國立交通大學

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博士論文

社群商務服務計算機制之設計

Designing Social Commerce Service Computing Mechanisms

研究生：賴政揚
指導教授：李永銘 博士

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Designing Social Commerce Service Computing Mechanisms

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中文摘要

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摘要

社群商務是電子商務在數位經濟中衍生出來的新模式，藉助社群媒體，透過人際網路的建立與互動來輔助並增進商業上的銷售和購買行為。本研究分別從消費者、網路賣家以及平台供應商三個面向進行探討，分別提出以社群網路為基礎的評價、廣告路徑規劃以及交易信譽評量機制，以期能有助於改善社群商務的運作。

首先，消費者購買商品時，會期望獲得朋友或是專業人士的意見與建議，作為選購商品時的參考依據。由於網路社群上存在著眾多知識淵博的使用者，因此，消費者的線上社群網路可以被視為是極大的智囊團，其意見足以作為使用者進行決策時的輔助。研究中所提出了社群評價機制，可以協助使用者將社群的知識力量化為己用，達到購物決策支援之目的。透過此機制，消費者可以有效地縮短線上購物時的資訊搜集和商品評價的過程，並且可以有效降低購入不適用產品的風險。

其次，販售方為提昇自己在市場中的銷售機會，大多會試圖在社群媒體中進行口碑行銷。透過在社群中熟識的朋友傳遞廣告，期望能實現爭取潛在的銷售機會，以及建立品牌印象兩大行銷策略。目前相關的市場行銷研究，多致力於從社群媒體使用者中找出潛在的高影響力使用者，透過他們傳播行銷訊息，以期能提高行銷效益。廣告路徑規劃機制的提出，主要著力於如何協助這些高影響力人群傳播行銷訊息，為廣告的接收者找出下一個最適的接收者，使行銷訊息能夠有效且持久的在線上傳播。藉由適當的路徑規劃，行銷人員可以適度的估算在不同行銷策略下，可能獲取的廣告效益。

最後，商業行為中，最難建立的就是賣家和買家之間的信任關係。買家在挑選賣家欲進行購物決策時，最常仰賴的就是電子商務平台所提供的賣家信譽評估系統。然而，雖然電子商務發展至今已有許多賣家信譽評估機制在商務平台上運作，但是，平台提供者和消費者至今仍然面對著信譽偽造的威脅。賣家為提高自己的交易機會，會設法偽造交易信譽評量。研究中所提出的社群參詢機制根據買家的社群網路中對該賣家曾給過的評價，核實賣方的線上交易信譽。如此可避免消費者誤與市場中偽造高信譽假象的賣家進行交易。

關鍵字： 社群網路、社群商務、決策支援、廣告傳播、交易信譽評量

ABSTRACT

Designing Social Commerce Service Computing Mechanisms

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Abstract

Social commerce is a term used to describe the online retail models or marketing strategies within the digital economics which incorporate established social networks or interpersonal interactions to raise business opportunities. This research contribute efforts to electronic commerce and applications which applied on social media from the perspectives of customer, vendor, and an electronic commerce platform provider and proposed social appraisal mechanism, advertising path planning mechanism, and reputation mechanism are proposed for enhancing social commerce.

First, with plentiful participation of knowledgeable users, an online social network could be seen as a large group of experts supporting the decisions of online users. The social appraisal mechanism is proposed to achieve social decision support for online users. Online users could efficiently expedite the decision-making process in their purchasing behaviors and reduce the risk of purchasing an unsuitable product. Second, most of current marketing researches discover potential influencers but not appropriately support them to diffuse advertisements. The proposed diffusing path planning mechanism could support influencers to propagate marketing information and supporting marketers to conservatively evaluate possible reward under different marketing strategies. Third, the electronic commerce market operators and the consumers are facing the trust fraud challenge. In this research, a social referral mechanism is developed to verify sellers from buyer’s social network for helping making transactions with reliable sellers in online marketplace.

Keywords: Social Network, Social Commerce, Social Appraisal, Social Diffusion, Social Referral

致　謝

六年的博士研究生涯，即將劃上句點。回首這些年來，論文構思與撰寫時苦惱著四處找人討論，國際研討論會上緊張的英文口語簡報，實驗室會議中一來一往熱烈的討論氣氛，成長的軌跡仍歷歷在目，將全數成為一生的記憶。

首先，我要感謝我的指導教授-李永銘博士，感謝您在這六年期間從研究想法、論文撰寫到為人處世鉅細靡遺的指導，同時也付出了無比的耐心，使我能在老師及實驗室的照護下安心成長。若非您的指導與付出，我恐將無法走完這趟博士研究的旅程。您實為學生若有朝一日執掌教鞭時的為師之範。博士論文的完成，也要感謝論文指導委員會的台灣大學資訊管理學系李瑞庭教授、中央大學資訊管理學系陳彥良教授、交通大學資訊管理研究所劉敦仁教授以及林妙聰教授的指導。您們對論文的缺失與改善，不吝提供寶貴意見，使這份論文更為詳實與嚴謹。在此對我的指導老師和各位口試委員，致上學生最誠摯的謝意。

實驗室裡相互扶持的諸位，謝謝您們給我的一切，在這跌跌撞撞的路途中，有您們這些無可取代的情誼，真好！易霖學長在我整個博士論文研究過程中，不論生活上亦或是研究上都提供了莫大的協助。您以親身說明了一個學生應有的態度，說明了一個學長應有的風範，也說明了一個成年人應有的器度。謝謝您，因為您我著實學到了不少也成長了不少。勇劭學長和治華學長，謝謝你們的協助，勇劭學長在夏威夷的臨場英文教學，治華學長的數學符號定義建議，為這博士研究生活增添了許多回憶也使論文更趨完整。

建邦、敬文、嘉豪，謝謝你們陪著我渡過了學術研究的前置訓練期。表面上是我協助你們將論文送上國際舞台，但實際上卻是你們協助我完成博士論文研究，沒有你們，後期的研究進度將不會如此順利。乃儁、子鳳和涵文，你們在最後關頭，為了論文連日挑燈夜戰管二館的景像仍歷歷在目。宗穎、雅玲和蕙如，你們用開心的心態面對研究，在鬥嘴之間討論論文，是我印象中最不愁冒苦臉的一屆。雖然蕙如最後並不如預期般的順利，但也還是走到了終點。郁卉和佳林，時不時的帶著名的滷味和親手手工小甜點來為我們加菜，補充了體力也轉換了心情。對背電影台詞和古詩詞小有信心的宣銘，你和易霖學長偶爾對上那麼幾句，著實也增進了我些許的國文造詣。文翔，期待著再次和你一同品嚐各地美酒，交換心得。詩雯的勇敢評論，帶動了當時的討論氣氛。此外，謝謝妳一手包辦了一起去英國

闖盪的行程。和我同一期畢業的致緯、竣智和潘強，謝謝你們的陪伴，最後一年的學生生活添加了許多回憶。尤其是你們口試完後，在實驗室裡開團打電動，分散了我面對口試時的緊張感。欣宸、銘彥、渝婷、復勛和光宇，我們相處僅一年的時光，謝謝你們在這一年來不斷的給我鼓勵和祝福。謝謝復勛在我口試時盡心盡力的協助，東奔西跑的訂購一切事物，著實讓我少費心許多而能專心於準備應戰。謝謝耿杰學長和鼎元學長這些年來的鼓勵、支持與經驗分享，這些寶貴的經驗使得這條研究路程好走了許多。仍然在實驗室奮戰的聯發、檸瑤和智華，一切加油了，頂住！堅持下去就會成功。期待著傳來您們的捷報。

