MRQAP, and the result is shown in Table 3.1.

Table 3.1 MRQAP analysis for friendship and social interactions

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5
			STANDARDIZED COEFFICIENT		
Comment	0.797967*	0.374767*	0.370484*	0.360939*	0.356697*
Like		0.601515*	0.593344*	0.580499*	0.574102*
Share			0.048184*	0.046932*	0.046455*
Photo tag				0.065572*	0.064567*
Activity					0.043365*
R^2	0.637	0.819	0.822	0.826	0.827
Adjusted R^2	0.637	0.819	0.822	0.825	0.827
N=11881	*p<0.001				

Table 3.1 shows that these social interactions are positively and significantly related to social relation, so in the system they were all included in the calculation of interaction.

3.3 System Framework

Based on consumer purchase decision-making process, the proposed system supports a consumer with necessary functions in purchase decision stage. The requirements for this system were governed by the objective of designing a system to support product purchasing decision processes on online social network. For more vivid picture of the study, Figure 3.2 serves as the research paradigm, and the symbols used in the proposed mechanism are listed in Table 3.2. In the social network analysis module, the centralities of each individual are calculated, and the similarity is measured in social similarity analysis. These data are processed in social influence analysis module to discover the influential friends, and the reference group (hereinafter referred to as "decision group") is constructed. And then the final selections are the output of alternatives selecting module. In the following, the important system modules are described in detail.

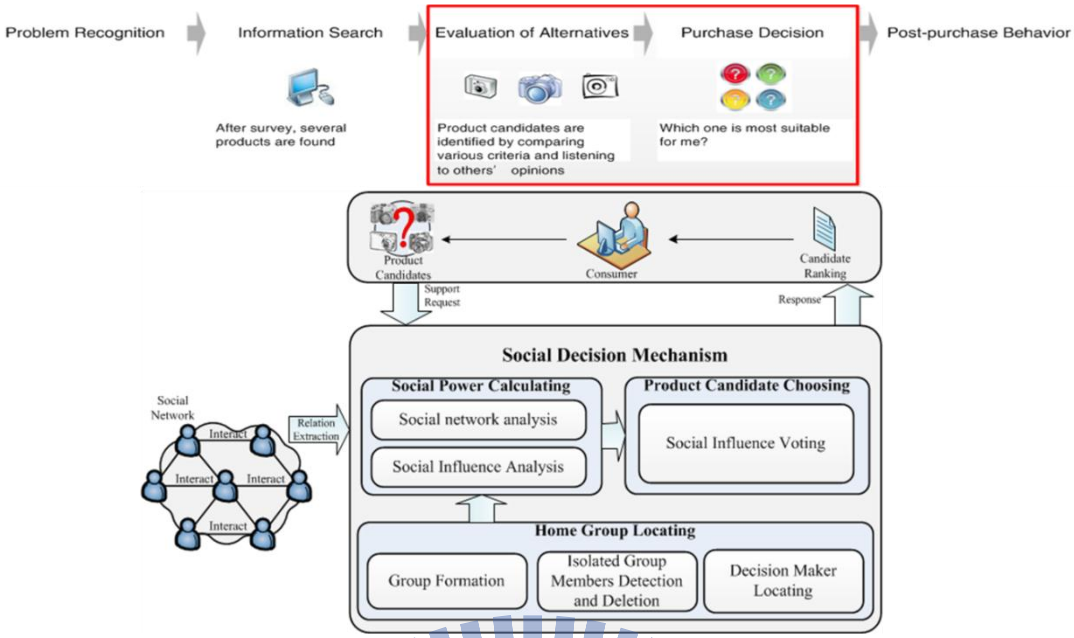

Figure 3.2 Social support mechanism system framework

Table 3.2 Symbols used in social support mechanism

SYMBOL	DESCRIPTION
$a(i, j)$	Adjacency of user *i* and *j*, $a(i, j) = 1$ if they are connected
$SS_D(i, j)$	Directly connected friend similarity between user *i* and *j*
$SS_{ID}(i, j)$	Indirectly connected friend similarity between user *i* and *j*
$SS_P(i, j)$	Personal profile similarity between user *i* and *j*
$SA(i, j)$	Social interaction between user *i* and *j*
$SS(i, j)$	Social similarity between user *i and j*
$PI(i)$	Number of profile items used to describe the characteristics of *i*
$DI(i,G)$	Degree of interaction between user *i* and group *G*
$N_p(i, j)$	Number of post between user *i and j*
$N_R(i, j)$	Number of reply between user *i and j*
$N_T(i, j)$	Number of photo tag between user *i and j*
N	Number of users in a specific social network or group
$d(i, j)$	Social distance between user *i* and *j*
$v(i)$	Voting of user *i*
$w(i)$	Voting power of user *i*
GC	Group centrality

3.3.1 Home Group Locating

3.3.1.1 Group Formation

In this module, the social network members were divided into groups, and the degree of activity and similarity were used to decide which group the consumer (decision maker) is belonged to. The primary goal of cluster analysis is to classify objects into categories, and the resulting clusters should show high internal homogeneity and external heterogeneity. In social network, friends in a clique are likely to share some characteristics and interests. So in this study, agglomerative hierarchical clustering was used to divide social network members into different groups. Centroid method, average linkage complete linkage, single linkage and Ward method are commonly used in hierarchical clustering. In this module, Ward method was used to perform clustering, and Sum of Square Error (SSE) was used to measure the effectiveness of clustering. The SSE is formulated as:

$$SSE = \sum_{i=1}^{|C|} \sum_{j=1}^{n} (z_j^i - x_j)^2 \tag{3.1}$$

, where $|C|$ is the number of groups after clustering process, and C_i is the members in a group, x is a certain member in a group, z_j^i is the *j*th attribute/characteristic of centroid member in a group, and x_j is the *j*th attribute/characteristic of x.

3.3.1.2 Isolated Group Members Detection and Deletion

To avoid the problem of being influenced by the isolated members in a group, some detection and deletion methods would be necessary. As a group is supposed to be homogeneous after the clustering process, so the similarity was used to detect the isolated members within certain group. The correlation between social similarity and influence has been studied and confirmed [20]. The more similar an online friend is in personal characteristics, the stronger is the social tie. In this research, an index was defined to measure social similarity, as shown in Figure 3.3.

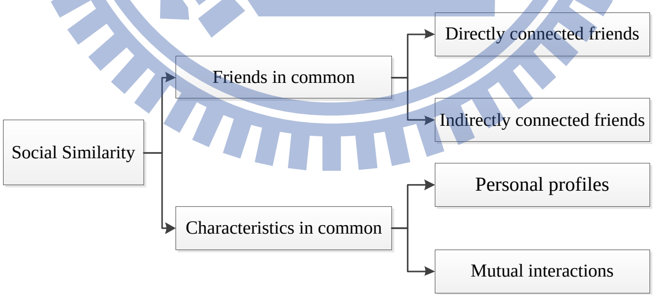

Figure 3.3 Combination of social similarity

The similarity index is composed of four parts; the first one is: directly connected friends in common. It is reasonable to say that two individuals have something in common if they share many of the same friends. In this research, the number of directly connected friends in common was used to measure social similarity. Jaccard index was used here:

$$SS_D(i,j) = \frac{F(i) \cap F(j)}{F(i) \cup F(j)}, \tag{3.2}$$

where $F(i)$ is the friends of i. For the second part: indirectly connected friends, i is similar to j if i has a friend k that is similar to j. Thus, the indirect connection friend similarity is:

$$SS_{ID}(i,j)=\sum_{k}a(i,k)\bullet SS_{ID}(k,j), \tag{3.3}$$

where $a(i,k)$ is an element of the adjacency matrix of the social network. $a(i,k)=1$ if there is a direct connection between i and j, 0 otherwise.

The third part of social similarity is characteristics in common. Personal profile similarity was defined by the number of profile data items shared. That is,

$$SS_P(i,j)=\begin{cases}0 & \text{if } P(i) \text{ or } P(j)=0,\\ \dfrac{P(i)\cap P(j)}{min(P(i),P(j))} & \text{otherwise,}\end{cases} \tag{3.4}$$

where $P(i)$ is the number of profile items used to describe the characteristics of i, and $P(i)\cap P(j)$ is the number of items both i and j have the same profile value. The fourth part is social interaction. The social interaction is defined as:

$$SA(i,j)=\begin{cases}0 & \text{if } \sum_{k=1}^{n}I(i,k) \text{ or } I(i,j) \text{ is } 0,\\ \dfrac{I(i,j)}{\sum_{k=1}^{n}I(i,k)} & \text{otherwise,}\end{cases} \tag{3.5}$$

where $I(i,j)$ is the total number of interactions between i and j. By combining all the above similarities together, the similarity index is defined as:

$$SS(i,j)=SS_D(i,j)+SS_{ID}(i,j)+SS_P(i,j)+SA(i,j). \tag{3.6}$$

Those who have low similarity were excluded in the group.

3.3.1.3 Decision Maker Locating

To find which group a consumer belongs to, it is required to identify his main group. In this study, degree of interaction was defined to figure out the level of interaction for each user. If a consumer is more active in a certain group, it is likely to say that he should be identified as the member of that group. Degree of interaction is defined as:

$$DI(i,G)=\sum_{j=1}^{N}\frac{N_P(i,j)+N_R(i,j)+N_T(i,j)}{N}, \tag{3.7}$$

where G is a specific group and N is the number of group members. $N_P(i,j)$, $N_R(i,j)$, and $N_T(i,j)$ are the number of post written by decision maker, reply on posts and tags on photo respectively. At the end of this process, the decision maker will be located in a certain group called home group (HG).

3.3.2 Social Power Calculating

3.3.2.1 Social Network Analysis

The purpose of this module was to collect data related to strength in social impact theory. People's brains are more responsive to friends than to strangers, even if the stranger has more in common [47]. There are psychological and evolutionary arguments for the idea that the social factors of ‘similarity’ and ‘closeness’ could get privileged treatment in the brain. However, a study suggests that social closeness is the primary factor, rather than social similarity, as previously assumed [47]. Measuring the network position is finding the centrality of an individual. These measures give us insight into the various roles and groupings within an online social network. Since SNA was introduced to analyse complex networks [16], in the proposed model three commonly used centrality metrics, i.e., closeness, betweenness and degree centrality were chose to be decision group selection factors.

Closeness is used to measure the immediacy in social impact [68]. It is defined as the total distance of a user from all other users, and can be formulated as [30]:

$$C_C(i)=\frac{1}{\sum_{j=1}^{N}d(i,j)}, \tag{3.8}$$

where N is the number of users and $d(i,j)$ is the distance between decision maker i and his friend j. Individuals who are higher in betweenness are considered to hold greater power in the network [43]. Betweenness centrality tracks the number of geodesic paths through the entire social network, and it is an approximation of influence [16]. Besides, betweenness centrality best measures which members, in a set of members, are viewed most frequently as a leader, than other social network analysis measures [5]. The betweenness centrality is defined as [30]:

$$C_B(i) = \sum_{j<k} \frac{g(j,i,k)}{g(j,k)}, i \neq j \neq k, \tag{3.9}$$

where $g(j,k)$ is the number of geodesic paths from j to k, and $g(j,i,k)$ is the number of these geodesics that pass through node i.

Degree refers to the attribute that can present an initiative action from a user. The higher the number of degree, the more motivation a user has to interact with others. When a target user posts comments or sends links to others, they make links of this type. Degree centrality is defined as [30]:

$$C_D(i) = \sum_{j=1}^{N} a(i,j), \tag{3.10}$$

where $a(i,j)=1$ if and only if i and j are connected. Otherwise, $a(i,j)=0$.

3.3.2.2 Social Influence Analysis

As social impact theory states, social influence is a function of strength, immediacy and number of influencing source. In this research, follow the similar idea, the power of social influence for individuals within the decision group was formulated as:

$$I = C\phi + S\psi, \tag{3.11}$$

where $I=[I_{i1}]$ is a $n \times 1$ matrix describing the value of social influence, $S=[SS(i,j)]$ is a $n \times n$ matrix for describing similarity between group members. The centralities (betweenness, closeness and degree) of all the users in a social network can be represented by centrality C, where C is a $n \times 3$ matrix of the above three centralities. ϕ and ψ are parameters whose values control the weight of the two components.

Both ϕ and ψ can be predefined or calculated from social network. To demonstrate both scenarios, in this research ϕ is predefined as:

$$\phi = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}, \tag{3.12}$$

and ψ is derived from social network. $\psi = [\psi(i, j)]$ is defined as:

$$\psi(i, j) = \begin{cases} 0 & \text{if there is no path from } i \text{ to } j, \\ \dfrac{1}{d(i, j)} & \text{otherwise.} \end{cases} \tag{3.13}$$

After the social influence is calculated, it will be used in the product candidates choosing module as the weight of voting.

3.3.3 Product Candidates Choosing

3.3.3.1 Social Influence Voting

In a conventional majority voting system, people are treated equally. For example, a home group with N members votes on whether to recommend a certain product p. Assume the sum of total voting is 1, and every member can vote $v(i)$ (agree/disagree) with $(1, 0)$. Therefore, the product will be recommended if:

$$\sum_{i=1}^{N} \frac{v(i)}{N} > 0.5. \tag{3.14}$$

In this study, the voting mechanism was improved by introducing social influence as weight of voting.

The consensus weight of the ith member depends on the influence of the member's strength relative to other members of the group. The stronger that member's position is to other members' positions, the more weight that member is given in defining the group consensus. Thus, the normalized voting power of the ith member is defined by:

$$w(i) = \frac{I_{i1}}{\sum_{j=1}^{N} I_{j1}}, \tag{3.15}$$

so the product will be recommended if:

$$\sum_{i=1}^{N} v(i) \bullet w(i) > 0.5. \tag{3.16}$$

Take Table 3.3 for example. In the conventional majority voting, P1 will be recommended and P2 will not. By introducing social influence into voting mechanism, decision group won't recommend P1, and P2 will be their choice.

Table 3.3 Example of proposed voting mechanism

	M1	M2	M3	M4	M5	RESULT	RECOMMEND?
Voting on product P1 $(v(i))$	0	1	0	1	1	3	Y
Majority voting	0.2	0.2	0.2	0.2	0.2	0.6	Y
Social influence voting $(w(i))$	0.3	0.2	0.2	0.2	0.1	0.5	N
Voting on product P2 $(v(i))$	1	0	0	0	1	2	N
Majority voting	0.2	0.2	0.2	0.2	0.2	0.4	N
Social influence voting $(w(i))$	0.4	0.1	0.1	0.2	0.2	0.6	Y

3.4 Experiment

3.4.1 Experiment Process

To further prove the feasibility of this design, an empirical study alone with system development was conducted. The procedures of experiment are described as Figure 3.4. To implement this system, one of the most popular social network sites Facebook was selected to be experiment platform to collect required data. To register a Facebook account, a user must provide the profile information (see Table 3.4). In this experiment, these data were collected to be master database for personal profile. A snowball sampling procedure with S stages K names is defined as follows. A random sample of individuals is drawn from a given population. Each one in the sample is asked to name K different persons, where K is a predefined number. For example, each person is asked to name K best friends. The persons who were not in the random sample but were named by individuals in it form the first stage. Each of the individuals in the first stage is then asked to name K different persons. This procedure repeats S times to complete the sampling process.

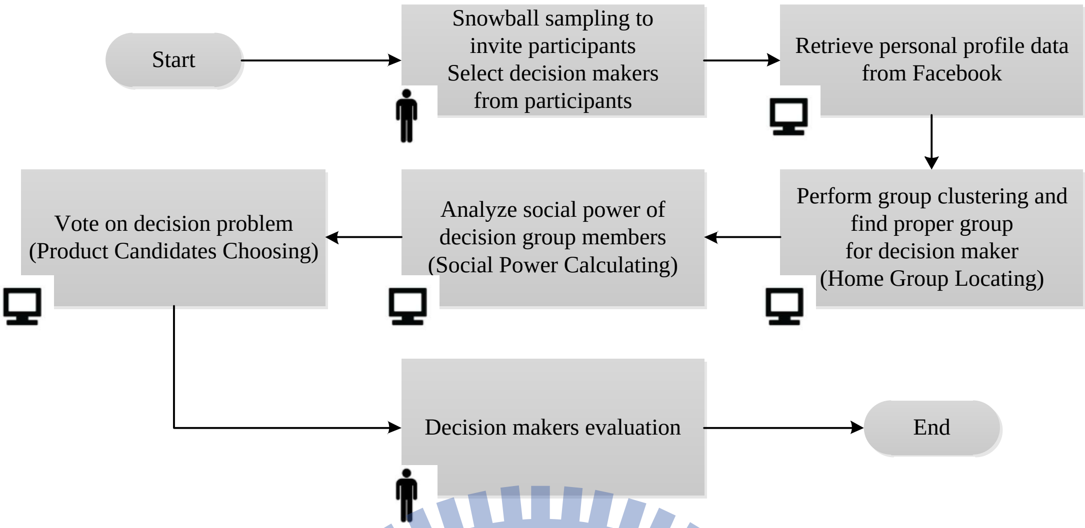

Figure 3.4 Experiment process for social support mechanism

Table 3.4 Facebook personal profile data for analyzing social similarity

PROFILE CATEGORY	DATA
Basic	Sex/Home town/Country
Personal	Activities/Interests
Education	College/High school
Work	Employer
Relationship	Friends in common/Comment/Share/Like/Photo tag

In the initial stage, by using snowball sampling 18 Facebook users were drawn randomly and divided them into groups by their lifestyle. After filtering out those users who were not willing to join the experiment, three groups were identified: student group, office worker and random member (those who cannot be classified into student or office worker) groups. By using 3 (S) stages 3 (K) names snowball sampling 120 participants were included in each group. That is, a specific network was formed by a continuous node expending process until a predefined maximum distance of connections (i.e. 3 hops in the experiment) was reached. After filtering the people not interested in this experiment, finally each group had 60 unique participants. Of all the 180 participants, 50 users were randomly selected to collect data required for SRI survey. The average year of Facebook usage was 2.1 years and the average number of friends was 216. The characteristics of these social networks are summarized in Table 3.5.