名豐、小傑、佳玉，謝謝你們這些年來充份的扮演了垃圾桶的角色，聽我訴說著研究工作的不順遂，並在最後階段安撫我對未來的擔憂和恐懼，讓那顆懸在半空的心能再一次獲得平靜。謝謝我的女友 Peggy，謝謝妳在我忙起來的時候，能體諒且不來中斷思緒，在我閒下來的時候，能陪著我，讓身、心、腦都獲得充份的休息，然後開始下一階段研究工作。雖說外行看熱鬧，偶然在閒聊中提出的見解，也的確激起了些許研究漣漪。謝謝妳一直以來支撐著我。

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賴政揚

2013 年 7 月　謹誌於　新竹　國立交通大學　光復校區

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CHAPTER 1 INTRODUCTION

1.1 Background

In recent years, social media, such as social networking sites (e.g. Facebook), blogospheres (e.g. Blogspot), and micro-blogospheres (e.g. Twitter and Plurk) is an online service, platform, or site that focuses on building and reflecting of social networks or social relations among people. It provides powerful means of organizing friend network, publishing contents, and sharing information [88]. With the advance of Internet, social media facilitate users seeking and sharing information among others. The importance and polarity of social media are continually increasing in people's daily life. The growing user population of social media reveals the importance of social media in business usage, especially in the electronic commerce field. 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. Academics, enterprises, and even individuals are increasingly conducting research and developing business models and applications on social networking sites. The increased popularity of social network has opened opportunities for electronic commerce, often referred to as social commerce.

Social commerce is a term used to describe the online retail models or marketing strategies within the new digital economics which incorporate established social networks or interpersonal communications to raise sales. It is a subset of electronic commerce that involves using social media to assist in the online buying and selling of products. It could be defined as the electronic commerce triggered by social media. That is, social commerce is the use of social media in the context of e-commerce transactions. Examples of social commerce include social recommendations of people or products, social search of capitals or referrals, social support of decision makings, social applications of marketing. In this research we aim to contribute to the effort of social commerce and applications applied on social media by evaluating the effects of the social network from the perspectives of customer, vendor, and an electronic commerce (EC) platform provider.

1.2 Perspective of Customer

Social support is generally defined as help from others when people are facing a difficult life event [24]. That is, social support refers to the assistance available from other people who are part of a social network. A business report by Steegenga and Forge [109] highlights that social media have a greatly increasing influence on consumers' online purchase decisions. Over 50% of consumers would access the Internet and their own social network for online shopping decision support. In this investigation, 35% of consumers report that they read reviews and rank products on social media platforms. Additionally, 25% of these consumers believe that it is important to use social networks to assist with their buying decisions. Recently, consumers have promisingly turned to seek shopping advice from their friends through online media [113].

In the context of electronic commerce, many sophisticated recommender systems are designed to identify a set of items suitable for and interesting to a user according to his/her personalized preferences, purchase history, past ratings, other similar customers, etc. Collaborative and content-based are two main types of recommender systems [114]. For instance, the former, for example the features “Customers Who Bought This Item Also Bought” in Amazon and “See What Other People Are Watching” in eBay, recommends items suitable for the targeted user by collectively analyzing the choices of the customers who have similar preferences. The latter, like the “More Items to Consider” and “Recommendations For You”, respectively on Amazon and eBay, identifies items suitable for the current user based on what she/he has viewed. The recommendation systems are mainly developed by online retailers for the purpose of sales improvement. However, the customers in the new economy have begun to mistrust official advertising/recommendations [72] and are turning to rely on the opinions and social appraisal support from their close friends.

As previous research [45] has noted, social support is one of the important functional contents of social networks; however, methods for building social support mechanisms on online media have not been widely discussed. Therefore, it is worthwhile investigating and designing a novel mechanism for supporting consumers' online shopping decision-making. From the perspective of customers' interest, it is beneficial to develop an appropriate social appraisal system analysing the collective opinions, to enhance online purchase decision support.

1.3 Perspective of Vendor

Social media marketing, delivering marketing information over the social media, has become one of significant promotion methods for businesses and has increasing year by year greatly (22% increase from 2010 to 2011) [101]. According to the report by Stelzner [110] and Nielsen's [93], 83% of marketers stated that social media were important to their promotional business strategies, and 93% of companies use social media for marketing purposes (50% of these companies had experience of applying social media in marketing strategies for more than one year and 73% of these companies planned to increase their marketing use of social media). Obviously, companies (enterprises and individuals) have promisingly turned to propagate marketing information through online media for seeking business opportunities (e.g. product advertisements) [73,119,122] and for establishing brand expression (e.g. branding messages) [61,67,68].

Information diffusion through online social networks has recently become an active research topic [2]. According to Brown and Hayes [15], the crucial work of influencer marketing is to identify the influencer or endorser for diffusing information, named key player problem [12]. Additionally, a way that could support the identified key player in disseminating information is needed. Generally, to our best knowledge, information-diffusion-related research applies relevant analysis techniques (e.g. social network analysis) to identify the powerful influencers or endorsers who might help to diffuse information the most [21,59,126]. However, the issue of how to propose the appropriate diffusion path planning to support them in delivering marketing information in order to achieve better marketing effectiveness (e.g. raising product sales or gaining brand awareness) has rarely been studied.

Influencers or endorsers are commonly selected through recommender systems, which are expected to reach and influence potential customers [62,74]. However, it is not well known how to guide and support these influencers/endorsers in passing on the marketing information. That is, which forward direction is the best for the diffusion process if the information to be diffused starts from him/her when an evaluated influencer/endorser receives the marketing information? Therefore, it is worthwhile investigating and designing a novel mechanism for supporting vendors to carry out social media marketing strategies.

1.4 Perspective of EC Platform Provider

Online reputation is defined as the collective measurement of the trustable ratings given by the members in a community [55] to help other customers select a superior target such as seller, product, service, and shop. In recent years, word-of-mouth (WOM) marketing has become one of the most significant and best-known marketing strategies. In order to utilize the power of WOM, many marketers pay for high ratings or positive reviews to increase sales. Nielsen [94] shows that approximately 70% of consumers trust online product reviews. At the same time, the report also shows that 92% of consumers trust the reviews and recommendations of their friends and family members. Besides, According to the business report provided by Gartner [33], enterprises continue to increase marketing spending on modeling online ratings and reviews. Analysts also predict that approximately 15% of all online ratings and reviews will be faked by 2014, implying that ratings and reviews are purposely modeled by companies. However, if the online reputation system of an election commerce platform is mistrusted, it would increase the traction risk of customers and they would not like to use the platform for making transactions.

Trust is one of the major issues that confuse online purchases because of distrust [82]. The plausibility of the reputation evaluation of sellers provided by the public evaluation system on the EC platform is one of the major concerns of buyers when they want to make an online transaction. In order to increase sales, sellers may attempt to improve their reputations. For example, sellers on eBay may launch an auction at a very low price and include some specific words, for example “feedback”, in the title or product description, which hints at positive feedback [16,28]. Also, Zhang et al. [129] use the Taobao, which is now in the prime position of China’s electronic commerce market, as an example to present the generations of development of trust fraud techniques for faking the trustworthy of seller him/herself. It means the trust fraud issues exist for many years and put buyers at risk of selecting seller according to possibly are manipulated reputations.

Nowadays, as sellers manipulate reputations in careful and secret ways, the trust fraud activities are very hard to detect [11,129]. Hence, a fairer and harder manipulated reputation mechanism for buyers is needed. The aim of this research is to utilize the power of social network of specific buyers for helping them to prevent trust fraud issue in online marketplace. The proposed mechanism refers sellers’ reputations from experienced friends to a buyer. It is necessary to define and measure the seller's reputation considering trustworthiness of voters that makes the online rating system more reliable for buyers. In other words, how to design a referral mechanism to effectively conquer the phenomenon and diminish this effect of feedback manipulation from the sellers is an important issue.

1.5 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 from the perspectives of customer, vendor, and EC platform provider. The contributions of this study are listed as follow.

- Perspective of customer.

In the work, we propose a social appraisal mechanism to achieve social decision support for online users. Through the proposed mechanism, online users could efficiently reduce their decision-making process and reduce the risk of purchasing an unsuitable product. The contributions are list as follows:

(1) The social companionship between the support requester and the decision supporters is identified.

(2) The collective opinions given by decision supporters is analysed and consolidated.

(3) The decision consensus on the alternative ranking to support online purchasing is obtained.

- Perspective of vendor.

In this study, we design a diffusion path planning mechanism to support influencers/endorsers diffuse information. It is a novel mechanism for supporting online marketing information propagation. The contributions of this study are list as follows:

(1) The mechanism can support marketers in conservatively evaluating the possible information diffusion effectiveness under different marketing strategies

(2) The mechanism can support the evaluated influencers in propagating information to specific individuals to continue the diffusion process.

(3) The mechanism could take advantage of both the egoism and the altruism sharing motivations and decrease the ineffective delivery ratio.

- Perspective of EC platform provider.

In this research, we build a social referral mechanism for EC platform. It could help buyers making transactions with the reliable sellers in the online marketplace. The contributions are list as follows:

(1) Helping platform providers effectively improve a healthy transaction environment due to buyers prevent the trust fraud faced in the online marketplace.

(2) Helping buyers making transactions with the reliable sellers in the online marketplace due to the system verifying the credibility of sellers according to the trustworthy ratings.

(3) Helping sellers attract more buyers to be involved in the market platform and significantly increase the revenue due to the system reducing the risk of business transaction risk for customers.

(4) Help online marketplace deal with the online trust fraud issues due to a more reliable reputation system is proposed.

1.6 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 social appraisal, diffusion path planning, and social referral 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.

1.7 Chapter Summary

In this chapter, we have introduced the circumstance of the social commerce development and pointed out the imperious demands of applications/mechanisms on social commerce. Additionally, the research questions this study tried to address and the important contributions were also spotlighted in this chapter.

CHAPTER 2 LITERATURE REVIEW

The review of the literature drew from the extant work of information systems and technologies, consumer behaviors, online marketing and social psychology in respect to the online purchase support, social media marketing and online reputation, which form the background for constructing the proposed model.

2.1 Social Support Mechanism

Social support is a concept involving the help provided by other people and the social network as a mediating construct of social support [41]. It provides people with a trustable environment for information exchange with friends. The opinions of the people with close friendships in social networks could be seen as helpful sources of social support, for example by providing answers to questions. Generally, a social network is expressed as the structural aspect while social support is investigated from the utilization aspect of a social network [96].

Social support and social network analysis are mutually reinforcing. They form one of the important functional contents of social networks [45]. Recently, the utilization of a social network in electronic commerce has mainly focused on information filtering [78,83,132] and spreading [53,71,130]. Meo et al. [83] propose an approach to recommend resources (e.g. similar users or articles) to a user in the social networking environment. Liu et al. [78] propose a novel hybrid recommendation method that integrates the segmentation-based sequential rule method to consider the sequence of customers' purchase behavior over time. Jansen et al. [53] find that the micro-blogosphere is an excellent platform for word-of-mouth communications and discuss how firms can build word-of-mouth marketing strategies to spread brand information based on social networking and trust. People's behaviors in broadcasting information they would like to share with their friends are explored by Zhao and Rosson [130].

These existing studies mainly aim to filter or provide information (e.g. filter unsuitable products and provide the products users might be interested in) to increase business opportunities. Although a large amount of research has been undertaken on information filtering and dissemination for increasing business opportunities on the firm side, few systems have been developed for the social support of users' online shopping behavior.

2.2 Social Media Marketing

Social media marketing is a new and rapidly growing way in which businesses are reaching out to potential customers. It refers to the process of gaining users' attention and acceptance through social media. Social media, like Facebook, Plurk, Twitter, etc., are online platforms used to deliver information through social interactions (e.g. communication with family, colleagues, and friends) [1]. Jackson et al. [52] show that online media are more effective in influencing consumers than classic marketing channels. Because consumers have begun to mistrust and refuse to accept official advertising [72], a message will be more acceptable if it is delivered by their close friends. The use of social networks allows companies to engage with customers to a degree that outpaces traditional advertising.

Social media marketing embraces many possible techniques for advertising and branding across social networks, such as social networking sites, blogospheres, and micro-blogospheres [116]. For example, Iyer et al. [51] examine advertising strategies and find that firms' advertising strategy should focus more on the consumers who have a strong preference for their product. Yang et al. [127] propose a data mining framework based on the customer's interaction data from social networks to support online advertising. Kazienko and Adamski [58] propose the AdROSA for personalized web advertising, which integrates web usage and data mining techniques to reduce user input and to respect users' privacy. Social media marketing has become one such important feature so that it is no longer a question of whether to use it, but how to use it [64].

2.3 Social Referral

In the new world of consumer-driven content and customers' reliance on the recommendations of others, the referral engine prescribes an approach to generate and harness customer word-of-mouth for competitive advantage [108]. Customers' products buying decisions would be influenced by friends. In the electronic commerce, most of applications of social referral programs are used for end-to-end marketing strategies. They use social relationships to propagate influence through social network, for example word-of-mouth marketing. Influential social nodes discovering for expediting marketing information diffusion is one of common referral programs [29,62]. For example, Cho et al [21] take diffusion speed and cumulative number of adopters into account to select the opinion leaders from a social network for marketing. Kiss and Bichler [62] propose methods to identify influencers by derived social factors to spread word-of-mouth information for firms. Recommender systems are another usage of social referral programs. Kautz et al [57] combines social networks and collaborative filtering to recommend personalized experts and generate the referral paths form a user to a recommended expert. Amin et al [4] leverage the connections between users and the reputation of users to generate content recommendation. It is much more effective if the content providers generate recommendations according to the reputation information consolidated from the social networks of the target users. However, most of the current researches focus on taking the advantages of social referral programs from the firms but not much attention has been paid in creating the value from social referral programs for the customers.

2.4 Source Credibility Theory

Credibility refers to a person's perception of the truth of a piece of information. Source credibility theory has been proposed in the WOM communications studies of consumer psychology and marketing [31,103]. For decades, marketers, professionals, and researchers of various fields have found that if the information is given by a high credibility source, it has higher impact on changing beliefs, attitudes, or behaviors of the audience [100]. According to the source credibility theory, the credibility of an information source has been commonly identified to consist of expertise, trustworthiness, co-orientation, and attraction [22,31,43,100,108]. Each factor is described as Table 2.1.

Table 2.1 The key factor descriptions of source credibility theory.