Table 3.5 Characteristics of the three networks

ATTRIBUTES	SOCIAL NETWORKS		
	STUDENT	OFFICE WORKER	RANDOM MEMBER
Number of participants	36	36	36
Age	20~32	26~45	22~35
Gender	Male: 56% Female: 44%	Male: 47% Female: 53%	Male: 64% Female: 36%
Average betweenness centrality	27.901	37.103	36.221
Average closeness centrality	31.919	35.956	39.440
Average degree	1.781	3.136	2.742

In the experiment, 18 randomly selected users (6 from each group) were invited to be decision makers. They can issue a decision problem and evaluate the effectiveness of decision criteria and alternatives. The decision makers were asked to issue 2 decision problems during the experiment, what to buy and where to buy. A desire product together with possible alternatives (what to buy) and shopping stores was listed (where to buy), and these problems were delivered to the decision group members selected by this system.

When the decision problem was presented to decision group, members were asked to vote on the candidate products together with stores to buy them. Follow the method proposed in this research, the suggested alternatives were collected and presented to decision makers. After reviewing the suggested alternatives, the decision makers were asked to rate how much they were satisfied. A 5-point Likert Scale was used for each alternatives presented to decision makers: Very Useful, Useful, Neither Useful nor Useless, Useless and Very Useless by a rating score of 5, 4, 3, 2 and 1. The experiments were conducted for each of the three group 3 times, and each experiment lasted for one week. The related settings of this experiment are listed in Table 3.6, and the result of group formation process is depicted in Figure 3.5 and Figure 3.6.

Table 3.6 Experiment settings of social support mechanism

ITEM	SETTING
Type of support	Product candidate list ranking
Participant sampling	Snowball sampling
No. of participants	Student: 60 Office worker:60 Random member: 60
No. of requestors	Student: 6 (out of 60) Office worker:6 (out of 60) Random member: 6 (out of 60)
No. of candidate list	2 for each support requestor Digital camera/mobile phone/notebook
Benchmark method	Random: rank products in candidate list randomly Social network analysis: select support group members by SNA Group centrality: select support group by group centrality
Evaluation method	Clickstream: browsing time on the product pages provided Perceived helpfulness: questionnaire survey by 5-point Likert scale Ranking comparison (Kendall's τ): order of requestors and system

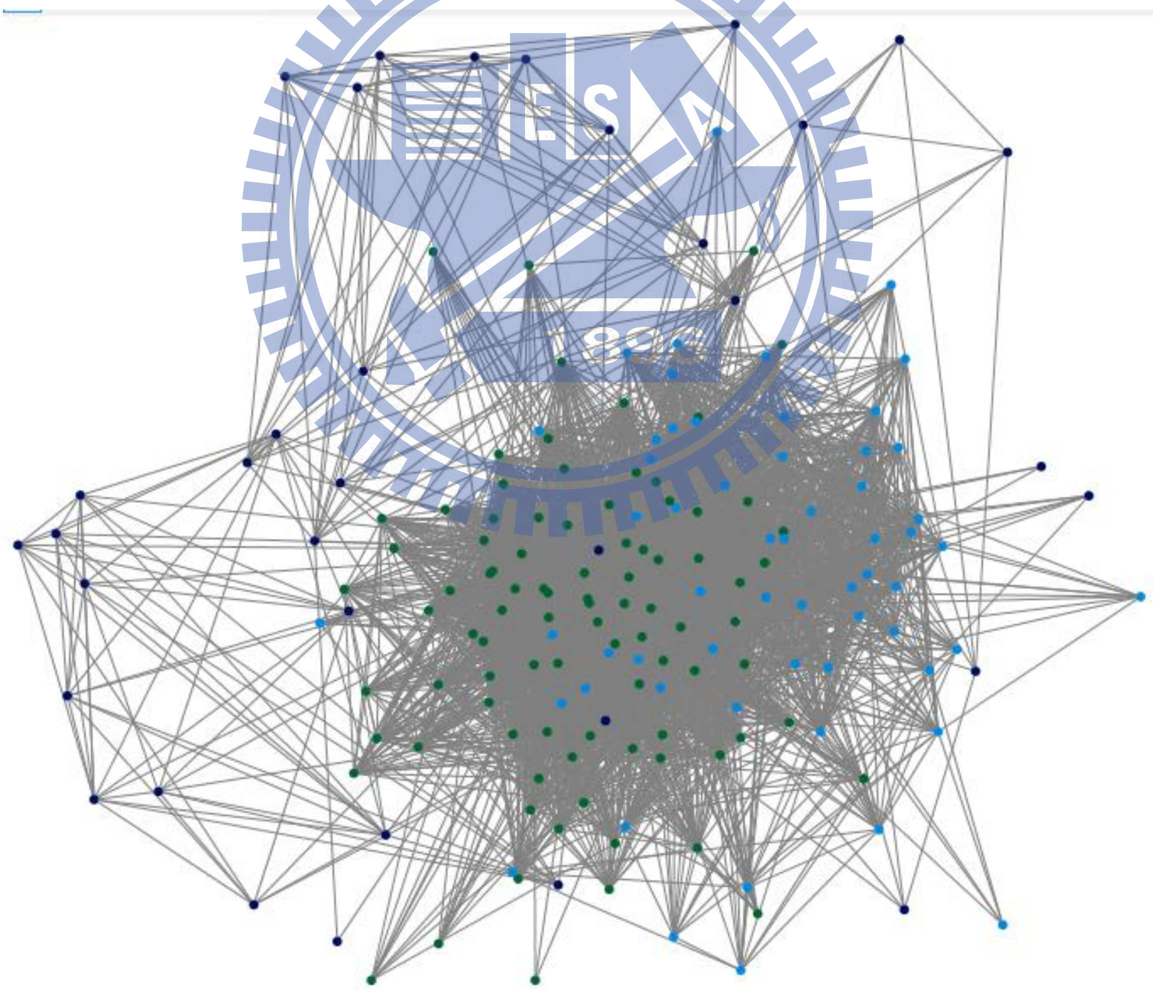

Figure 3.5 Social network before group formation

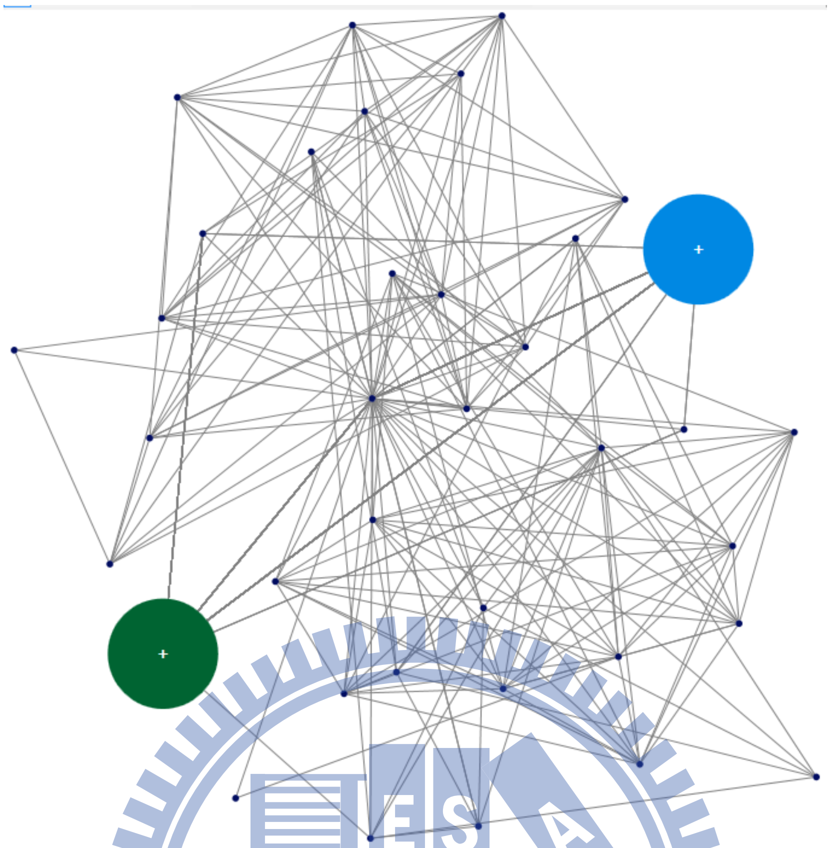

Figure 3.6　　The result of decision maker locating

3.4.2　Benchmark Methods

To compare the proposed mechanism with others, three methods were selected as benchmark.

- Random: this method was used as baseline benchmark. All the experiment process was the same as proposed mechanism except the alternatives and stores were randomly selected from the desire list of decision makers.
- Social network analysis (SNA): the decision group members were selected by considering centrality only. That is, $I = \phi C$.
- Group centrality method (*GCM*): to further compare the influence of different decision support group, a group centrality measure was designed to be another method for selecting decision group from clustering results. Suppose DG is a decision group, and V is the complete social network. Assume $|N(DG)|$ is the number of members who are not in DG but connect with members in DG, and $|V|$ is the total members of social network. Group centrality is defined to

calculate the number of members outside DG that are connected with the members of DG, it is defined and normalized as:

$$GC = \frac{|N(DG)|}{|V| - |DG|}. \tag{3.17}$$

Rather than locating decision maker into a certain group by measuring degree of interaction, in this benchmark method, the group with highest GCM was selected as decision group. For example, consider a social network with two groups (see Figure 3.7). Both group A and B have 4 members, and the entire social network has 15 members. 2 out of 11 members who are not in group A are connected with the members in group A, and 3 of them are connected with group B. Therefore, group B has higher group centrality than A.

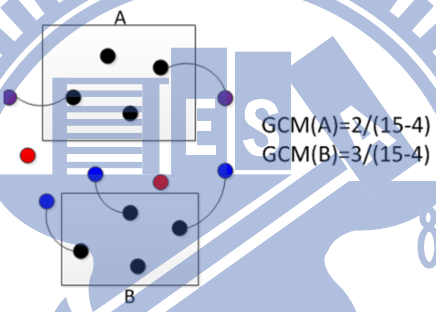

Figure 3.7 Example of group centrality

3.5 Result and Discussion

In this experiment every alternative and store presented to decision makers were collected, and the average product usefulness level of different methods and groups is plotted in Figure 3.8. As shown, the proposed mechanism attracted decision makers to be more satisfied on the products and stores than other methods. Moreover, as shown in Figure 3.9, the average usefulness level of stores suggested by proposed mechanism was also higher than other methods. To further examine if there were significant differences in average usefulness level for products and stores, a statistical method was required.

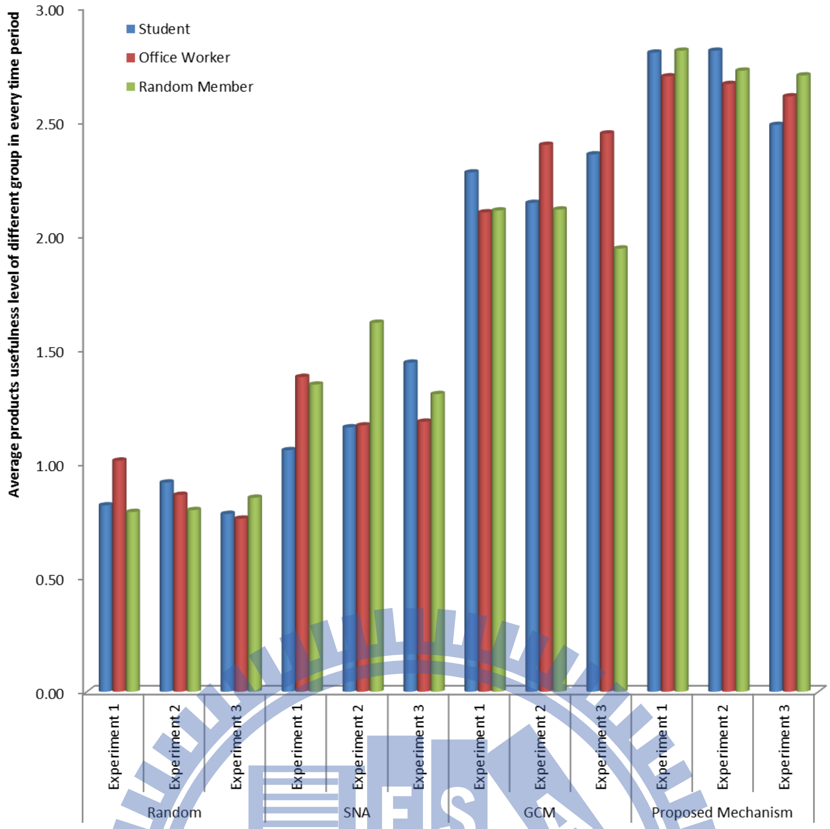

Figure 3.8 Average usefulness level about product ranking

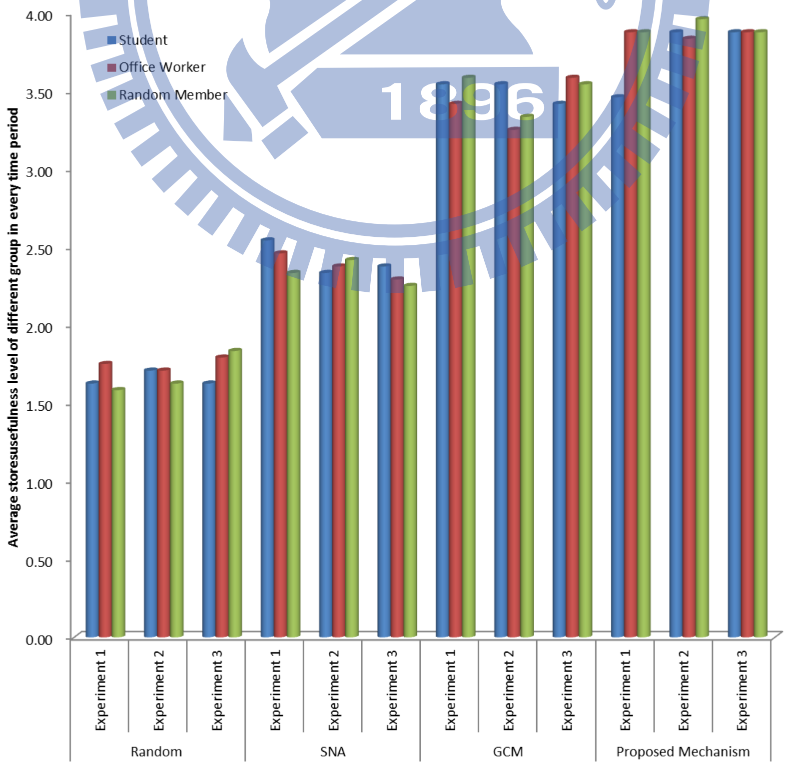

Figure 3.9 Average usefulness level about store ranking

Two-way analysis of variance (ANOVA) is a statistical analysis in which two independent factors are examined with regard to their impact on a dependent variable and on one another. To test the impact of method used and user group on average product and store usefulness level, in this work two-way ANOVA was used. As shown in Table 3.7, the method used in the experiment has impact on the average product satisfaction as the test result is significant at 0.05 (as 0.00<0.05). In contract, the user group has no impact as 0.92>0.05. For the same reason, based on Table 3.8 the store satisfaction can only be influenced by method used during the experiment.

Table 3.7 Tests of between-subjects effects for average product usefulness level

Dependent Variable: Average Product Usefulness Level

SOURCE	TYPE III SUM OF SQUARES	DEGREE OF FREEDOM	MEAN SQUARE	F	SIG.
User group	0.061	2	0.031	0.084	0.92
Method	462.41	3	154.137	422.274	0.00

Table 3.8 Tests of between-subjects effects for average store usefulness level

Dependent Variable: Average Store Usefulness Level

SOURCE	TYPE III SUM OF SQUARES	DEGREE OF FREEDOM	MEAN SQUARE	F	SIG.
User group	0.113	2	0.057	0.166	0.847
Method	628.361	3	209.454	614.831	0.00

Post hoc tests such as Tukey's test most commonly compare every group mean with every other group mean. Knowing that the methods used in the experiments could affect stay time and usefulness level, Tukey’s test was used to see if there is a significant difference between different methods. As observed from Table 3.9 and Table 3.10, there were significant differences between the proposed mechanism and other benchmark methods; also the average product and store usefulness level were higher than other methods. Based on these statistic results, it is likely that proposed approach is more effective when compared with other methods.

Table 3.9 Multiple comparisons of product voting usefulness level

(I) METHOD	(J) METHOD	MEAN DIFFERENCE (I-J)
Random	SNA	-0.4528*
	GCM	-1.3662*
	Proposed Mechanism	-1.8565*
SNA	Random	0.4528*
	GCM	-0.9134*
	Proposed Mechanism	-1.4037*
GCM	Random	1.3662*
	SNA	0.9134*
	Proposed Mechanism	-0.4903*
Proposed Mechanism	Random	1.8565*
	SNA	1.4037*
	GCM	0.4903*

*. The mean difference is significant at the .05 level.

Table 3.10 Multiple comparisons of store voting usefulness level

(I) METHOD	(J) METHOD	MEAN DIFFERENCE (I-J)
Random	SNA	-0.6806*
	GCM	-1.7731*
	Proposed Mechanism	-2.1389*
SNA	Random	0.6806*
	GCM	-1.0926*
	Proposed Mechanism	-1.4583*
GCM	Random	1.7731*
	SNA	1.0926*
	Proposed Mechanism	-0.3657*
Proposed Mechanism	Random	2.1389*
	SNA	1.4583*
	GCM	0.3657*

*. The mean difference is significant at the .05 level.

Besides the stay time and usefulness survey, in the experiment the decision makers were also asked to provide ranking of the product candidates list so that the ranking result from social support mechanism can be compared. Kendall's τ is a measure of correlation, and so measures the similarity of the ranking between two lists r_a and r_b . It is a coefficient that represents the degree of concordance between two columns of ranked data. It requires that the two variables are paired observations, for example, ranking from teacher and student for each book in the sample. Then, provided both variables are at least ordinal, it would be possible to calculate the correlation between them. For each variable separately the values are put in order and numbered, 1 for the lowest value, 2 for the next lowest and so on. Kendall's tau takes values between -1 and +1. The greater the numbers of inversions, the smaller the coefficient will be. A positive correlation indicating that the ranks of both observations increase together whilst a negative correlation indicates that as the rank of one variable increases the other one decreases. Kendall's tau is formulated as [41]:

$$\tau(r_a, r_b) = \frac{N_C - N_D}{N_C + N_D}, \tag{3.18}$$

Where N_C and N_D are the number of concordant and discordant pair. An example for calculating Kendall's τ is given in Table 3.11, and the value of Kendall's τ in this example is $\frac{60-6}{60+6} = 0.818$. In this study, Kendall's τ was used to measure the similarity of the ranking result from system and users.

Table 3.11 Example of Kendall's Tau value calculating

Teacher	Student	N_C	N_D
1	2	10	1
2	1	10	0
3	4	8	1
4	3	8	0
5	6	6	1
6	5	6	0
7	8	4	1
8	7	4	0
9	10	2	1
10	9	2	0
11	12	0	1
12	11	-	-
	Sum	60	6

Table 3.12 summarizes the Kendall's τ values. As 70% (75/108) of these values are positive, it is likely to conclude that the proposed mechanism can provide good enough ranking information for users.

Table 3.12 Kendall's τ value of system and user ranking similarity

Group	Member	Kendall's τ Value					
Student	A	0.467	-0.2	0.733	0.2	0.333	0.467
	B	-0.333	0.067	0.333	-0.467	-0.2	0.2
	C	0.333	-0.067	-0.2	0.6	0.333	-0.2
	D	-0.2	0.467	-0.067	0.2	0.333	-0.067
	E	-0.333	-0.067	0.067	0.6	-0.2	-0.067
	F	-0.067	0.333	-0.467	0.333	0.333	0.067
Office Worker	A	-0.467	-0.067	0.333	0.2	0.067	0.6
	B	-0.467	0.333	0.2	0.333	-0.333	-0.067
	C	0.733	-0.333	-0.2	0.333	0.067	0.2
	D	0.333	-0.067	-0.2	0.067	0.067	-0.733
	E	0.2	0.2	0.067	-0.467	0.067	-0.333
	F	0.333	-0.2	0.467	-0.333	0.467	-0.333
Random Member	A	0.467	0.6	0.2	0.467	0.333	0.067
	B	-0.067	-0.6	0.467	0.467	0.2	0.467
	C	-0.333	0.067	0.067	0.333	0.333	0.2
	D	0.067	0.867	0.467	1	0.333	0.2
	E	0.467	0.467	0.6	0.733	0.467	0.2
	F	0.6	0.333	0.2	1	0.867	0.733

No. of positive value: 75, No. of negative value: 33(21 from store, 12 from product)

3.6 Chapter Summary

In this chapter, social network analysis, social influence and adaptive majority voting were used to design a social support mechanism for product purchasing decision-making process. From the viewpoint of academic contribution, by utilizing MRQAP analysis the relations between friendship and social interactions in online social network sites were tested and verified. Social network analysis skills were used to profile individual users within online social networks. A home group locating method was also proposed to place the decision maker in right group so that the members can provide better suggestion. Furthermore, an adaptive voting mechanism was also suggested to further improve the majority voting on social network related research. An empirical study further proved the feasibility and effectiveness. This research successfully introduced the decision process theory and social psychology into the development of social network-based application. Besides, this study also extended the concept of decision support system development to utilize social network platform. From the viewpoint of practice, this study showed a feasible way to develop a social network-based decision support system together with the related techniques for the purpose of product purchasing decision-making. By dividing the system framework into modules, those who are interested in developing such kind of applications can further improve the system by plugging in new modules as needed.

CHAPTER 4

SOCIAL RECOMMENDATION MECHANISM

As online social network are so popular, their users are getting used to make decisions based on advices collected from friends. In this chapter, a recommendation mechanism is proposed to provide personalized recommendation results based on social network.

4.1 Scenario of Social Recommendation Mechanism

When buying items, it is likely that something cared about has been in consumer's mind, so we can see some posts like: "Need advice on what camera to buy, considering the price, size and megapixel" in discussion forums. At this point, the criteria of selecting desired items have been identified by consumer, and he/she wants someone to provide suggestions based on them. The purpose of this chapter was to design a recommendation mechanism to deal with this situation. The proposed mechanism receives criteria from consumer, regardless of how they are identified, and generates a product list which meets the requirements. The sketch map of this mechanism is illustrated in Figure 4.1.

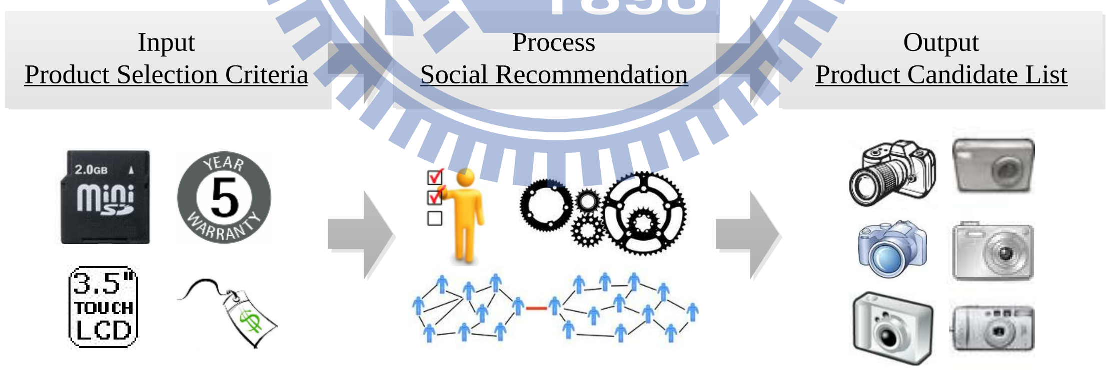

Figure 4.1 Scenario of social recommendation mechanism

4.2 System Framework

Based on consumer purchase decision-making process, the proposed system supports a consumer with necessary functions in information search, evaluation of alternatives and purchase decision stage. For clearer picture of this chapter, Figure 4.2 serves as the research paradigm of this chapter, and the symbols used in the proposed mechanism are listed in Table 4.1. In the following, the important modules are described in detail.

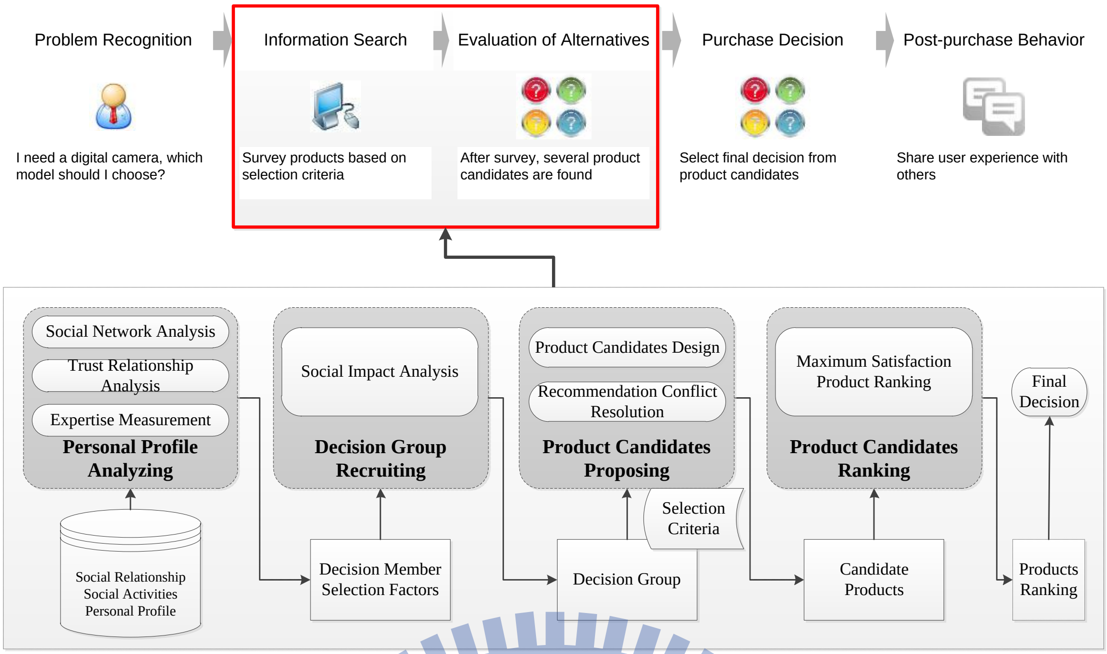

Figure 4.2 Social recommendation mechanism system framework

Table 4.1 Symbols used in social recommendation mechanism

SYMBOL	DESCRIPTION
$C_B(i), C_C(i), C_D(i)$	Betweenness, Centrality and Degree centrality
$g(j,k)$	Number of geodesic paths from user *j* to user *k*
$TR(i,j)$	Trustworthiness of user *j* to *i*
$F(i)$	Friends of user *i*
$EC(i)$	Expertise of user *i*
$SI(i)$	Social impact of user *i*
$CA_p(i)$	Change of Attitude about product *p* of user *i*
DS_p	Recommendation dissimilarity of product *p*
RS_p	Recommendation strategy of product *p*

4.2.1 Personal Profile Analyzing

4.2.1.1 Social Network Analysis

As social network analysis is used to analyze complex networks [16], in the proposed model betweenness, closeness and degree were chose to be characteristics of system users. As these metrics were defined in chapter 3, they are omitted here.

4.2.1.2 Trust Relationship Analysis

Trust forms the basis of social interaction in any society, including virtual ones [1]. O'Donovan and Smyth [63] suggested that the simplest way to incorporate trust in to the recommendation process is to combine trust and similarity to produce a compound weighting. Besides, social interaction may stimulate trust and perceived trustworthiness [78]. Since the positive relationship between trust and similarity has been shown [87] and trust is the basis of social interaction, it would be reasonable to measure the value of trust by using similarity and interaction. Inspired by trust value computation in Golbeck and Hendler [33], our work followed similar formulation and proposed social similarity and social interaction to be the replacement of trust value.

Social similarity (SS) and social interaction (SA) are two important factors for analysing friendship. Compared with social similarity, social interaction is a more dynamic relation that contains all kinds of people's actions [22], and these actions can reveal social closeness. In this research, these two factors were used to define social relation. Trustworthiness (TR) between i and j is defined as:

$$TR(i, j) = SS(i, j) + SA(i, j). \tag{4.1}$$

In this research, the number of directly connected friends in common was used to measure social similarity. Jaccard index was used here:

$$SS(i, j) = \frac{F(i) \cap F(j)}{F(i) \cup F(j)}, \tag{4.2}$$

where $F(i)$ is the friends of i. Besides, the social interaction between i and j is measured by the activities related to information sharing. For example, friends usually post their own status, share photos or comment on friends' status on Facebook. Therefore, the social interaction is defined as:

$$SA(i, j) = \begin{cases} 0 & \text{if } \sum_{k=1}^{n} I(i,k) \text{ or } I(i, j) \text{ is } 0, \\ \dfrac{I(i, j)}{\sum_{k=1}^{n} I(i,k)} & \text{otherwise}, \end{cases} \tag{4.3}$$

where $I(i, j)$ is the total number of interactions between i and j.

4.2.1.3 Expertise Measurement

Expertise characterization (EC) was devised to measure the relative expertise level of individual members within a decision group. Here a problem naturally arises: how to define expertise level? To represent the expertise into different level quantitatively, it is defined based on the number of products an individual has bought, used, or joined its fan page. A list of products from the top rated list in Amazon was presented to the individuals and based on the percentage e_i of products that an individual has bought, used or surveyed, the expertise was represented quantitatively. Therefore, the normalized expertise level of i can be formulated as:

$$EC(i) = \frac{e_i}{\sum_{j=1}^{N} e_j}, \tag{4.4}$$

where N is the number of members in decision group.

4.2.2 Decision Group Recruiting

In this work, social impact was used to be the selection factor of decision group members. Social impact was governed by social forces, psychosocial law and multiplication versus division of impact [50]. Social forces law states that social impact is affected by strength (S), immediacy (I) and number of people (N), and it's generic function is defined as:

$$SI(i) = f(S, I, N) \tag{4.5}$$

The greater the number of sources of social impact in a social situation, the greater the impact would be. In this research, by applying the result from social profile analysis, the social impact of i is defined as:

$$SI(i, j) = TR(i, j) \bullet EC(i) \bullet C_B(i) \bullet C_C(i) \bullet C_D(i). \tag{4.6}$$

Friends with higher social impact can be selected as recommendation group members.

4.2.3 Product Candidates Proposing

4.2.3.1 Product Candidates Design

In this module, the group members were asked to recommend product candidates based on the selection criteria from consumer. QOC schema was used to describe the relationship of selection criteria and the products recommended. The members proposed their recommendation together with weighting on each criterion, and the sum of weights is equal to 1. At the end of this process, a product candidates QOC schema like Figure 4.3 can be obtained. After the schemas were collected, they were translated into table format as shown in Table 4.2 and presented to all decision members. As product P3/P2 was not recommended by decision member M1/M2, these lines are blank. Then the members were required to fill in the recommendation and confidence columns on the products he does not propose as product candidates, and the product candidates will be shown as Table 4.3.

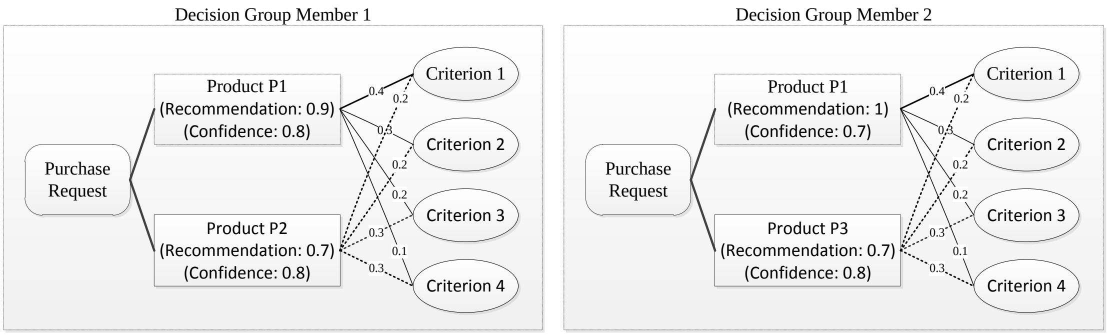

Figure 4.3 Alternatives selection process

Table 4.2 Translation of QOC schema

MEMBER	PRODUCT	CRITERIA				RECOMMENDATION	CONFIDENCE
		C1	C2	C3	C4		
M1	P1	0.4	0.3	0.2	0.1	0.9	0.8
M1	P2	0.2	0.2	0.3	0.3	0.7	0.8
M1	P3						
M2	P1	0.4	0.3	0.2	0.1	1	0.7
M2	P2						
M2	P3	0.2	0.2	0.3	0.3	0.7	0.8

Table 4.3 Product candidates table

MEMBER	PRODUCT	CRITERIA				RECOMMENDATION	CONFIDENCE	RXC
		C1	C2	C3	C4			
M1	P1	0.4	0.3	0.2	0.1	0.9	0.8	0.72
M1	P2	0.2	0.2	0.3	0.3	0.7	0.8	0.56
M1	P3	0.3	0.3	0.2	0.2	-0.9	0.8	-0.72
M2	P1	0.4	0.3	0.2	0.1	1	0.7	0.7
M2	P2	0.3	0.2	0.4	0.1	0.3	0.9	0.27
M2	P3	0.2	0.2	0.3	0.3	0.7	0.8	0.56

4.2.3.2 Recommendation Conflict Resolution

As observed from Table 4.3, there is a conflict on product P3 as it was recommended by M2, but not recommended by M1. To resolve this conflict, a corresponding function was developed. As the group members are likely to affect each other. Some members may be persuaded and concur on others' options. Suppose the decision group consists of N members. Each of them can have opposite attitude on a certain criteria proposed by other members. Denote the recommendation of member i on product p as $R_p(i)$, $-1 \le R_p(i) \le 1$. Member i is very confident of the product he recommends if $R_p(i) = 1$, and vice versa. Members can influence each other, and each of them is characterized by confidence $C_p(i), 0 < C_p(i) \le 1$, which is the strength of confidence about his/her recommendation. The change of attitude is determined by the in-group social impact exerted on every member:

$$CA_p(i) = \left(\left| \sum_{j=1, j \neq i}^{N} C_p(j) \bullet R_p(j) \right| \right) - \left| C_p(i) \bullet R_p(i) \right|. \tag{4.7}$$

After the conflict resolution process, the sample output is shown as Table 4.4. Those products which have negative R*C value were excluded in the candidate list as they were not recommended by group members.