Factors	**Descriptions**
Expertise	The extent to which a source is perceived as being capable of providing correct information
Trustworthiness	The degree to which a source is perceived as providing information that reflects the source's actual feelings or opinions
Co-orientation	The degree to which a source is similar to the target audience members, or is depicted as having similar problems or other characteristics relating to the use of a particular product or brand
Attractiveness	The extent to which a source elicits positive feelings from audience members, such as a desire to emulate the source in some way

The basic idea of the trust and reputation system is to derive a score for users. The concept of source credibility theory is commonly used for building collaborative systems. Kwon et al. [66] employees the credibility attributes of expertise and calculates the similarity between users to estimate the trust for building a collaborative neighbor selection recommendation. Cho et al. [22] proposed a collaborative reputation system based on expertise and co-orientation factors to compute trust score. Xiong and Liu [124,125] based on feedback records, similarity and relation context for comparing the trustworthiness of peers. The aim of this research is to appropriately quantify each credibility factor for voters to adjust an online reputation system and make it more reliable for users. It is expect to decrease transaction risk for buyer.

2.5 Social Relationships and Social Network Analysis

Social network analysis (SNA) is one of the most important mathematical and graphical analyses for identifying the strength of social relationship by investigating the social interactions. Social relationship is a ubiquitous part of psychological and behavioral functions throughout the lifespan. Recently, social network analysis has become one of the most important methodologies for estimating tie strength by investigating the complex activities of actors in a social networking environment.

The connections between people are generally built up by information exchange, for example daily chat, sharing, discussion etc. [38]. According to SNA, the social connections and reciprocal interacts would enhance the interpersonal tie strength, which means that the friendships will go deeper if there are a lot of information exchanged behaviors between two individuals. A person who has stronger ties indicates that the person might be more trustworthy [34,98]. Also, they might know each other's preferences, habits, and needs.

In practice, the structural dimension (e.g. possessing friend networks [38,107]) and the behavioral dimension (e.g. interaction frequency [71,75]) are two measurement proxies that substitute for tie strength. Granovetter [38] defines tie strength as the relative overlap of the neighborhood of two nodes in the networks. Shi et al. [107] indicate that communities are composed of various people with strong ties, and social networks are composed of overlapping communities. Li and Du [75] use the frequency of the interactions to represent the social tie and measure the relationships between blog readers and authors by analyzing the similarity.

When the ties between two persons are stronger, they will be more willing to share opinions with each other openly. Levin and Cross [71] use the interaction effects between knowledge seekers and knowledge sources as one of the important factors to investigate the effectiveness of knowledge transfer.

2.6 Information Propagation and Key Player Problem

Information propagation on online social networking sites has attracted great research interest recently. Informative diffusion and persuasive diffusion are the two major purposes of the information diffusion process [6,89,90]. Informative diffusion focuses on delivering information to receivers who have a high level of interest in it. In the marketing field, for example, marketers could perform informative diffusion to deliver the promotional information of products to consumers to seek business opportunities. Persuasive diffusion focuses on delivering information to impress the receivers. In the marketing field, for example, marketers could carry out persuasive diffusion to deliver the branding information of products to consumers to establish brand impressions.

Information diffusion techniques in social networks are broadly used for influencing and informing people [32]. The positive effects of viral marketing to influence [70], and word-of-mouth [36] to inform potential consumers have been observed. Obviously, information (e.g. informative and persuasive information) transmitted by friends is more trustable and acceptable than that from marketers [72]. Peer influence means that an individual might lead other individuals to act according to the information gathered from him/her. Park and Kim [99] focus on revealing the effectiveness of persuasive information (online consumer reviews) on purchasing intention for experts and novices. [59] and [126] focus on effective ways to diffuse the informative promotional information of products. However, marketers do not focus on one strategy for marketing.

The key player problem (KPP) is a procedure to find a set of key players in a social network for different purposes. Borgatti [12] defines the key player problem positive (KPP-POS) and the key player problem negative (KPP-NEG), which are two related problems for discovering sets of key players. KPP-POS is defined as the identification of key players who could be used as seeds for the purpose of diffusing some information on the network. KPP-NEG is defined as the identification of key players who could be used as the breaking points for the purpose of disrupting or fragmenting the network. However, the research field of social media marketing focuses majorly on KPP-POS for the purpose of maximizing the advertising effectiveness.

Prior works have shown that peer influence has a positive effect in online marketing [20,27,117] to select the key player for marketing purposes. Accordingly, influence quantifying models have been proposed to solve the KPP-POS problem. In [126], the authors develop a linear influence model to predict the possible influential nodes in the network for modeling the information diffusion in online social media. Kempe et al. [59] propose an algorithm that finds the minimum set of influencers for maximizing the social influences in social networks. However, according to Brown and Hayes [10], implementing influencer marketing not only begins with the key influencer selection but also looks for a way to work with them to help them carry out their job better.

2.7 Vague Information and Multi Criteria Decision Making

The opinions received from a person’s friend network play an important role in the human decision-making process [60]. However, the opinions expressed by natural language are likely to be vague. As a result, the related decision information (i.e. criteria weights and criteria evaluation of alternatives) might be completely unknown or incompletely known in a decision-making process because of the time pressure, lack of knowledge, and limited expertise of decision supporters regarding the problem domain [23]. Recently, intuitionistic fuzzy sets (IFSs) have been found to be highly useful in dealing with vagueness in the semantic web [44,71]. Conceptually, an IFS, having feasible presentation for the degree of membership, degree of non-membership, and degree of uncertainty [5], is very well suited to modeling the fuzziness and uncertainty of opinions used in social appraisal support. In order to handle the issue of vague information gathered from social networks and deal with multi-criteria fuzzy decision-making problems, the IFS could be applied to represent the characteristic criteria values of alternatives by fuzzy numbers [79,128].

The multi-criteria decision-making (MCDM) technique is commonly applied to identify the compromised or optimal solution from all the feasible alternatives evaluated according to multiple criteria [65,76]. MCDM has been particularly influential in contributing insights into the domain of decision-making. It simplifies the complex human decision-making process into the quantified distance using relative closeness coefficient measurements. The technique for order preference by similarity to the ideal solution (TOPSIS) is an appropriate tool for resolving multiple-attribute decision-making problems [47]. The concept of TOPSIS is to select an alternative that is closer to the positive ideal solution and farther from the negative ideal solution simultaneously. In the proposed social appraisal mechanism, the IFS and TOPSIS are incorporated to consolidate the collective opinion and generate consensus decision analysis with complex and unintelligible information from social networks.

2.8 Chapter Summary

In addition to introducing related studies, the purpose of this chapter is to identify the difference between the study and others. For shopping decision support, most of online purchase support is built to filter out suitable item candidates for the targeted user. This research is to investigate ways to achieve external appraisal support for supporting online shopping decision making. For social media marketing, few studies pay attention on how to propose the appropriate diffusion path planning to support them to deliver marketing information for getting better marketing effectiveness. For online reputation estimation, finally, most of existing reputation systems has quantified the reputation value of users or items by accumulating the rating records without taking the trust concept for voters into account so that the EC market operators are still facing trust fraud challenge. In the present research, we study these issues by focusing on the points prior studies rarely considered.

CHAPTER 3 SOCIAL SUPPORT

With plentiful participation of knowledgeable users, an online social network could be seen as a large group of experts supporting the decisions of online users. The collective opinions solicited from friends are largely beneficial for online purchase support and can create significant opportunities for sales. In this chapter, a social appraisal mechanism, composed using the methodologies of social companionship analysis, collective opinion analysis, and consensus decision analysis, is proposed for the online users of the micro-blogosphere. The proposed mechanism can successfully summarize the collective opinions and expedite the decision-making process in users' purchasing behaviors.