Table 4.4 Product candidates table after recommendation conflict resolution

MEMBER	PRODUCT	CRITERIA				RECOMMENDATION	CONFIDENCE	R*C
		C1	C2	C3	C4			
M1	P1	0.4	0.3	0.2	0.1	0.9	0.8	0.72
M1	P2	0.2	0.2	0.3	0.3	0.7	0.8	0.56
M1	P3	0.3	0.3	0.2	0.2	-0.9	0.8	-0.08
M2	P1	0.4	0.3	0.2	0.1	1	0.7	0.7
M2	P2	0.3	0.2	0.4	0.1	0.3	0.9	0.27

4.2.4 Product Candidates Ranking

As dissimilarity describes the disagreement between any two group members [3], a decision alternative with high dissimilarity is not easy to be consensus. In this study, the dissimilarity (DS) of product p is defined as:

$$DS_p = \frac{\sum_{i=1}^{N} (R_p(i) \bullet C_p(i) - \overline{R \bullet C})^2}{N} \tag{4.8}$$

, where p is a product candidate and $\overline{R \bullet C}$ is the average evaluation of p. For the product candidate p, the recommendation strategy (RS) of decision group was selected by:

$$RS_p = w_1 * max\left(EC(i) \bullet R_p(i) \bullet C_p(i)\right) + w_2 * (1 - DS_p), \tag{4.9}$$

where w_1 and w_2 denote the relative importance of preference of these two characterizations, $w_1 + w_2 = 1$. At the end of proposed mechanism, a list was presented to consumer as the recommendation from decision group.

4.3 Experiment

4.3.1 Experiment Process

To implement the proposed mechanism, Facebook was selected as data source and the experiment process is shown in Figure 4.4. For the purpose of collecting basic data required, a group of social network users were invited to be participants. Snowball sampling is a feasible way when studying social network issues [2], so it was used to construct the experiment. By using 3 (S) stages 3 (K) names snowball sampling 40 participants were invited in each social network (group). The characteristics of these social networks are summarized in Table 4.5.

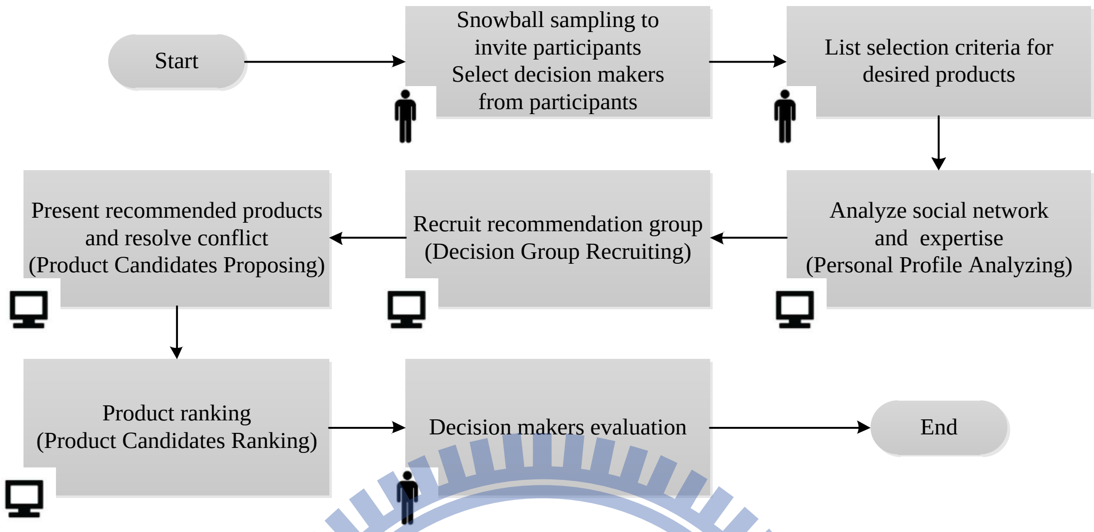

Figure 4.4 Experiment process for social recommendation mechanism

Table 4.5 Characteristics of the three networks

ATTRIBUTES	SOCIAL NETWORKS		
	STUDENT	OFFICE WORKER	RANDOM GROUP
Number of participants	40	40	40
Age	20~35	25~45	22~43
Gender	Male: 21 Female: 19	Male: 25 Female: 15	Male: 22 Female: 18

After the networks were built, 9 randomly selected users (3 from each group) were invited to be decision-makers. In the experiment, they can issue a decision problem and evaluate the effectiveness of decision alternatives. The decision-makers were asked to issue 2 product purchasing problems (one for mobile phone and one for digital camera) together with their criteria of product selection during the experiment, and these problems were delivered to the decision group members selected by system. When a decision problem was presented to decision group, members can express their design by QOC schema. During the experiment, a product list containing 40 products selected from Amazon top rated items was presented to decision group, and the percentage of the products they ever used/surveyed was recorded to calculate expertise level.

Every recommended product was asked to provide a hyperlink containing related information, so that the click stream data can be collected to compare with other methods. Besides, every recommended product was evaluated manually by the decision makers to see if they are satisfied with the alternatives presented. To avoid information overloading, the first two product candidates of each method were selected. Since there is a strong tendency for users to spend a greater length of time reading articles of interest to them [32, 56], these data were collected to evaluate the effectiveness of proposed mechanism. The click count and stay time of each page linked to alternatives were recorded, and satisfaction was rated on a 5-point Likert Scale for each alternatives presented to decision makers: Very Useful, Useful, Neither Useful nor Useless, Useless and Very Useless by a rating score of 5, 4, 3, 2 and 1. The related settings of this experiment are listed in Table 4.6.

Table 4.6 Experiment settings of social recommendation mechanism

ITEM	SETTING
Type of support	Product candidate list recommendation based on provided criteria
Participant sampling	Snowball sampling
No. of participants	Student: 40 Office worker:40 Random member: 40
No. of requestors	Student: 3 (out of 40) Office worker:3 (out of 40) Random member: 3 (out of 40)
Provided criteria	Digital camera: camera type, resolution, price Mobile phone: screen size, price, size and weight
Benchmark method	Minimum regret for recommendation strategy Average satisfaction for recommendation strategy Maximum satisfaction without social impact for decision group selection
Evaluation method	Clickstream: browsing time on the product pages provided Perceived helpfulness: questionnaire survey by 5-point Likert scale

4.3.2 Benchmark Methods

To compare proposed mechanism with others, three methods were selected as benchmark.

- Minimum regret: this method was used as baseline benchmark. All the experiment process was the same as proposed mechanism except the products were recommended for minimized regret. the selection rule was changed from equation (4.9) to :

$$RS_p = w_1 \bullet min\left(EC(i) \bullet R_p(i) \bullet C_p(i)\right) + w_2 \bullet (1 - DS_p) \tag{4.10}$$

- Average satisfaction: the decision group member were select as above method, and the selection rule was changed from equation (4.9) to :

$$RS_p = w_1 \bullet avg\left(EC(i) \bullet R_p(i) \bullet C_p(i)\right) + w_2 \bullet (1 - DS_p)\,. \tag{4.11}$$

- Maximum satisfaction: the decision group members were selected by considering the result of social profile analysis only, that is, the social impact was not included.

4.4 Result and Discussion

In the experiment clickstream data of every alternative presented was collected, and the average stay time of different methods and groups on every alternative is plotted in Figure 4.5. As shown in the figure, the proposed mechanism attracted decision makers to spend more time on the alternatives than other methods. Moreover, as shown in Figure 4.6, the average usefulness level of alternatives generated by proposed mechanism is also higher than other methods. To further examine if there are significant differences in average stay time and average usefulness level, a statistical method is required.

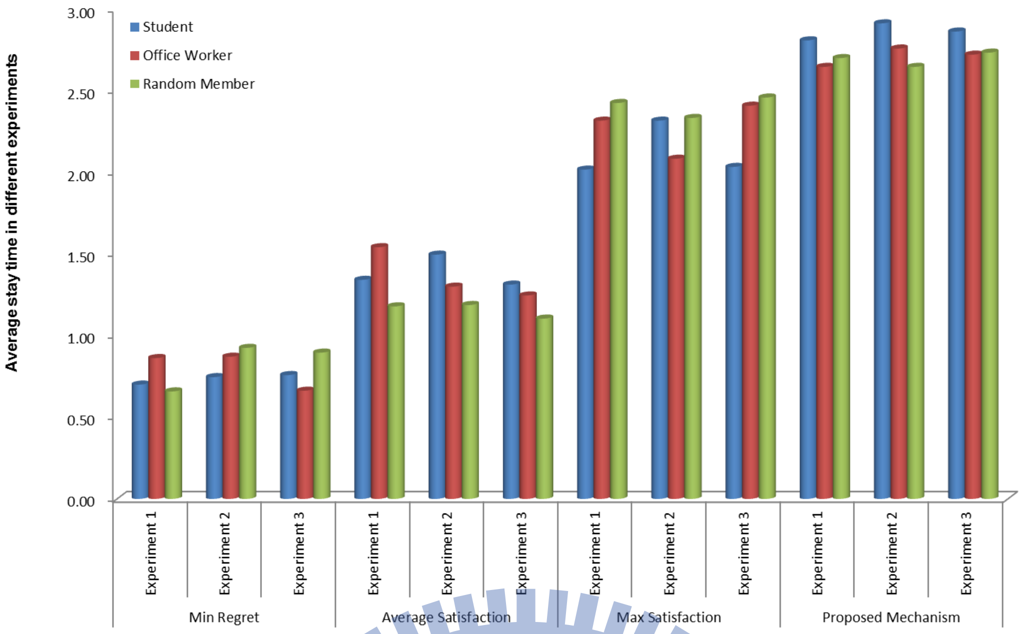

Figure 4.5 Average stay time for different groups and methods

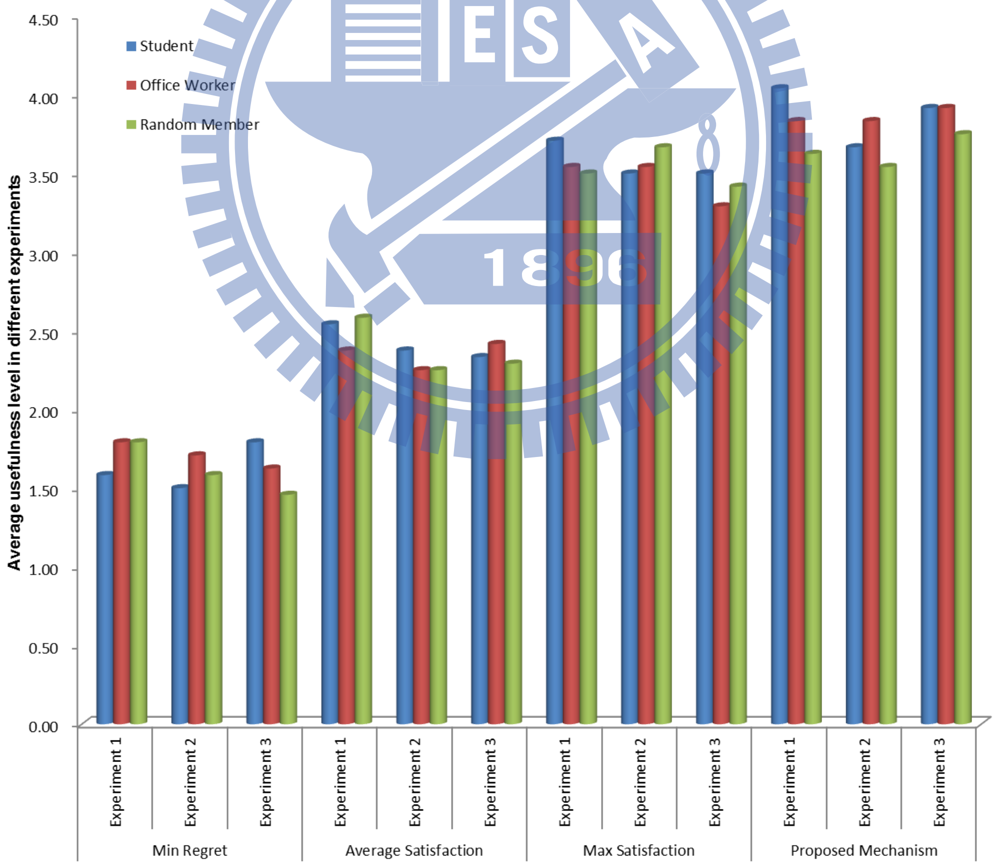

Figure 4.6 Average usefulness level for different groups and methods

Two-way analysis of variance (ANOVA) is a statistical analysis in which two independent factors are examined with regard to their impact on a dependent variable.

In this work two-way ANOVA was used to test the impact of method used and user group on average stay time and average usefulness level. As seen from Table 4.7, the method used in the experiment has impact on the average stay time as the test result is significant at 0.05 (as 0.00<0.05). In contract, the user group has no impact as 0.961>0.05. For the same reason, based on Table 4.8 the satisfaction can only be influenced by method used during the experiment. Post hoc tests such as Tukey's test most commonly compare every group mean with every other group mean. Knowing that the methods used in the experiments could affect stay time and usefulness level, Tukey's test was used to see if there is a significant difference between different methods. From Table 4.9 and Table 4.10, there are significant differences between proposed mechanism and other benchmark methods, and the average stay time and average usefulness level are higher than other methods.

Table 4.7 Tests of between-subjects effects for average stay time

Dependent Variable: Average Stay Time

SOURCE	TYPE III SUM OF SQUARES	DEGREE OF FREEDOM	MEAN SQUARE	F	SIG.
Group	0.030	2	0.015	0.039	0.961
Method	518.683	3	172.894	451.907	0.000

Table 4.8 Tests of between-subjects effects for average usefulness level

Dependent Variable: Average Usefulness Level

SOURCE	TYPE III SUM OF SQUARES	DEGREE OF FREEDOM	MEAN SQUARE	F	SIG.
Group	1.037	2	0.519	1.648	0.193
Method	647.652	3	215.884	685.997	0.000

Table 4.9 Multiple comparisons of average stay time

(I) METHOD	(J) METHOD	MEAN DIFFERENCE (I-J)
	Average Satisfaction	-0.5144*
Min Regret	Max Satisfaction	-1.4792*
	Proposed Mechanism	-1.9676*
	Min Regret	0.5144*
Average Satisfaction	Max Satisfaction	-0.9648*
	Proposed Mechanism	-1.4532*
	Min Regret	1.4792*
Max Satisfaction	Average Satisfaction	0.9648*
	Proposed Mechanism	-0.4884*
	Min Regret	1.9676*
Proposed Mechanism	Average Satisfaction	1.4532*
	Max Satisfaction	0.4884*

*. The mean difference is significant at the .05 level.

Table 4.10 Multiple comparisons of average usefulness level

(I) METHOD	(J) METHOD	MEAN DIFFERENCE (I-J)
	Average Satisfaction	-0.7315*
Min Regret	Max Satisfaction	-1.8704*
	Proposed Mechanism	-2.1435*
	Min Regret	0.7315*
Average Satisfaction	Max Satisfaction	-1.1389*
	Proposed Mechanism	-1.4120*
	Min Regret	1.8704*
Max Satisfaction	Average Satisfaction	1.1389*
	Proposed Mechanism	-0.2731*
	Min Regret	2.1435*
Proposed Mechanism	Average Satisfaction	1.4120*
	Max Satisfaction	0.2731*

*. The mean difference is significant at the .05 level.