3.1 Social Appraisal Mechanism

To implement the SAM, we develop an application on the Plurk platform, utilizing the available official APIs. The developed Plurk application is a software agent, named AppPlurk, which will automatically reply information to a request according to the message it receives. To use this agent, users can simply add it as one of his/her friends and initiate an appraisal request in a specific message format to activate the mechanism. A user who is making a purchase choice from a list of alternative products, which were previously surveyed by the user or recommended by the retailers, can send an appraisal request to AppPurk for decision support.

The procedures for a user to solicit decision support from his/her friend network in the context of online purchasing are shown in Figure 3.1 and detailed as follows.

(1) The support requester initiates a request message with a list of product alternatives. For example, the message is described as "[DC]: [Camera 1, Camera 2, Camera 3]", where DC denotes "Digital Camera".

(2) The agent would automatically reply the related decision criteria by seeking the suggestions from his/her friends (decision supporters) in the micro-blogosphere according to the product category. For example, the message is described as "[Criteria]: [Resolution, Price, Lens]".

(3) The support requester could set the personal criteria importance rating according to the criteria obtained in step 2. For example, the message is described as

"[Weighting]: [3, 1, 2]". The group weighting would be used if the support requester did not provide criteria importance rating.

(4) Those friends who receive the request message and reply opinions (including criteria evaluations and importance ratings) become the decision supporters. For example, the message is described as "[ans]: [Good, Bad, Unknown], [Unknown, Good, Good], [Bad, Good, Bad], [1, 3, 2]". While a Friend A replied his/her opinions to the request message initiated by the originator, the social companionship analysis module would use social interactions and friend list for identifying the companionship level to evaluate the importance degree of the opinion given by Friend A during the decision process.

(5) The agent responds the result of decision analysis. The received feedbacks are consolidated by the proposed mechanism to rank the product candidates. For example, the message is described as "[Rank]: [Camera 2 > Camera 1 > Camera 3]". After collect the replied opinions, the collective opinion analysis module would convert the opinions into intuitionistic fuzzy expressions and build the decision matrix then feed into consensus decision analysis module. Finally, the consensus decision analysis module would output the product candidates ranking result according to a multi criteria decision making method.

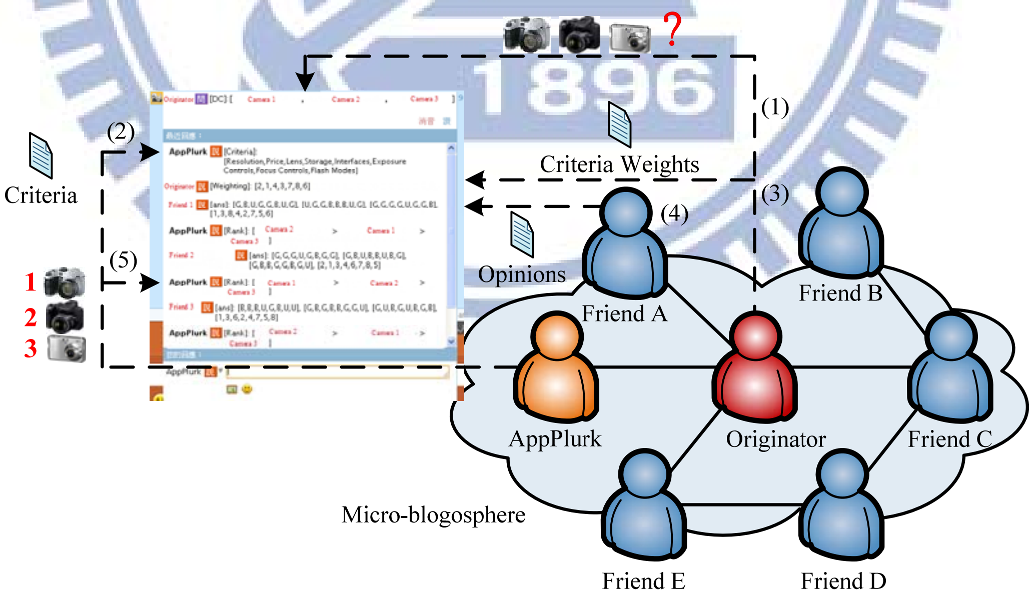


Figure 3.1 Processes of the social appraisal mechanism.

Table 3.1 Symbols used in social appraisal mechanism

Symbol	Description
$G=(M\cup U,I)$	Bipartite graph consist of micro-blogging message set (M), user set (U), and interaction relation set (I)
BT_{ij}	Behavioral tie strength between decision supporter i and support requester j
ST_{ij}	Structural tie strength between decision supporter i and support requester j
SC_{α}	Social companionship degree of decision supporter α
$SP(DS_{adj},PP)$	Length of the shortest path between the adjective used by decision supporter (DS_{adj}) and the positive polar adjective (PP) within the synonymous adjective graph
$SP(DS_{adj},NP)$	Length of the shortest path between DS_{adj} and the negative polar adjective (NP) within the synonymous adjective graph
$SO(DS_{adj})$	Tendency of semantic orientation of DS_{adj}
$\mu_A(x)$	Degree of membership of x in IFS of alternative A
$v_A(x)$	Degree of non-membership of x in A
$\pi_A(x)$	Degree of hesitancy of x in A
CD	Collective decision matrix
w_{C_j}	Criteria importance of group suggestion of criteria c_j
$\mathrm{ED}(A_i,A^+)$	Euclidean distance between alternative A_i and intuitionistic fuzzy positive ideal solution (A^+)
$\mathrm{ED}(A_i,A^-)$	Euclidean distance between alternative A_i and intuitionistic fuzzy negative ideal solution (A^-)
CC_{A_i}	Relative closeness coefficient of alternative A_i
CSS	Rate of correct social support is made
CSU	Rate of wrong social support is avoided
SS	Rate of overall successful support

Figure 3.2 depicts the framework of our system model and the symbols used in the proposed mechanism are listed in Table 3.1. The proposed model is comprised of three main components: the social companionship analysis module, collective opinion analysis module, and consensus decision analysis module:

(1) *Social companionship analysis module*: the purpose of social companionship analysis is to identify the importance degree of a decision supporter based on the companionship between the support requester and the decision supporter. We consider the social factors in both the behavioral and the structural dimension to derive the social companionship.

(2) *Collective opinion analysis module*: the aim of collective opinion analysis is to discover the criteria and evaluations from the opinions of the decision supporters. The responses of the decision supporters are transformed into a collective decision matrix, which is expressed by intuitionistic fuzzy values to represent the uncertainty and incompleteness of collective criteria evaluations.

(3) *Consensus decision analysis module*: the objective of consensus decision analysis is to consolidate the collective opinions to generate a list of ranked alternatives. Combining the personal preference criteria of the support requester and the collective evaluations of the decision supporters, the TOPSIS method is utilized to rank all the alternatives by evaluating the distance of an alternative relative to an ideal choice.