4.5 Chapter Summary

In this chapter, a personalized while socialized recommendation was proposed. QOC representation schema was used to describe the design logic of product candidates. Decision group selection mechanism and recommendation conflict resolution within decision group were proposed and served as tools to select adequate products for decision maker. An empirical study further proved the feasibility and effectiveness of proposed mechanism. This chapter successfully introduced the social impact theory and design rationale into the development of social network-based decision support mechanism. Besides, this study also extended the concept of decision support system development to utilize social network platform. From the viewpoint of practice, this work showed a feasible way to develop a social network-based decision support system together with the related techniques for semi-structured decision problems. By dividing the system framework into modules, those who are interested in developing such kind of applications can further improve the system by plugging in new modules as needed.

CHAPTER 5

SOCIAL INTELLIGENCE MECHANISM

This chapter intended to design an information discoverer mechanism to collect product information and suggest possible product alternatives from trustworthy sources.

5.1 Scenario of Social Intelligence Mechanism

Not all consumers have the ability to clearly identify the product selection criteria or find possible product candidates by themselves. If there is a need of buying camera, this kind of consumer may simply ask: “Need advice on what camera to buy, and what to look out for when buying a camera?” In this chapter, for consumers with less experience about the product they intend to buy, a system framework was developed to find possible selection criteria from friends’ comments and show a product reference list to consumer. A typical case of this scenario is shown in Figure 5.1.

Figure 5.1 Scenario of social intelligence mechanism

5.2 System Framework

The requirements for this system are governed by the objective of designing a system to support first scenario as mentioned above. Typically, a group decision process includes choosing the decision group members, determining the evaluation criteria, aggregating members’ criteria and suggesting alternatives. Figure 5.2 serves as the research paradigm, and the symbols used in the proposed mechanism are listed in Table 5.1. In the following, the important system modules are described in detail.

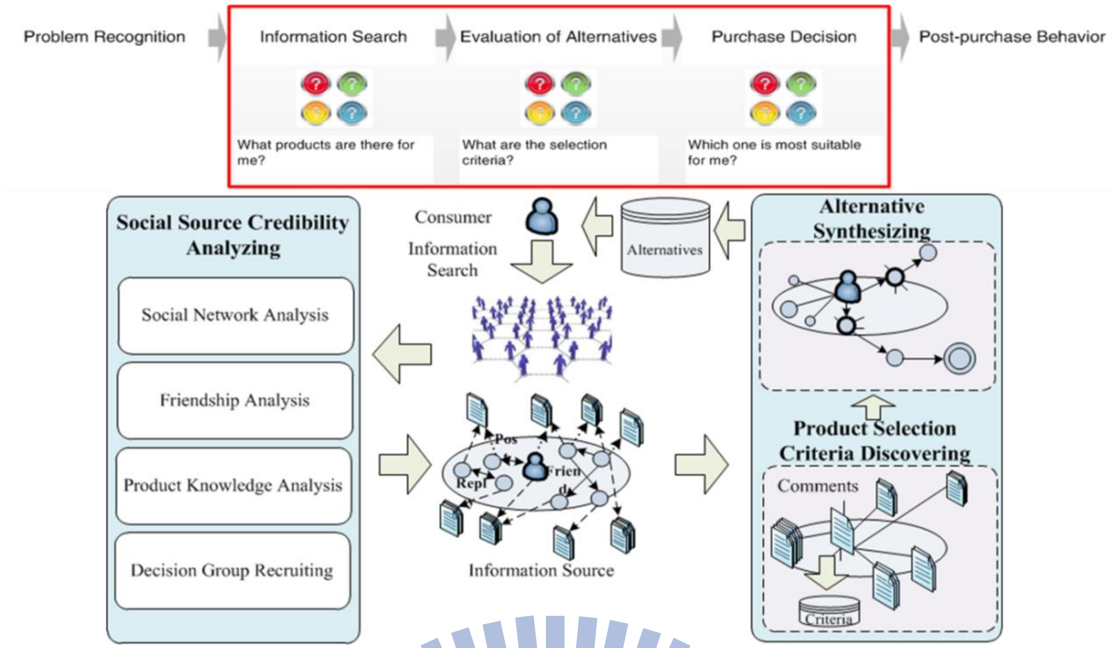

Figure 5.2 Social intelligence mechanism system framework

Table 5.1 Symbols used in social intelligence mechanism

SYMBOL	DESCRIPTION
$\tau_t(i, j)$	Friendship deposited for friend *i* and *j*
$\triangle\tau_t(i, j)$	Amount of friendship changed in time t
$\rho_t(i, j)$	Friendship evaporation coefficient
$L_t(i, j)$	Number of mutual interaction of friend *i* and *j* in time *t*
$\overline{L_t(i, j)}$	Average number of interaction over time periods
S_t	Standard deviation of interaction between friend *i* and *j*
N_t	Number of time periods used to calculate $\overline{L_t(i, j)}$
$FE_t(i, j)$	Friendship estimation between friend *i* and *j* in time *t*
$PK_P(i)$	User *i*'s knowledge about product category *p*
$SSC_t(i, j)$	Social source credibility of friend *j* to user *i* in time *t*
$A(E(i))$	Average agreement degree of user *i*
$RAD(i)$	Relative agreement degree of user *i*
$RI(i)$	Relative importance degree of user *i*
$CDC(i)$	Consensus degree coefficient of user *i*

5.2.1 Social Source Credibility Analyzing

People's brains are more responsive to friends than to strangers [47]. There are psychological and evolutionary arguments for the idea that the social factors of 'similarity' and 'closeness' could get privileged treatment in the brain. Huffaker shows that online leaders influence others through high communication activity and network centrality [36]. A user with higher betweenness centrality is often considered as an opinion leader [31]. Betweenness centrality best measures which members, in a set of members, are viewed most frequently as a leader, than other social network analysis measures [31]. Social similarity provides a means for making the decision and resolving the uncertainty [67]. In this study, the components of social source credibility are shown in Figure 5.3.

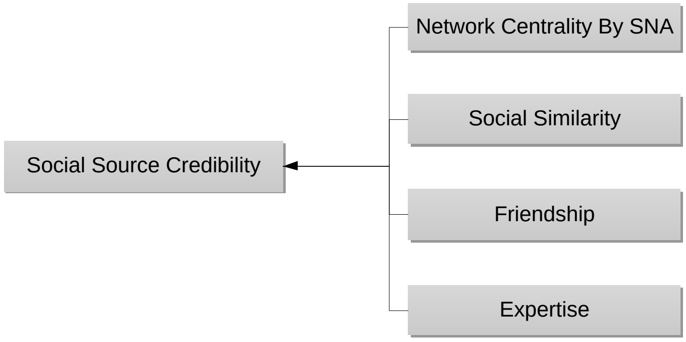

Figure 5.3 The components of social source credibility

5.2.1.1 Social Similarity Analysis

In this module, the betweenness centrality, closeness centrality, degree centrality and social similarity are calculated. As the first two indicators have been defined in previous chapter, they are omitted here. Traditional social similarity index considered only directly linked friends. In this work, the social similarity measure index defined in [21] was used to include both directed and indirect connection. Social similarity (SS) is defined as:

$$SS(i, j) = A \times A_I, \tag{5.1}$$

where A is a $n \times n$ symmetric matrix and n is the number of friends a given user has linked, and A_I is a $n \times m$ matrix where m is the number of friends that have not directly been linked, but may be indirectly accessible through a direct link friend.

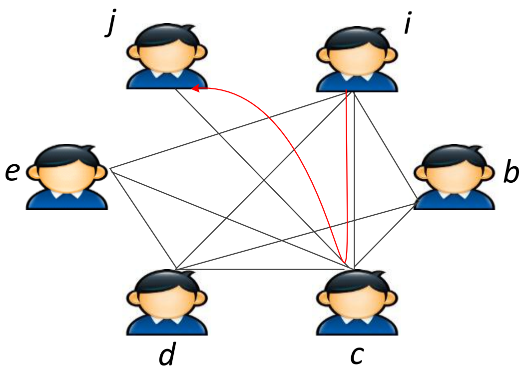

Figure 5.4 A sample social network for social similarity calculation

For example, consider a sample social network in Figure 5.4. User *i* has direct link with *b*,*c*,*d* and *e*, and there is a connection between *c* and *j*. Therefore, user *i* can reach user *j* through user *c*, and the social similarity for i $(SS(i, j))$ is calculated as:

$$SS(i,j) = A \times A_I = \begin{array}{c} \\ u_i \\ u_b \\ u_c \\ u_d \\ u_e \end{array} \begin{array}{c} \begin{array}{cccccc} u_i & u_b & u_c & u_d & u_e & u_j \end{array} \\ \begin{bmatrix} 0 & 1 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \end{array} = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}. \tag{5.2}$$

5.2.1.2 Friendship Analysis

However, even two people are close friends; friendship may evaporate as time goes by if they do not interact frequently. To measure how the friendship changes within a time period, an evaporation function was defined to be a new factor of evaluating friendship among friends. The evaporation function is formulated as:

$$\tau_{t+1}(i,j) = (1-\rho_t(i,j)) \bullet \tau_t(i,j) + \vartriangle\tau_t(i,j), \tag{5.3}$$

where

$$\begin{aligned} &\rho_t(i,j) = \frac{\overline{L_t(i,j)} - L_t(i,j)}{S_t / \sqrt{N_t}}, \\ &\vartriangle\tau_t(i,j) = \begin{cases} [L_{t+1}(i,j) - L_t(i,j)] / L_t(i,j) & \text{if interaction exists between } (i,j), \\ 0 & \text{otherwise.} \end{cases} \end{aligned} \tag{5.4}$$

However, using a single value to measure friendship may not be accurate enough. In this research a weighted average of three numbers was used to come up with a final friendship. Friendship Estimator (FE) is defined as:

$$FE_t(i,j) = \frac{O + 4M + P}{6}, \tag{5.5}$$

where

P : the most pessimistic friendship when two users are nodding acquaintance, $P = \tau_{t-1}(i,j)$.

O: the most optimistic friendship when two users are best friend, $O = 1$.

M : the most likely friendship calculated based on interaction history, $M = \tau_t(i, j)$.

Notice that friendship estimator is moved slightly toward either the optimistic or pessimistic value, depending on which one is furthest from the most likely. This also reflects real life situation as friendship are not likely to change dramatically in general case.

5.2.1.3 Product Knowledge Analysis

This module used a PageRank-like algorithm to measure individual expertise on a certain type of product. The idea is that if *i* replies *j*'s post on a certain product, and *k* also responds to *i*'s question about that product, *k*'s expertise should be boosted not just because they respond to a post/question about that product, but because they were able to answer a question of someone who had some expertise. Assume *i* has ever replied to *j*'s post/comment on certain product *p*, so the expertise of *i* on product *p* is defined as:

$$PK_P(i) = (1-d) + d * \sum \frac{PK_P(j)}{C_P(j)}, \tag{5.6}$$

where $C_P(j)$ is defined as the total number of users answering *j*'s post/comment on certain product, and *d* is usually set to 0.85.

5.2.2 Decision Group Recruiting

Regression analysis is a tool for the investigation of relationships between variables, and its major use is prediction or forecasting [19]. Usually, the investigator seeks to ascertain the causal effect of one variable upon another. To explore the friendship between friends, this study assembled data on the underlying variables of interest (in this work, closeness, betweenness and evaporation) and employed regression to estimate the quantitative effect of these three variables upon friendship. Social source credibility (SSC) of friend *j* to decision maker *i* in time *t*:

$$SSC_t(i, j) = \beta_0 + \beta_1 \bullet \sum C(j) + \beta_2 \bullet SS(i, j) + \beta_3 \bullet FE_t(i, j) + \beta_4 \bullet PK_P(i), \tag{5.7}$$

where β is parameter, $\sum C(j) = C_B(j) + C_C(j) + C_D(j)$ and ε is error term. After the regression model is built, it can be used this to measure decision maker's most likely friend and select required decision group.

5.2.3 Product Selection Criteria Discovering

This study used FDM for the screening of alternate factors [35]. The fuzziness of common understanding of experts could be solved by using the fuzzy theory, and the efficiency and quality of questionnaires could be improved. To implement typical FDM process, comments from decision group have to be collected first. However, traditional questionnaire survey for criteria collecting is time consuming, so a criteria extraction and screening module was designed to do the job.

The criteria extraction and screening module reads the comments made by decision group members, and the word similarity is measured. Given two words, the word similarity determines how similar their meaning is. The higher the similarity, the more similar the meaning of the two words. The steps for computing similarity are described as follow:

1. Partition each comment into a list of words and remove stop words. Stop words are frequently occurring, insignificant words.

2. Identify the correct part of speech (POS) of each word. A Part-Of-Speech Tagger (POS Tagger) reads text and assigns parts of speech to each word, such as noun, verb and adjective. In the proposed system framework, POS tagger developed by Stanford University was adopted to identify part of speech. The tagged nouns were considered to be keywords from decision group members.

3. Find the most appropriate sense for every keyword and compute their similarity. WordNet [80] is a large lexical database in which nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets are interlinked by means of conceptual-semantic and lexical relations. To measure the semantic similarity between two synsets, hyponym/hypernym (or *is-a* relations) were used. Figure 5.5 shows an example of the hyponym taxonomy in WordNet used for computing path length similarity measurement, and the path length is measured in nodes. For instance, the length

between car and auto is 1, car and truck is 3. In this work the similarity was defined as:

$$Sim(s,t) = \frac{1}{distance(s,t)}, \tag{5.8}$$

where $distance(s,t)$ is the node counting between s and t.

Therefore, $Sim(\text{car,truck}) = 1/3$, and $Sim(\text{car,auto}) = 1$. Note that the length of the path between two members of the same synset is 1, that is, car and auto are synonym.

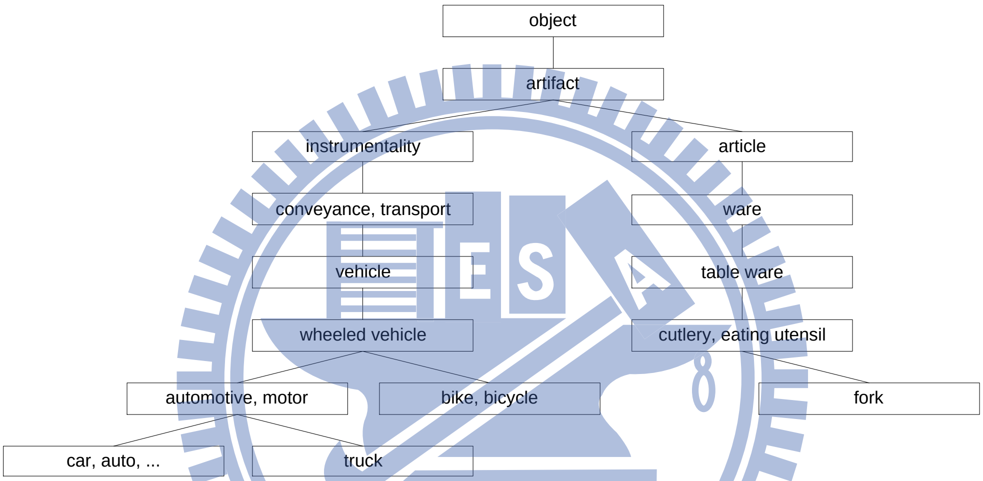

Figure 5.5 Example of the hyponym taxonomy in WordNet

An ancestor node of two synsets is known as a subsumer, and for those keywords with similarity higher than threshold value their least common subsumer is then selected as decision criteria. For instance, the similarity threshold is defined as 1/3. In Figure 5.5, "car" and "truck" have similarity 1/3 and the least common subsumer of (car, auto..) and (truck..) is (automotive, motor). So (automotive, motor) is selected as aggregated keywords.

After collecting all the keywords, fuzzy Delphi method was used to filter keywords and construct the final decision criteria set. In this work, the fuzzy Delphi implementation procedure from [13] was adopted. The value of triangular fuzzy number of all keywords was calculated and discovered the significance triangular fuzzy number of factors. By using simple center of gravity method to defuzzify, the fuzzy weight of each keyword can be converted to definite value. Finally, proper keywords can be filtered out as decision criteria. At the end of these steps, a set of decision criteria $\{N\}$

extracted from comments of decision group members was obtained. The detail process of this module is depicted in Figure 5.6.