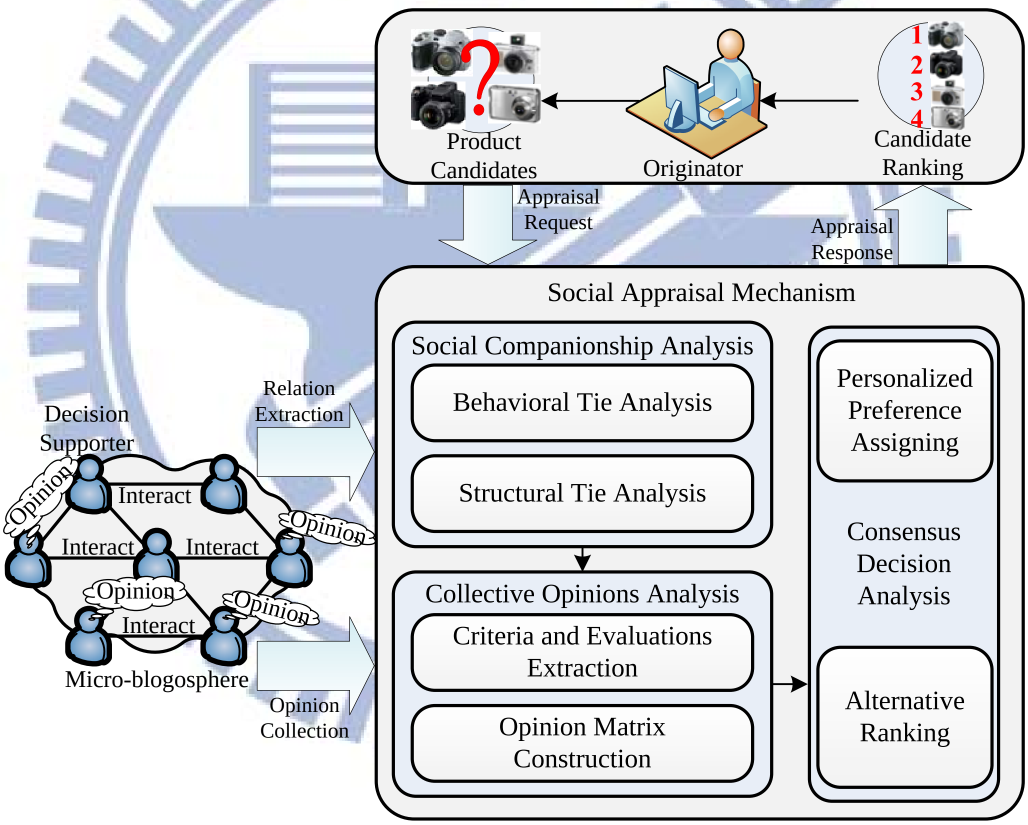


Figure 3.2 The framework of the social appraisal mechanism

3.1.1 Social Companionship Analysis

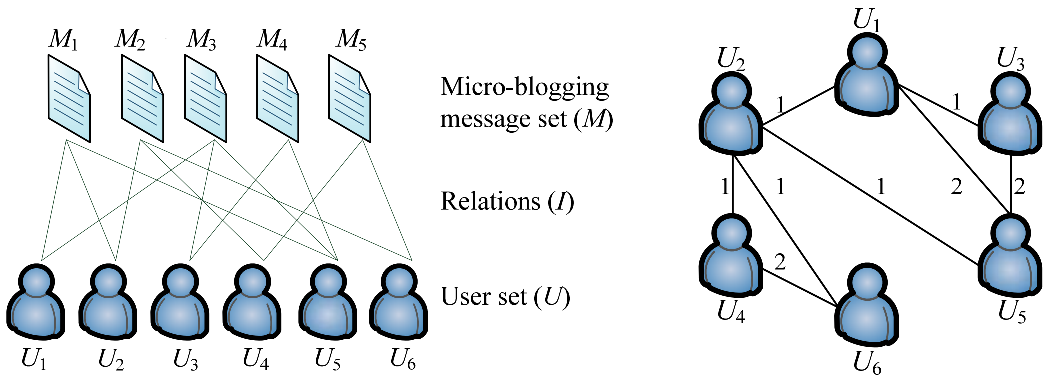
Onnela et al. [98] point that two social actors have a deeper relation if there are strong ties between them. That is, they might know each other's preferences and real needs. Therefore, the goal of social companionship analysis is to estimate the tie strength between the support requester and the supporters in order to represent the social companionship degree.

Tie strength determination could be simply separated into the behavioral dimension (e.g. interaction frequency [71,75]) and the structural dimension (e.g. possession of a friend network [38,107]). We analyze the interaction network and the friend network in the micro-blogosphere to measure the tie strengths of these two dimensions, respectively. According to these, we can measure the decision support's relevance and closeness to the support requester.

3.1.1.1 Behavioral Tie Analysis

Granovetter [38] describes social interaction tie strength as a combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services that characterize the tie. In this study, social interaction tie strength measured by the interaction frequency in a time period is used to represent the social companionship degree of the members of the micro-blogosphere.

Two-mode network data could be defined as two sets of social units and contain relation measurements from the elements of one social unit set to the elements of another social unit set [120]. For instance, in this study, the social network of users interacting with micro-blogging messages is a kind of a two-mode network that includes two social unit sets, a set of users and a set of micro-blogging messages, and the relations reflecting the social interactions. The two-mode network in the context of the micro-blogosphere is depicted in Figure 3.3-(a). The user set is a set of users who interact with the support requester. The set of micro-blogging messages is a pool of messages posted by the members of the user set. A relation is established by posting or replying to a message. A two-mode network can be represented as a bipartite graph $G = (M \cup U, I)$, where *M* and *U* indicate the message set and the user set, respectively, and *I* stands for the set of interaction relations between *M* and *U*.



(a) Bipartite graph of the micro-blogosphere (b) User interaction network

Figure 3.3 Two-mode network of the micro-blogosphere

After constructing the two-mode network of the micro-blogosphere, we then compress it into a user-projection network (named the user interaction network). The compressed network describes the social interactions between the support requester and the decision supporters and can be used to obtain the behavioral tie strength based on the interaction frequency between the requester and each decision supporter. Figure 3.3-(b) depicts the interaction network of the bipartite graph, in which the value attached to an edge between two nodes in set U represents the total number of messages in set M associated with these two nodes. That is, the relation values of users are measured by counting the micro-blogging messages in which the users have commonly interacted, and vice versa. For example, in Figure 3.3-(b), there is an edge between U_1 and U_2 and the relation value is marked by 1 because they have commonly participated in only one micro-blogging message M_1 in Figure 3.3-(a). Similarly, the relation value between U_1 and U_3 is 2 as they interacted via messages M_1 and M_5.

Before being combined with the structural tie strength, the behavioral tie strength should be normalized. The normalized behavioral tie strength value between a decision supporter i and the support requester j is formulated as:

$$BT_{ij(normalized)} = \frac{BT_{ij} - BT_{\min}}{BT_{\max} - BT_{\min}}, \tag{3.1}$$

where $BT_{\min}$ and $BT_{\max}$ respectively indicate the weakest and strongest behavioral tie strengths from all the decision supporters to the support requester.

3.1.1.2 Structural Tie Analysis

In order to determine the structural tie strength, the friend network first has to be extracted based on the friend list in the blogosphere. Then, we can determine the structural tie strength from the friend network. Onnela et al. [98] use the aggregated duration of communications between two social units within a time period as the tie strength, utilizing a communication network data set. They indicate that there is a stronger tie between two social units if most of their friends overlap. In this research, we use the following formula to estimate the structural tie strength [131]:

$$ST_{ij} = \frac{n_{ij}}{(d_i - 1) + (d_j - 1) - n_{ij}}, \tag{3.2}$$

where n_{ij} is the number of common acquaintances of social unit i and j. d_i and d_j are the degrees of social unit i and j, respectively. In this paper, we define ST_{ij} as the structural tie strength between decision supporter i and support requester j.

Note that Onnela et al. [98] apply in-degree centrality in the above formula to discover the weak ties for information diffusion. However, according to Kiss and Bichler [62], out-degree centrality performs better in influencer identification. An information seeker in online media follows other users' information regularly, including daily chat from friends and information from professionals [54]. Therefore, a person with a higher out-degree (making friend with many other users) could simply infer that he/she might be an information seeker so that he/she could give helpful product appraisals according to preferences, habits, and needs from daily chat information observed from other professionals. Therefore, in our research, we use out-degree centrality to measure tie strength. The out-degree centrality of node i is defined as

$$d_i = \sum_{j=1}^{n} f_{ij}, \tag{3.3}$$

where f_{ij} is 1 while the edge from node i to node j exists in a relation matrix, otherwise it is 0.

After obtaining the behavioral and structural tie strengths, the social companionship degree (SC_α) of decision supporter α is measured as $SC_\alpha = BT_{\alpha j} \times ST_{\alpha j}$. Finally, the obtained social companionship can be further normalized as:

$$\lambda_\alpha = \frac{SC_\alpha}{\sum_{i \in \Theta_S} SC_i}, \tag{3.4}$$

where Θ_S denotes the set of decision supporters included in the user set, SC_α denotes the relation measurement value of the decision supporter α, and λ_α denotes the importance weight of the decision supporter α. Decision supporters with a greater social companionship degree will be allocated greater importance weight during the decision process support and their opinions are more trustable to the support requester.

3.1.2 Collective Opinion Analysis

Constructing the decision criteria, evaluating the alternatives, and making a decision are the three sequential routines of the decision-making phase [87]. The aim of the collective opinion analysis module is to deal with criteria extraction and alternative evaluation to construct the collective decision matrix. Generally speaking, differentiated by the process of product information acquirement for product evaluation prior to purchasing, products can be categorized into search goods (e.g. consumer electronics, etc.) and experienced goods (e.g. restaurants, movies, and peripheral products, etc) [91]. In this section, we would like to first describe the basic concept of collective opinion analysis for search goods and then extend the module to experienced goods by adding semantics analysis.

3.1.2.1 Criteria and Evaluation Extraction - Search Goods

In economics, search goods are products or services with features and characteristics easily evaluated before purchase [91]. For search goods, the procedures involved in this module are depicted in Figure 3.4.

Criteria extraction. For constructing the decision criteria, the decision criteria can be extracted from the public and impartial third parties and automatically reply to the request message while originator initiates appraisal request. Then, the decision supporters give their criteria evaluation according to the explicit criteria.

Evaluation extraction. The decision supporters can directly evaluate the alternatives according to each criterion by answering “G,” “B,” or “U,” respectively representing “good,” “bad,” or “unknown,” to evaluate each criterion. However, this approach cannot be applied directly to the experienced goods as their product characteristics and evaluation criteria are implicit or not described.

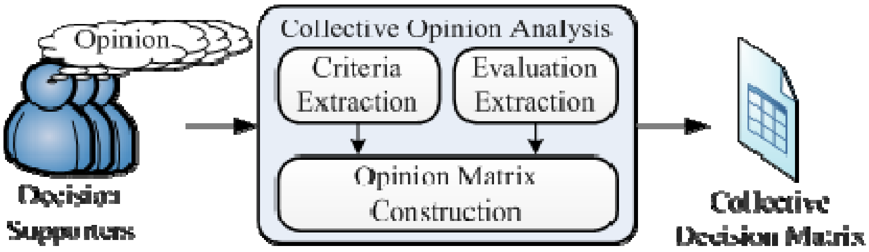


Figure 3.4 Collective opinion analysis module for search goods

3.1.2.2 Criteria and Evaluation Extraction - Experience Goods

In economics, experience goods are contrasted with search goods [91] which mean that the features and characteristics could not be evaluated before purchase. The collective opinion analysis module is extended to deal with experience goods. We design a lightweight criteria construction and evaluation mechanism using semantic analysis of the micro-blog messages. The procedures involved in this extended module are depicted in Figure 3.5. Micro-blogospheres are platforms with message length limited communication. The users usually write short sentences with a simple sentence structure [80,112]. In the current paper, we use semantic analysis to extract the criteria and evaluation from micro-blog messages. After a decision supporter posts an opinion, we first utilize the NLProcessor linguistic parser, a text analysis toolkit [95], to parse the sentences and yield the part-of-speech (POS) tag of each word (whether the word is a noun, verb, adjective, etc.). For each sentence in an opinion, the nouns are extracted as one of the criteria and the nearby adjectives are identified as the criteria evaluation. In order to identify the semantic orientation of criteria evaluation posted by a decision supporter, a lexical database is required. In this research, WordNet [85,86] is applied as the lexical database. Over the years, WordNet has successfully evolved and has been widely used as one of the important lexical resources for natural language processing systems. It enables users to access lexical information in a much faster and more convenient way [3]. Finally, the extracted criteria and evaluations are then used to construct a collective decision matrix.

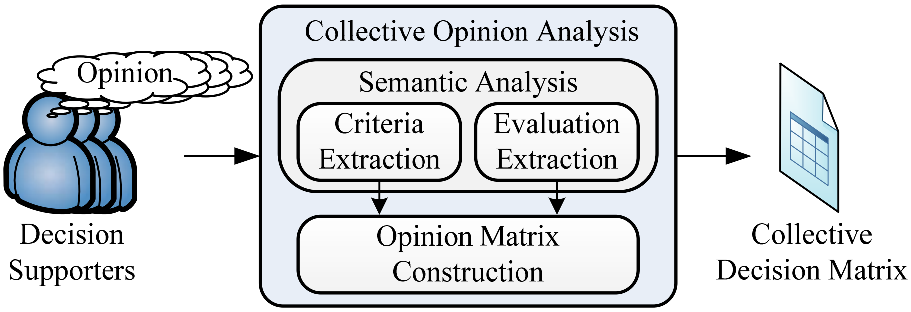


Figure 3.5 Collective opinion analysis module for experience goods

Criteria extraction. After the NLProcessor linguistic parser has parsed the opinions posted by the decision supporters, the POS tag of each word is tagged. The noun and noun phrase followed by adjectives would be extracted as one of the criteria. In order to reduce the criteria set, we construct synonym matching between the criterion and each previously extracted criterion contained in the criteria set established on WordNet. The criterion would not be added to the criteria set if it matches a synonym in the criteria set.

Evaluation extraction. Typically and intuitively, adjectives have been indicated as useful indicators of the sentiment [3]. The semantic orientation of adjectives is identified as the evaluation of criteria. Due to the length limitation of a post (140 words per post) within the micro-blogosphere, an opinion has to be concise rather than lengthy. Besides, the aim of the proposed mechanism is to ascertain whether a decision supporter gives positive or negative evaluations for criteria to support the decision-making of the originator. Therefore, we focus on identifying the semantic orientation of short text messages. In this research, the semantic orientation (positive, negative, or vague orientation) of an adjective is identified as criteria evaluation. In the proposed method, the orientation identification begins with building an undirected synonymous adjective graph, $G_a = (A, E)$, and we add edges (E) between the seed word and non-duplicate synonyms ($a_i \in A$) representing the synonymous relationship. As suggested by Turney and Littman [115], we use a seed word set of adjectives that defines a subjective positive and negative word set with a total of 14 words.