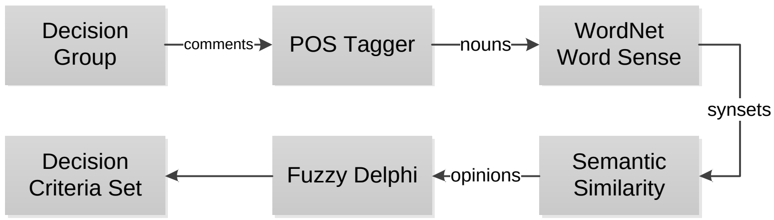

Figure 5.6 The detail process of product selection criteria discovering module

5.2.4 Alternative Synthesizing

In the decision criteria discovering module, the decision criteria conforming to a decision problem has been identified. Hsu and Chen [34] proposed a fuzzy similarity aggregation method (SAM), in which similarities between decision group members were collated and fuzzy numbers assigned directly to each member to determine the agreement degree between them. Taking the degree of importance of each member into consideration, the original weighting method was modified as below. In Hsu and Chen [34], the average agreement degree of member $i, i = 1, 2, ..., n$ is given by:

$$AE(i) = \frac{1}{n-1} \sum_{j=1, j \neq i}^{n} S(i, j), \tag{5.9}$$

where $S(i, j)$ is the agreement degree, and n is the number of decision group members. $S(i, j)$ is defined as:

$$S(i, j) = \frac{Count(\{N_i\} \cap \{N_j\})}{Count(\{N_i\} \cup \{N_j\})}, \tag{5.10}$$

where $\{N_i\}, \{N_j\}$ is decision criteria derived from comments of decision group member i, j respectively, and $\{N_i\}, \{N_j\} \in \{N\}$. For example, if $\{N_i\} = \{A, B, C\}$ and $\{N_j\} = \{A, C, D, E\}$, then $S(i, j) = \frac{Count(\{A, C\})}{Count(\{A, B, C, D, E\})} = \frac{2}{5} = 0.4$. Besides, $RAD(i)$ is the relative agreement degree of decision group member i, which is formulated as [34]:

$$RAD(i) = \frac{AE(i)}{\sum_{k=1}^{n} AE(k)}. \tag{5.11}$$

However, the relative importance of experts varies. Some are more important than the others, and some are more experienced than others. Therefore, the relative importance weight of each expert was considered. The most important person among experts was selected and assign him weight one. The relative importance of expert *i* is formulated as [34]:

$$RI(i) = \frac{r(i)}{\sum_{k=1}^{n} r(k)}. \tag{5.12}$$

For $RI(i)$, in the original definition the weight of the most important member is 1, that is, $r(i)=1$. Then the kth member is compared with the most important one, and a relative weight $r(k)$ is assigned. This work improved the calculation of relative importance of decision group member and consensus degree coefficient was improved to capture the spirit of social network. Since the decision group was selected based on friendship, the member with highest friendship index is considered to be the most important one with $r(i)=1$, for all other members, $r(k) = FE_t(i,k)/FE_t(i,j)$. Therefore, the relative importance of members was reformulated as:

$$RI(i) = \frac{FE_t(i,j)}{\sum_{k=1}^{n} FE_t(i,k)}. \tag{5.13}$$

Meanwhile, the consensus degree coefficient of member $E_i (i=1,2,...n)$ is defined as [34]:

$$CDC(i) = \gamma(i) \bullet RI(i) + (1-\gamma(i)) \bullet RAD(i). \tag{5.14}$$

Finally, the aggregation result R can be defined as [34]:

$$R = \sum_{i=1}^{n} (CDC(i) \bullet R(i)), \tag{5.15}$$

where $R(i)(i=1,2,...,n)$ is the estimated ratings of decision group member $E(i)$ on decision criteria.

Having decision criteria in hand, fuzzy AHP was used to construct the alternatives of decision problem. In the proposed system, the same fuzzy AHP process from prior works [13, 14] was adopted, and the important data required to complete this process is describe as follows:

1. the problem hierarchical structure: the decision problem is structured hierarchically at different levels, each level consisting of decision criteria. The top level of the hierarchy represents the overall goal of decision problem, while the lowest level is composed of all possible alternatives. One or more intermediate levels embody the decision criteria and sub-criteria. In the proposed system, the decision criteria and the possible alternatives are obtained from decision criteria discovering module. For the simplicity of system implementation, if a decision group member proposed possible alternatives in his comments, the alternatives are tagged with predefined syntax so that they can be easily identified and avoid confusion with decision criteria.
2. the pair-wise comparison matrix: the relative importance of the decision criteria is assessed by using equation (5.15).

At the end of this process global priorities are used for final ranking of the alternatives.

5.3 Experiment

5.3.1 Experiment Process

To further prove the feasibility, an empirical study alone with system development was conducted. The procedures of this experiment are depicted in Figure 5.7. To implement proposed mechanism, one of the most popular social network sites Facebook was selected to be experiment platform to collect required data. First, a linear regression model is required to measure friendship index between friends. For the purpose of collecting basic data required by building regression model, a group of social network users were invited to be participants. By using 3 (S) stages 3 (K) names snowball sampling, 96 participants for each social network (group) were invited. After filtering the people not interested in the experiment, finally 156 participants, 52 for each group, were included in the experiment. Of all the 156 participants, 50 users were randomly selected to collect data needed for constructing friendship regression model. The average year of Facebook usage is 1.6 years and the average number of friends is 205. The characteristics of these social networks are summarized in Table 5.2.

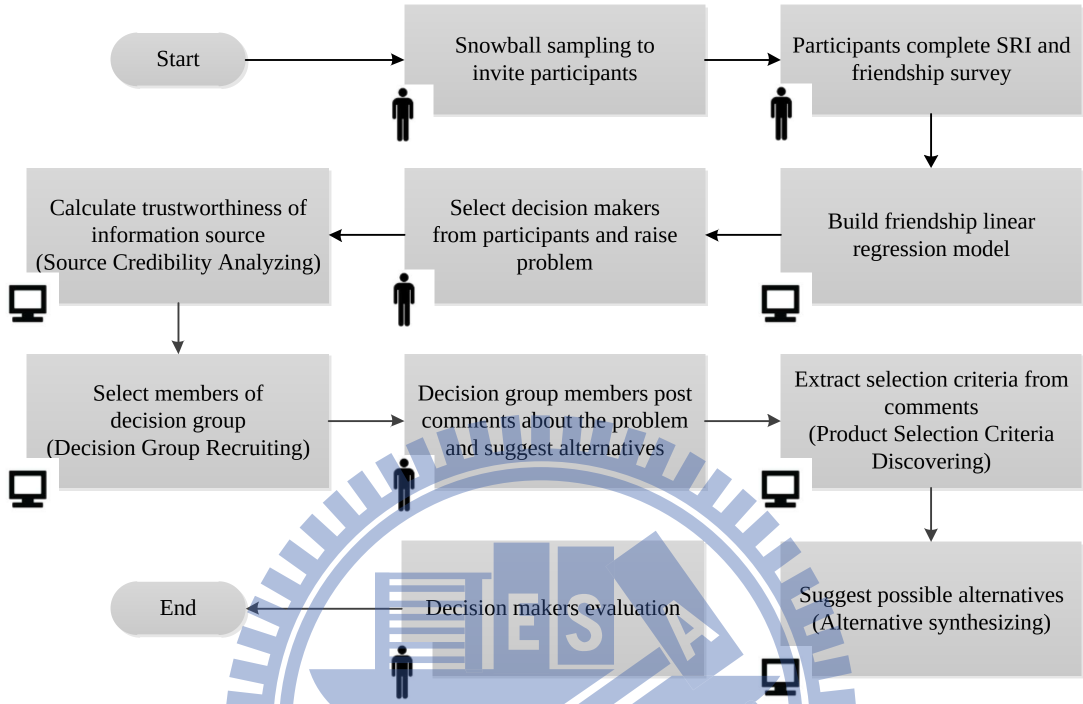

Figure 5.7 Experiment process for social intelligence mechanism

Table 5.2 Characteristics of the three networks

ATTRIBUTES	SOCIAL NETWORKS		
	STUDENT	OFFICE WORKER	RANDOM MEMBER
Number of participants	60	60	60
Age	20~32	23~45	18~43
Gender	Male: 55% Female: 45%	Male: 49% Female: 51%	Male: 63% Female: 37%
Average betweenness centrality	37.901	40.103	38.221
Average closeness centrality	56.919	56.956	57.440
Average distance	1.758	1.757	1.742

Since the closeness centrality, betweenness centrality and social similarity can be calculated without participants' help, only the data required to build up friendship estimation regression model has to be collected. The social relationships index (SRI) was developed as a self-report version of the social support interview [11, 12, 66], and this scale has demonstrated good test–retest reliability and internal consistency [79]. An online survey package, including a cover letter explaining the research objectives and the questionnaire was distributed to the 50 users to survey their friendship with those friends who also participated in the experiment. These friends were then rated in terms of how helpful and upsetting they were (1 = not at all, 10 = very much) when the participant needed support such as advice, understanding, or a favor. Using responses on this measure, friendship quality was classified as "supportive" or "ambivalent" as described by Uno, Uchino, and Smith [81]. For example, if user A was selected to provide friendship data for the purpose of regression model building, and his friends B,C and D also participated in the experiment, then he will receive an online SRI questionnaire survey to rate his friendship with B,C and D. After collecting the friendship dataset, SPSS was used to build the regression model by entering friendship from SRI, social similarity, closeness and betweenness centrality as base data. This model was then used to predict the friendship index at the time when a decision problem is issued.

After the regression model was built, 18 randomly selected users (6 from each group) were invited to be decision makers. In the experiment, they can issue a decision problem and evaluate the effectiveness of decision criteria and alternatives. The decision makers were asked to issue 2 decision problems during the experiment, and these problems were delivered to the decision group members selected by the system. Users with top-5 friendship index were selected as decision group members, and the processes repeated every time when a problem was issued. When a decision problem was presented to decision group, members can make their comments online. They were asked to post their comments together with alternatives about the decision problems. Every alternative was asked to provide a hyperlink containing related information, so that the click stream data can be collected to compare with other methods. Follow the method proposed in this research, decision criteria and alternatives are collected and presented to decision makers.

To maintain basic requirement of Delphi method, during the process, individual comments are unknown to others. The alternatives collected from both this work and benchmark methods (described in next section) are presented to decision makers in the same page, and the links are listed randomly to minimize interfere of presentation order. To avoid information overloading, the first decision alternative of each method were selected, and total 4 alternatives were presented to decision makers for each problem. Finally, the click count and stay time of each page linked to alternatives were recorded, and satisfaction was rated on a 5-point Likert Scale for each alternatives presented to decision makers: Very Useful, Useful, Neither Useful nor Useless, Useless and Very Useless by a rating score of 5, 4, 3, 2 and 1. The experiment was executed in each of the three group 3 times, and each experiment lasted for one week. The parameters of this experiment are shown in Table 5.3.

Table 5.3 Experiment setting of social intelligence mechanism

ITEM	SETTING
Type of support	Product selection criteria and candidates listing
Participant sampling	Snowball sampling
No. of participants	Student: 52 Office worker:52 Random member: 52
No. of requestors	Student: 6 (out of 52) Office worker:6 (out of 52) Random member: 6 (out of 52)
Regression model	Social relationships index survey: 50 participants (randomly selected)
Benchmark method	Random: rank products in candidate list randomly Social network analysis: select support group members by SNA Group centrality: select support group by group centrality
Evaluation method	Clickstream: browsing time on the product pages provided Perceived helpfulness: questionnaire survey by 5-point Likert scale

5.3.2 Benchmark Methods

To compare proposed mechanism with others, three methods were selected as benchmark.

1. Random: this method was used as baseline benchmark. All the experiment process was the same as proposed mechanism except the decision group members were randomly selected from the friends of decision makers.

2. SNA: this method used social relation data to be selection rule. The friendship estimation was derived purely from participants' profile. This is a baseline to test if it is useful to include time factor when estimating friendship to select decision group members. The regression model used in this method can be rewritten based on equation (5.7) as:

$$SSC_t(i,j) = \beta_0 + \beta_1 \bullet \sum C(j) + \beta_2 \bullet SS(i,j). \tag{5.16}$$

3. SNA with single point friendship estimation: to see if the proposed friendship estimator (equation (5.5)) is better than using single point friendship estimation (equation (5.3)), a single-point friendship estimator regression model was also included in the benchmark methods. The regression model can be formulated based on equation (5.7) as:

$$SSC_t(i,j) = \beta_0 + \beta_1 \bullet \sum C(j) + \beta_2 \bullet SS(i,j) + \beta_3 \bullet \tau_{ij}^{t-1} + \beta_4 \bullet PK_P(i). \quad (5.17)$$

Table 5.4 The coefficients of regression models

Factor	Proposed Mechanism	SNA	SNA + Single Point
	Coefficient (β)		
Constant	0.375	5.128	5.509
Similarity	0.361	0.777	0.596
Friendship	6.385	-	0.827
Centrality	0.607	0.841	0.802
Expertise	2.356	-	2.431

5.4 Result and Discussion

To evaluate the result from selection criteria discovering module in the proposed mechanism, the precision and similarity between keywords from Epinions.com and extracted selection criteria were calculated based on the product information page of Epinions.com. For example, resolution, camera type, optical zoom and LCD screen size were listed in the Epinions.com as product selection condition for digital camera. These keywords were used to expand their synonym set, and this set was used to compare with the possible selection criteria extracted from proposed mechanism. Illustrations of these processes are depicted in Figure 5.8 and Figure 5.9. The average precision rate is 0.63, and the average word similarity is 0.61.

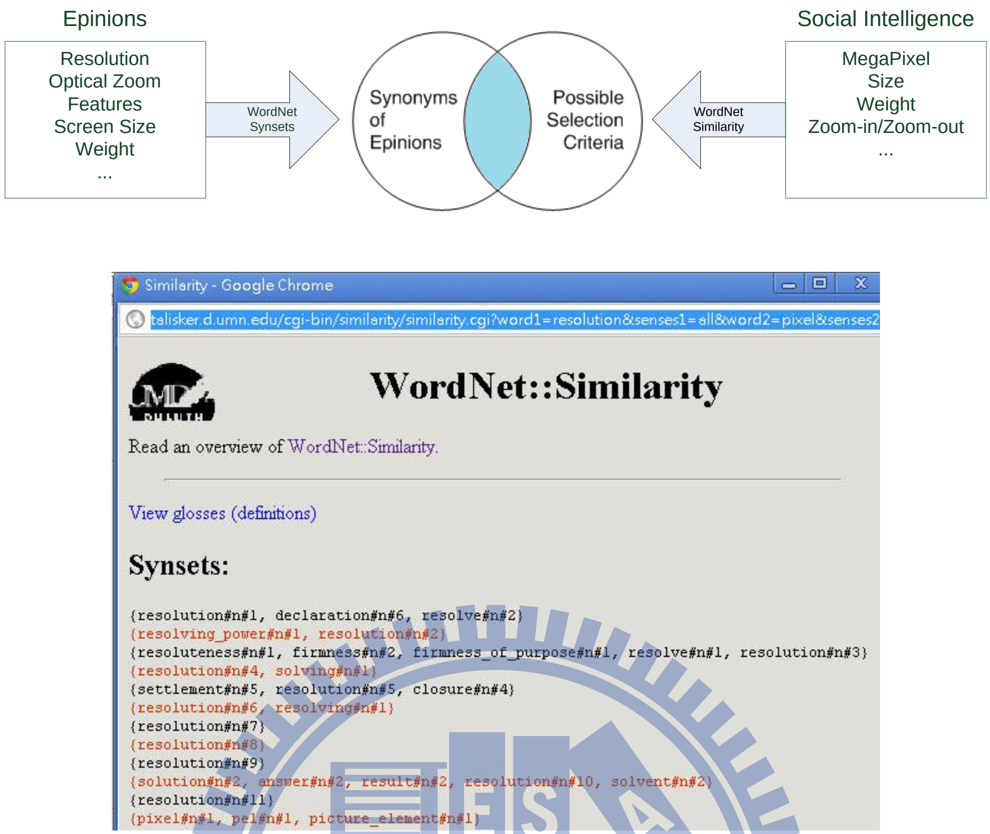

Figure 5.8 Precision and similarity calculation process of selection criteria

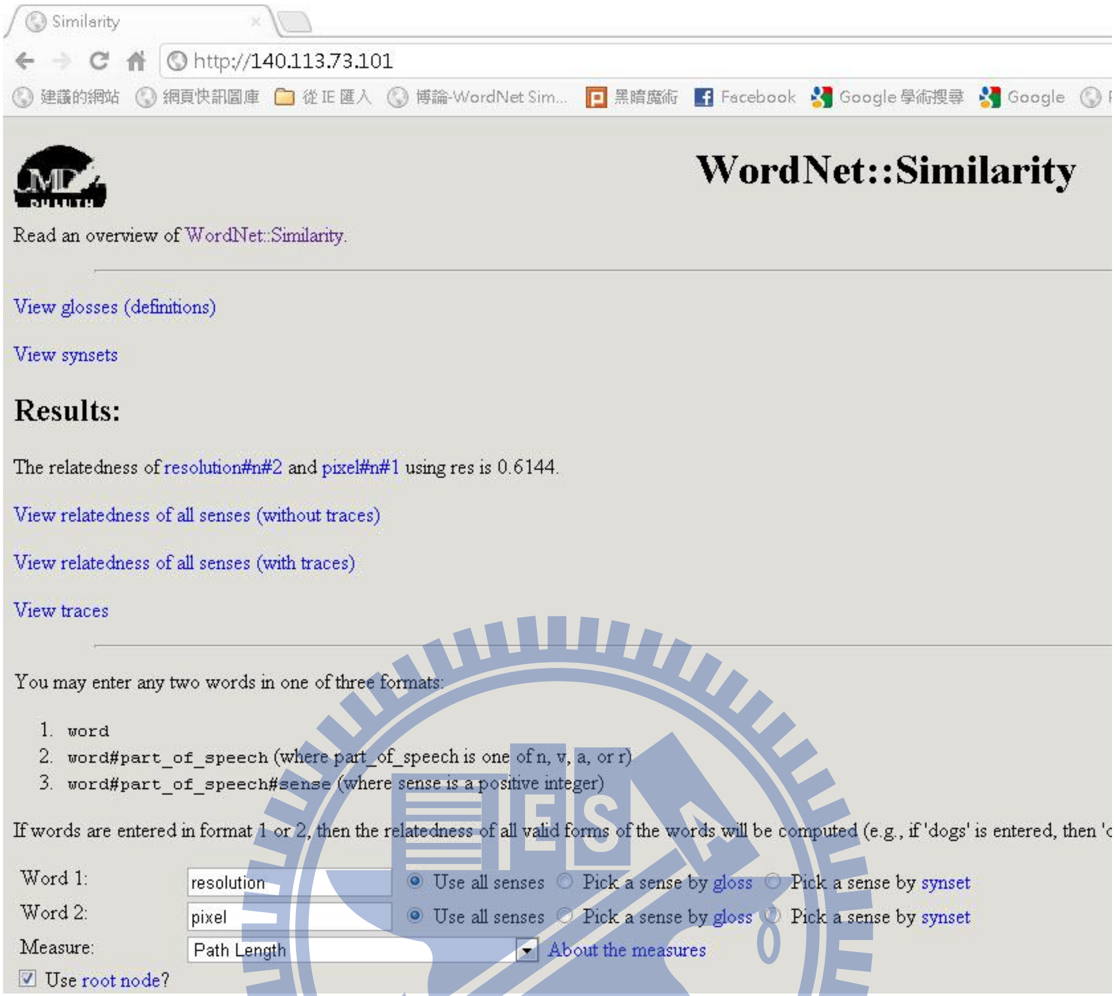

Figure 5.9 Similarity comparison of Epinions keyword and extracted criteria

During the experiment, clickstream data of every alternative presented was collected, and the average stay time of different methods and groups on every alternative was plotted. As shown in Figure 5.10 , the proposed mechanism attracted decision makers to spend more time on the alternatives than other methods. More, as shown in Figure 5.11, the average usefulness level of alternatives generated by the proposed mechanism is also higher than other methods. To further examine if there are significant differences in average stay time and average usefulness level, a statistical method is required.

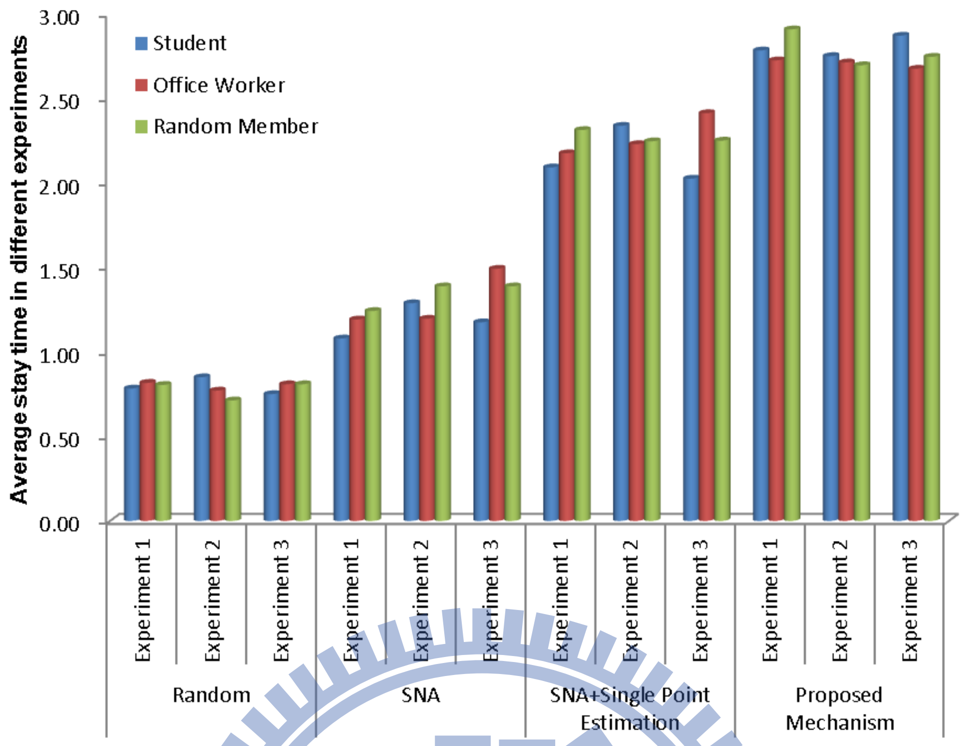

Figure 5.10 Average stay time for different groups and methods

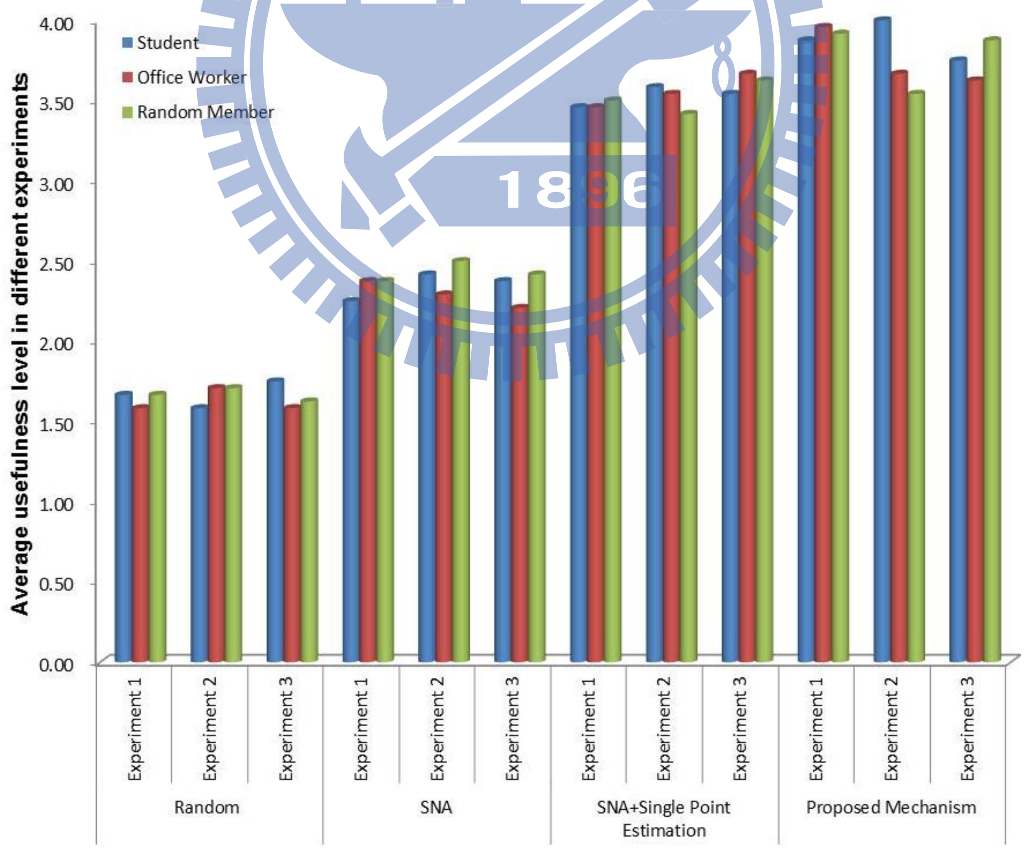

Figure 5.11 Average usefulness level for different groups and methods

Two-way analysis of variance (ANOVA) is a statistical analysis in which two independent factors are examined with regard to their impact on a dependent variable and on one another. To test the impact of method used and user group on average stay time and average usefulness level, in this work two-way ANOVA was used. Asseen from Table 5.5, the method used in the experiment has impact on the average stay time as the test result is significant at 0.05 (as 0.00<0.05). In contract, the user group has no impact as 0.51>0.05. For the same reason, based on Table 5.6 the satisfaction can only be influenced by method used during the experiment.

Table 5.5 Tests of between-subjects effects for average stay time

Dependent Variable: Average Stay Time

SOURCE	TYPE III SUM OF SQUARES	DEGREE OF FREEDOM	MEAN SQUARE	F	SIG.
User Group	0.52	2	0.26	0.66	0.51
Method	520.38	3	173.46	444.41	0.00

Table 5.6 Tests of between-subjects effects for average usefulness level

Dependent Variable: Average Usefulness Level

SOURCE	TYPE III SUM OF SQUARES	DEGREE OF FREEDOM	MEAN SQUARE	F	SIG.
User Group	0.40	2	0.20	0.61	0.54
Method	657.94	3	219.31	673.96	0.00

Post hoc tests such as Tukey's test most commonly compare every group mean with every other group mean. Knowing that the methods used in the experiments could affect stay time and usefulness level, Tukey's test was used to see if there is a significant difference between different methods. Table 5.7 and Table 5.8 show that there are significant differences between the proposed mechanism and other benchmark methods; also the average stay time and average usefulness level are higher than other methods. Since there is a strong tendency for users to spend a greater length of time reading articles of interest to them [32, 56], it is likely that the proposed approach is more effective when compared with other methods.

Table 5.7 Multiple comparisons of stay time

(I) METHOD	(J) METHOD	MEAN DIFFERENCE (I-J)
Random	SNA	-0.4815*
	SNA + Single Point Estimation	-1.4417*
	Proposed Mechanism	-1.9736*
SNA	Random	0.4815*
	SNA + Single Point Estimation	-0.9602*
	Proposed Mechanism	-1.4921*
SNA + Single Point Estimation	Random	1.4417*
	SNA	0.9602*
	Proposed Mechanism	-0.5319*
Proposed Mechanism	Random	1.9736*
	SNA	1.4921*
	SNA + Single Point Estimation	0.5319*

*. The mean difference is significant at the .05 level.

Table 5.8 Multiple comparisons of usefulness

(I) METHOD	(J) METHOD	MEAN DIFFERENCE (I-J)
Random	SNA	-.7037*
	SNA + Single Point Estimation	-1.8796*
	Proposed Mechanism	-2.1481*
SNA	Random	.7037*
	SNA + Single Point Estimation	-1.1759*
	Proposed Mechanism	-1.4444*
SNA + Single Point Estimation	Random	1.8796*
	SNA	1.1759*
	Proposed Mechanism	-.2685*
Proposed Mechanism	Random	2.1481*
	SNA	1.4444*
	SNA + Single Point Estimation	.2685*

*. The mean difference is significant at the .05 level.

To test the influence of friendship index in the selection of decision group, all the decision problems were issued at different time period. Since the selection rule of decision group was based on friendship index which is influenced partially by time, this study investigated if the members change across different time. For example, when decision maker A issued his first problem, a decision group consisting of 5 members was built, say $(M_1, M_2, M_3, M_4, M_5)$. At the time when second problem was issued, another decision group, say $(M_1, M_2, M_3, M_7, M_8)$, was built. In these two decision process, there were 10 users selected as decision group, but only 7 unique users since (M_1, M_2, M_3) was overlapped. The detail numbers are listed in Table 5.9. Further analysis found that decision makers with a large number of unique users are more active than those who with small number. However, no evidence showed that there was significant difference of time spent on the alternatives suggested by different decision groups even if there exists different number of unique users. This observation showed that the proposed mechanism was stable enough and won't be influenced by the uniqueness of decision group.

5.5 Chapter Summary

In this chapter, time factor was introduced into social network analysis. From the viewpoint of academic contribution, by using regression a friendship estimation model was proposed to predict friendship between two users in specific time period. By equipping FDM with online decision criteria filtering mechanism, time consuming problem of conventional Delphi method was solved. Furthermore, an adoptive SAM was also suggested to further improve the application of FAHP on social network related research. An empirical study further proved the feasibility and effectiveness of this work. This research successfully introduced the decision process theory and social psychology into the development of social network-based application. Besides, the concept of decision support system development was extended to utilize social network platform. From the viewpoint of practice, a feasible way to develop a social network-based decision support system together with the related techniques was demonstrated. By dividing the system framework into modules, those who are interested in developing such kind of applications can further improve the system by plugging in new modules as needed.

Table 5.9 The number of unique decision group members

DECISION MAKER	TOTAL NUMBER OF USERS SELECTED AS DECISION GROUP	NUMBER OF UNIQUE USERS
Student 1	30 (5 decision group members for each problem, 2 problems for each experiment, 3 experiments, 5*2*3=30)	23
Student 2		20
Student 3		24
Student 4		19
Student 5		15
Student 6		19
Office Worker 1		16
Office Worker 2		25
Office Worker 3		19
Office Worker 4		19
Office Worker 5		22
Office Worker 6		16
Random Member 1		19
Random Member 2		17
Random Member 3		23
Random Member 4		16
Random Member 5		22
Random Member 6		15

CHAPTER 6

CONCLUSION

6.1 Summary

As online social network is becoming parts of our daily life, companies are trying to stimulate the needs of consumers through the power of social networks. Many social media-based applications were designed for the purpose of delivering advertisements by way of word-of-mouth. While conventional decision support system has been extensively investigated, little specific mechanism, however, on how social networks can help users with online purchasing decision-making is developed. This study first examined if friendship and social interactions are positively correlated in an online social network context. Then different mechanisms were designed based on the decision makers' online social networks to meet the requirements of different product purchasing scenario. By combining social psychology, consumer purchase decision-making process and information technology, three social influence-based decision support mechanisms were proposed. By introducing design rationale and social impact theory into system development, information technology was used to implement a social network-based decision support system framework for consumer purchase decision problems. QOC schema was used to describe the reasoning process of possible product alternatives. Further, social impact was used to select the decision group members and measure the effect of changing decision members' attitude toward a specific options or criteria. Time factor was used to improve current social relation analysis techniques. Instead of using single value to estimate friendship, a three-point estimator was proposed. Besides, traditional fuzzy Delphi and fuzzy analytic hierarchy process methods was improved to meet the requirements of system development on online social network sites. The empirical study further showed that the proposed system frameworks can perform better than benchmark methods. For consumers, this study proposed a set of tools to help them with selecting proper products in different scenario.

6.2 Future Works

Being one of the pilot studies in the development of social network based decision support mechanism for electronic commerce, although the research has reached its aims, there were some unavoidable limitations. First, because of the time limit, this research was conducted only on a small size of population who were the users of Facebook. Therefore, to generalize the results over different social network platforms, the study should have involved more participants from other social networks. Second, although some factors like degree centrality and social similarity used in proposed mechanisms can be acquired directly by analysing existing connections between users, the initial friendship data requires manual collection. To make the proposed system more feasible, an automatic friendship data collecting mechanism would be necessary. Third, post-purchase behavior may be important as purchase experience can play an important role when selecting items. As the proposed mechanisms cover three of five stages in consumer decision-making process, it would be a natural extension to include a feedback mechanism in proposed system frameworks so as to take purchase history into consideration.

APPENDIX

Publication List

Journal Papers

1. "Online Social Advertising via Influential Endorsers," Y.-M. Li, Y.-L. Lee and N.-J. Lien, International Journal of Electronic Commerce, Vol. 16(3) 2012, pp.119-154, 2012. (SSCI)
2. "Pricing Peer-Produced Service: Quality, Capacity, and Competition Issues," Y.-M. Li and Y.-L. Lee, European Journal of Operational Research, Vol. 207 (3), pp.1658-1668, 2010. (SCI)
3. "Auditing and Provision Strategies of Utility Computing Service: A Game Theoretic Perspective," Y.-M. Li and Y.-L., Lee, Journal of Information Management, Vol. 14 (S), pp.239-260, 2007. (TSSCI)

Conference Papers

1. "Designing A Social Support Mechanism for Online Consumer Purchase Decision Making", Li, Y.-M., Yi-Lin Lee, 16th Pacific Asia Conference on Information Systems, Ho Chi Minh City, Vietnam, July, 2012 (forthcoming).
2. "Building Social Decision Support Mechanisms with Friend Networks", Li, Y.-M., Yi-Lin Lee, Proc. 45th Hawaii International Conference on System Science (HICSS-45), Maui, Hawaii, USA, January, 2012.
3. "Economic Investigation of Peer Produced Services", Y.-M. Li, Y.-L. Lee, Proc. 12th Pacific Asia Conference on Information Systems (PACIS 2008), pp.1526-1535, Suzhou, China, July, 2008.
4. "Agent-based Social Decision Mechanism For EC Service Quality Evaluation", Y.-M. Li, Y.-L. Lee and C.-Y .Lai, 4th Proc. International Conference on Business and Information 2008 (BAI 2008), pp.1-9, CD-ROM:D4-545-1733-1-DR, Seoul, Korea, July, 2008.
5. "Pricing Web 2.0 Related Services: Peer Production", Li, Y.-M., Y.-L. Lee, Proc. 9th International Conference on Electronic Commerce (ICEC 2007), pp.441-448, Minneapolis, USA, August, 2007.
6. "Auditing and Provision Strategies of Utility Computing Service: A Game Theoretic Perspective", Lee, Y.-L. and Li, Y.-M., CD-ROM Proc. 9th

National Conference of Information Management for PhD, Kaohsiung City, Taiwan, April, 2007. (Best Paper Award)

REFERENCES

[1] Abdul-Rahman, A. and Hailes, S. Supporting Trust in Virtual Communities. In *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences*, Maui, Hawaii, USA: IEEE, 2000, pp.1-9.

[2] Ahn, Y.-Y.; Han, S.; Kwak, H.; Moon, S. and Jeong, H. Analysis of Topological Characteristics of Huge Online Social Networking Services. In *Proceedings of the 16th International Conference on World Wide Web*, Alberta, Canada: ACM, 2007, pp.835-844.

[3] Amer-Yahia, S.; Roy, S. B.; Chawlat, A.; Das, G. and Yu, C. Group Recommendation: Semantics and Efficiency. In *Proceedings of the VLDB Endowment*, 2009, pp.754-765.

[4] Arrow, K. J. and Sen, A. K. *Handbook of Social Choice and Welfare*. Vol. 1: North Holland, 2002.

[5] Bearden, W. O. and Etzel, M. J. Reference Group Influence on Product and Brand Purchase Decisions. *Journal of Consumer Research*, 9, 2(1982), 183-194.

[6] Bell, D. R. and Song, S. Neighborhood Effects and Trial on the Internet: Evidence from Online Grocery Retailing. *Quantitative Marketing and Economics*, 5, 4(2007), 361-400.

[7] Beuker, I. *Social Commerce Profit or Perish?*, http://www.viralblog.com/social-commerce-2/infographic-social-commerce-profit-or-perish/, Accessed May-09-2012.

[8] Bonacich, P. Power and Centrality: A Family of Measures. *American Journal of Sociology*, 92, 5(1987), 1170-1182.

[9] Borgatti, S. P. and Cross, R. A Relational View of Information Seeking and Learning in Social Networks. *Management Science*, 49, 4(2003), 432-445.

[10] Borgatti, S. P.; Mehra, A.; Brass, D. J. and Labianca, G. Network Analysis in the Social Sciences. *Science*, 323, 5916(2009), 892-895.

[11] Bushman, B. B. and Holt-Lunstad, J. Understanding Social Relationship Maintenance among Friends: Why We Don't End Those Frustrating Friendships. *Journal of Social and Clinical Psychology*, 28, 6(2009), 749-778.

[12] Campo, R. A.; Uchino, B. N.; Holt-Lunstad, J.; Vaughn, A.; Reblin, M. and Smith, T. W. The Assessment of Positivity and Negativity in Social Networks: The Reliability and Validity of the Social Relationships Index. *Journal of Community Psychology*, 37, 4(2009), 471-486.

[13] Cheng, J. H.; Lee, C. M. and Tang, C. H. An Application of Fuzzy Delphi and Fuzzy Ahp on Evaluating Wafer Supplier in Semiconductor Industry. *WSEAS Transactions on Information Science and Applications*, 6, 5(2009), 756-767.

[14] Cheng, J. H. and Tang, C. H. An Application of Fuzzy Delphi and Fuzzy AHP for Multi-Criteria Evaluation on Bicycle Industry Supply Chains. *WSEAS Transactions on Systems and Control*, 4, 1(2009), 21-34.

[15] Chevaleyre, Y.; Endriss, U.; Lang, J. and Maudet, N. A Short Introduction to Computational Social Choice. *Lecture Notes in Computer Science*, 4362, 2007(2007), 51-69.

[16] Chi, L.; Holsapple, C. W. and Srinivasan, C. Competitive Dynamics in Electronic Networks: A Model and the Case of Interorganizational Systems. *International Journal of Electronic Commerce*, 11, 3(2007), 7-49.

[17] Childers, T. L. and Rao, A. R. The Influence of Familial and Peer-Based Reference Groups on Consumer Decisions. *Journal of Consumer Research*, 19, 2(1992), 198-211.
[18] Company, N. *Global Advertising: Consumers Trust Real Friends and Virtual Strangers the Most*, http://blog.nielsen.com/nielsenwire/consumer/global-advertising-consumers-trust-real-friends-and-virtual-strangers-the-most/, Accessed Jan-04-2012.
[19] Copas, J. B. Regression, Prediction and Shrinkage. *Journal of the Royal Statistical Society*, 45, 3(1983), 311-354.
[20] Crandall, D.; Cosley, D.; Huttenlocher, D.; Kleinberg, J. and Suri, S. Feedback Effects between Similarity and Social Influence in Online Communities. In *Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Las Vegas, Nevada, USA: ACM, 2008, pp.160-168.
[21] Daly, E. M. and Haahr, M. Social Network Analysis for Routing in Disconnected Delay-Tolerant Manets. In *Proceedings of the 8th ACM International Symposium on Mobile Ad Hoc Networking and Computing*, Montreal, Quebec, Canada: ACM, 2007, pp.32-40.
[22] De Meo, P.; Nocera, A.; Terracina, G. and Ursino, D. Recommendation of Similar Users, Resources and Social Networks in a Social Internetworking Scenario. *Information Sciences*, 181, 7(2010), 1285-1305.
[23] Dekker, D.; Krackhardt, D. and Snijders, T. A. B. Sensitivity of Mrqap Tests to Collinearity and Autocorrelation Conditions. *Psychometrika*, 72, 4(2007), 563-581.
[24] Dembosky, A. *Companies Embrace the F Word*, http://www.ft.com/intl/cms/s/0/4c880bb0-b933-11e0-b6bb-00144feabdc0.html#axzz1tyxVOB4Y, Accessed Jan-03-2012.
[25] Deutsch, M. and Gerard, H. B. A Study of Normative and Informational Social Influences Upon Individual Judgment. *The Journal of Abnormal and Social Psychology*, 51, 3(1955), 629.
[26] Dillon, S. M. Descriptive Decision Making: Comparing Theory with Practice. *Unpublished manuscript, Department of Management Systems, University of Waikato, New Zealand*, (1998).
[27] Eagle, N.; Pentland, A. and Lazer, D. Inferring Friendship Network Structure by Using Mobile Phone Data. *Proceedings of the National Academy of Sciences*, 106, 36(2009), 15274-15278.
[28] Fishburn, P. C. *The Theory of Social Choice*. Vol. 264: Princeton University Press, New Jersey, 1973.
[29] Fodness, D. and Murray, B. A Model of Tourist Information Search Behavior. *Journal of Travel Research*, 37, 3(1999), 220-230.
[30] Freeman, L. C. Centrality in Social Networks Conceptual Clarification. *Social Networks*, 1, 3(1979), 215-239.
[31] Freeman, L. C. A Set of Measures of Centrality Based on Betweenness. *Sociometry*, 40, 1(1977), 35-41.
[32] Ganesan, V. and Seiji, Y. Behavior-Based Web Page Evaluation. In *Proceedings of the 2006 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology Workshops*, Hong Kong, China: IEEE, 2006, pp.409-412.
[33] Golbeck, J. and Hendler, J. Filmtrust: Movie Recommendations Using Trust in Web-Based Social Networks. In *Proceedings of the 3rd IEEE Consumer*

Communications and Networking Conference, Las Vegas, Nevada, USA, 2006, pp.282-286

[34] Hsu, H.-M. and Chen, C.-T. Aggregation of Fuzzy Opinions under Group Decision Making. *Fuzzy Sets and Systems*, 79, 3(1996), 279-285.

[35] Hsu, Y.-L.; Lee, C.-H. and Kreng, V. B. The Application of Fuzzy Delphi Method and Fuzzy Ahp in Lubricant Regenerative Technology Selection. *Expert Systems with Applications*, 37, 1(2010), 419-425.

[36] Huffaker, D. Dimensions of Leadership and Social Influence in Online Communities. *Human Communication Research*, 36, 4(2010), 593-617.

[37] Ibarra, H. and Andrews, S. B. Power, Social Influence, and Sense Making: Effects of Network Centrality and Proximity on Employee Perceptions. *Administrative Science Quarterly*, 38, 2(1993), 277-303.

[38] Iyengar, R.; Van den Bulte, C.; Valente, T. W. and Institute, M. S. *Opinion Leadership and Social Contagion in New Product Diffusion*: Marketing Science Institute, 2008.

[39] Kameda, T.; Ohtsubo, Y. and Takezawa, M. Centrality in Sociocognitive Networks and Social Influence: An Illustration in a Group Decision-Making Context. *Journal of Personality and Social Psychology*, 73, 2(1997), 296.

[40] Kaplan, M. F. and Miller, C. E. Group Decision Making and Normative Versus Informational Influence: Effects of Type of Issue and Assigned Decision Rule. *Journal of Personality and Social Psychology*, 53, 2(1987), 306.

[41] Kendall, M., *Ranking Correlation Methods*. 1970, Griffin, London.

[42] Kilduff, M. and Tsai, W. *Social Networks and Organizations*: Sage Publications, 2003.

[43] Killeya-Jones, L. A.; Nakajima, R. and Costanzo, P. R. Peer Standing and Substance Use in Early-Adolescent Grade-Level Networks: A Short-Term Longitudinal Study. *Prevention Science*, 8, 1(2007), 11-23.

[44] Kim, Y. A. and Srivastava, J. Impact of Social Influence in E-Commerce Decision Making. In *Proceedings of the 9th International Conference on Electronic Commerce*, Minneapolis, Minnesota, USA: ACM, 2007, pp.293-302.

[45] Kotler, P. *Marketing Management: Analysis, Planning, Implementation, Control*. 9th ed: Prentice Hall, 1997.

[46] Krackhardt, D. Predicting with Networks: Nonparametric Multiple Regression Analysis of Dyadic Data. *Social Networks*, 10, 4(1988), 359-381.

[47] Krienen, F. M.; Tu, P.-C. and Buckner, R. L. Clan Mentality: Evidence That the Medial Prefrontal Cortex Responds to Close Others. *The Journal of Neuroscience*, 30, 41(2010), 13906-13915.

[48] Labianca, G.; Brass, D. J. and Gray, B. Social Networks and Perceptions of Intergroup Conflict: The Role of Negative Relationships and Third Parties. *Academy of Management Journal*, 41, 1(1998), 55-67.

[49] Latané, B. Dynamic Social Impact: The Creation of Culture by Communication. *Journal of Communication*, 46, 4(1996), 13-25.

[50] Latane, B. The Psychology of Social Impact. *American Psychologist*, 36, 4(1981), 343-356.

[51] Leenders, R., *Longitudinal Behavior of Network Structure and Actor Attributes: Modeling Interdependence of Contagion and Selection*, in *Evolution of Social Networks*. 1997. p. 165-184.

[52] Li, Y. M.; Lee, Y. L. and Lien, N. J. Online Social Advertising Via Influential Endorsers. *International Journal of Electronic Commerce*, 16, 3(2012), 119-154.
[53] Li, Y. M. and Shiu, Y. L. A Diffusion Mechanism for Social Advertising over Microblogs. *Decision Support Systems*, In press, (2012).
[54] MacLean, A.; Young, R. M.; Bellotti, V. M. E. and Moran, T. P. Questions, Options, and Criteria: Elements of Design Space Analysis. *Human–Computer Interaction*, 6, 3-4(1991), 201-250.
[55] Manski, C. F., *Economic Analysis of Social Interactions*. 2000, National Bureau of Economic Research.
[56] Morita, M. and Shinoda, Y., *Information Filtering Based on User Behavior Analysis and Best Match Text Retrieval*, in *Proceedings of the 17th Annual International ACM SIGIR Conference on Research and Development in information Retrieval*. 1994, Springer-Verlag, New York: Dublin, Ireland. p. 272-281.
[57] Murray, K. B. A Test of Services Marketing Theory: Consumer Information Acquisition Activities. *The Journal of Marketing*, 55, 1(1991), 10-25.
[58] Murray, T.; Pipino, L. and Van Gigch, J. A Pilot Study of Fuzzy Set Modification of Delphi. *Human Systems Management*, 5, 1(1985), 76-80.
[59] Nemeth, C. J. Differential Contributions of Majority and Minority Influence. *Psychological Review*, 93, 1(1986), 23-32.
[60] Noorderhaven, N. G. *Strategic Decision Making*: Addison Wesley, 1995.
[61] Nowak, A.; Szamrej, J. and Latané, B. From Private Attitude to Public Opinion: A Dynamic Theory of Social Impact. *Psychological Review*, 97, 3(1990), 362-376.
[62] Nowak, A. and Vallacher, R. R. Information and Influence in the Construction of Shared Reality. *IEEE: Intelligent Systems*, 20, 1(2005), 90-93.
[63] O'Donovan, J. and Smyth, B. Trust in Recommender Systems. In *Proceedings of the 10th International Conference on Intelligent User Interfaces*, San Diego, California, USA: ACM, 2005, pp.167-174.
[64] Otte, E. and Rousseau, R. Social Network Analysis: A Powerful Strategy, Also for the Information Sciences. *Journal of Information Science*, 28, 6(2002), 441-453.
[65] OTXResearch. *Engaging Consumers Online-the Impact of Social Media on Purchasing Behavior*, http://174.133.170.120/files/DEIStudy-Engaging%20ConsumersOnline-Summary.pdf, Accessed Mar-29-2012.
[66] Pagel, M. D.; Erdly, W. W. and Becker, J. Social Networks: We Get by with (and in Spite of) a Little Help from Our Friends. *Journal of Personality and Social Psychology*, 53, 4(1987), 793.
[67] Pfeffer, J.; Salancik, G. R. and Leblebici, H. The Effect of Uncertainty on the Use of Social Influence in Organizational Decision Making. *Administrative Science Quarterly*, 21, 2(1976), 227-245.
[68] Rashotte, L., *Social Influence*, in *The Blackwell Encyclopedia of Social Psychology*, Ritzer, G., Editor. 2007, Blackwell Publishing: Malden, Massachusetts, USA. p. 4426-4429.
[69] Richarme, M., *Consumer Decision-Making Models, Strategies, and Theories, Oh My!*, in *Decision Analyst*. 2005.
[70] Robins, G.; Pattison, P. and Elliott, P. Network Models for Social Influence Processes. *Psychometrika*, 66, 2(2001), 161-189.

[71] Saaty, T. L. and Shang, J. S. Group Decision-Making: Head-Count Versus Intensity of Preference. *Socio-Economic Planning Sciences*, 41, 1(2007), 22-37.

[72] Sen, A. The Possibility of Social Choice. *The American Economic Review*, 89, 3(1999), 349-378.

[73] Sen, A. Social Choice Theory: A Re-examination. *Econometrica: Journal of the Econometric Society*, 45, 1(1977), 53-89.

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

[75] Steegenga, W. and Forge, S. *Ibm Study Finds Social Networks Influence More Than Half of Shoppers' Decision-Making - Even in the Store*, http://www-03.ibm.com/press/uk/en/pressrelease/35340.wss#release, Accessed Jan-30-2012.

[76] Streeter, C. L. and Gillespie, D. F. Social Network Analysis. *Journal of Social Service Research*, 16, 1(1993), 201-222.

[77] T.Reis, H.; Collins, W. A. and Berscheid, E. The Relationship Context of Human Behavior and Development. *Psychological Bulletin*, 126, 6(2000), 844-872.

[78] Tsai, W. and Ghoshal, S. Social Capital and Value Creation: The Role of Intrafirm Networks. *Academy of Management Journal*, 41, 4(1998), 464-476.

[79] Uchino, B. N.; Holt-Lunstad, J.; Uno, D. and Flinders, J. B. Heterogeneity in the Social Networks of Young and Older Adults: Prediction of Mental Health and Cardiovascular Reactivity During Acute Stress. *Journal of Behavioral Medicine*, 24, 4(2001), 361-382.

[80] Uinversity, P. *Wordnet: A Large Lexical Database of English*, http://wordnet.princeton.edu/, Accessed 12-May-2012.

[81] Uno, D.; Uchino, B. N. and Smith, T. W. Relationship Quality Moderates the Effect of Social Support Given by Close Friends on Cardiovascular Reactivity in Women. *International Journal of Behavioral Medicine*, 9, 3(2002), 243-262.

[82] Vaidya, O. S. and Kumar, S. Analytic Hierarchy Process: An Overview of Applications. *European Journal of Operational Research*, 169, 1(2006), 1-29.

[83] Von Neumann, J.; Morgenstern, O.; Rubinstein, A. and Kuhn, H. W. *Theory of Games and Economic Behavior*: Princeton University Press, 2007.

[84] Zagenczyk, T. J.; Scott, K. D.; Gibney, R.; Murrell, A. J. and Thatcher, J. B. Social Influence and Perceived Organizational Support: A Social Networks Analysis. *Organizational Behavior and Human Decision Processes*, 111, 2(2010), 127-138.

[85] Zhang, H. and Dantu, R. Predicting Social Ties in Mobile Phone Networks. In *Proceedings of the 2010 IEEE International Conference on Intelligence and Security Informatics*, Vancouver, British Columbia, Canada: IEEE, 2010, pp.25-30.

[86] Zhang, J.; Hsee, C. K. and Xiao, Z. The Majority Rule in Individual Decision Making. *Organizational Behavior and Human Decision Processes*, 99, 1(2006), 102-111.

[87] Ziegler, C. N. and Golbeck, J. Investigating Interactions of Trust and Interest Similarity. *Decision Support Systems*, 43, 2(2007), 460-475.