Positive: *good, nice, excellent, positive, fortunate, correct, superior*

Negative: *bad, nasty, poor, negative, unfortunate, wrong, inferior*

This word set is used to search non-duplicate synonyms from WordNet to expand the synonymous adjective graph for identifying semantic orientation. The semantic orientation of an adjective could be measured by comparing the length of the shortest paths from this adjective to the selected polar positive adjective and from this adjective to the selected polar negative adjective [56]. Denote PP as the positive polar adjective and NP as the negative polar adjective. SP is the length of the shortest path between the adjective used by decision supporter (DS_{adj}) and the polar adjective within the synonymous adjective graph G_a. The tendency of semantic orientation of an adjective SO is formulated as:

$$SO\left(DS_{adj}\right) = SP(DS_{adj}, PP) - SP(DS_{adj}, NP)\,. \tag{3.5}$$

According to the quantified semantic orientation, we can judge that

$$DS_{adj} \text{ has } \begin{cases} \text{positive orientation (G) if } SO < 0, \\ \text{negative orientation (B) if } SO > 0, \\ \text{vague orientation (U) if } SO = 0. \end{cases} \tag{3.6}$$

Note that if there is “no” or “not” in front of an adjective in the sentence, the identified orientation would be reversed, except the vague orientation.

The following example demonstrates the semantic orientation identification process. Suppose that the expanded synonymous adjective graph is structured as shown in Figure 3.6. If a decision supporter gives an adjective “fat” in his/her opinion, we can derive $SP("fat", PP) = 2$, $SP("fat", NP) = 1$, and $SO = 2 - 1 = 1$. Because “fat” is far away from PP (2 steps) and closer to NP (1 step), the semantic orientation of “fat” ($SO > 0$) would be identified as a negative orientation (B).

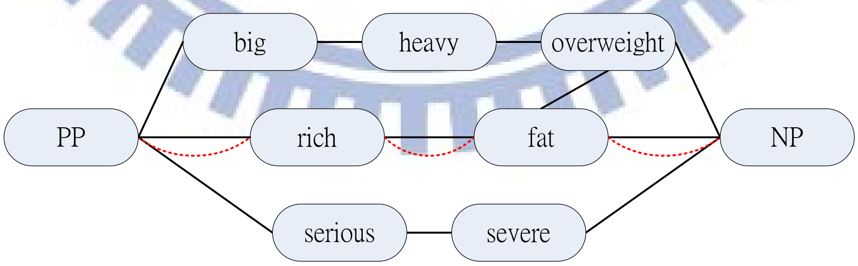


Figure 3.6 Semantic orientation identification

3.1.2.3 Decision Matrix Construction

We can obtain the collective decision matrix according to the evaluations submitted by the decision supporters. Suppose that the decision-making originator releases m alternatives (A) and n criteria (C) and there are k decision supporters who have evaluated each alternative with respect to the criteria given by the support requestor. As previously mentioned, the evaluation of whether an alternative A_i satisfies a criterion C_j can be expressed as (1) "good/positive orientation (G)," (2) "bad/negative orientation (B)," or (3) "unknown/vague orientation (U)". Denote d_{ij}^{l} as decision supporter l's evaluation of alternative A_i with respect to the criterion C_j. k decision matrixes are collected:

$$D^{\alpha} = \left[d_{ij}^{\alpha} \right]_{m\times n}, \text{ where } d_{ij}^{\alpha} \in \{G, B, U\}, \alpha \in \{1,\cdots,k\}, i \in \{1,\cdots,m\}, j \in \{1,\cdots,n\}. \tag{3.7}$$

As the criteria evaluation may diverge among different decision supporters, we apply the technique of the intuitionistic fuzzy sets (IFSs) to quantify the collective opinions. IFSs were introduced by Atanassov [5] and are an extension of the classical fuzzy set theory. They represent a suitable way to deal with the problem of information vagueness. An IFS A in a finite set X is defined by the following form:

$$A = \{< x, \mu_A(x), v_A(x) > | \, x \in X\}, \text{where } \mu_A : X \to [0,1], v_A : X \to [0,1]. \tag{3.8}$$

The values of $\mu_A(x)$ and $v_A(x)$ denote the degree of membership of x in A and the degree of non-membership of x in A, respectively. $\mu_A(x)$ and $v_A(x)$ satisfy the following condition:

$$0 \le \mu_A(x) + v_A(x) \le 1, \forall x \in X. \tag{3.9}$$

Notice that a fuzzy set could be viewed as a special case of an intuitionistic fuzzy set. An IFS A will become a crisp set if for $\forall x \in X$, either $\mu_A = 0$, $v_A = 1$ or $\mu_A = 1$, $v_A = 0$. According to [5], we will use the following definition as the intuitionistic index of x in A. It is a general measurement of the hesitancy degree of x to A.

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x), \tag{3.10}$$

where $0 \le \pi_A(x) \le 1$ for each $x \in X$. A smaller value of $\pi_A(x)$ means that the knowledge about x is more certain. On the contrary, the knowledge about x is more uncertain if the value of $\pi_A(x)$ becomes greater.

Denote G_{ij} and B_{ij} as the set of decision supporters who respond "good" and "bad" to the alternative A_i regarding the criterion C_j, respectively. A decision supporter $\alpha \in G_{ij}$ if $d_{ij}^{\alpha} = G$ and $\alpha \in B_{ij}$ if $d_{ij}^{\alpha} = B$. The collected evaluations are transformed into a collective decision matrix expressed in the form of intuitionistic fuzzy values. That is, each element of the collective decision matrix denotes the opinion of the majority and is comprised of membership, non-membership, and indeterminacy of a fuzzy concept "excellence." The collective decision matrix can be expressed as:

$$CD = \left[cd_{ij} \right]_{m \times n}, \tag{3.11}$$

in which the characteristics of the alternatives cd_{ij} are represented as:

$$cd_{ij} = \left\{ < \mu_{A_i}(C_j), v_{A_i}(C_j) > | \, C_j \in C \right\}, i \in \{1, \cdots, m\}, j \in \{1, \cdots, n\}. \tag{3.12}$$

where $\mu_{A_i}(C_j)$ and $v_{A_i}(C_j)$ indicate the degree to which the alternative A_i satisfies and does not satisfy the criterion C_j, respectively, and are formulated as:

$$\mu_{A_i}(C_j) = \sum_{\alpha \in G_{ij}} \lambda_\alpha \text{ and } v_{A_i}(C_j) = \sum_{\alpha \in B_{ij}} \lambda_\alpha . \tag{3.13}$$

Note that the third intuitionistic index $\pi_{A_i}(C_j) = 1 - \mu_{A_j}(C_j) - v_{A_j}(C_j)$ is used to evaluate the collective level of hesitation in criterion C_j. Specifically, a larger value of $\pi_{A_i}(C_j)$ indicates a higher hesitation margin of the decision supporters regarding the alternative A_i with respect to the criterion C_j.

3.1.3 Consensus Decision Analysis

After the intuitionistic fuzzy decision matrix has been obtained, consensus decision analysis is conducted to analyze the collective evaluations and provide the ranking list of alternatives for supporting the decision-making originator. In this research, TOPSIS is utilized to consolidate the evaluations from the decision supporters. The procedures of TOPSIS calculation for consensus decision analysis are described as follows:

Step 1. Obtain the criteria weight set.

In the decision analysis process, the support requester might have different criteria importance preferences for the alternative evaluation. The support requester could give his/her criteria weight set (w). If the support requester does not set their criteria weight, we simply use the defaulted group weighting.

The criteria importance of group weighting is formulated as follows:

$$w_{C_j} = \frac{\sum_{i=1}^{n} R_{C_j}^{DS_i}}{\sum_{j=1}^{n}\sum_{i=1}^{n} R_{C_j}^{DS_i}}, \tag{3.14}$$

where the w_{C_j} indicates the criteria importance of group suggestion of criteria j, $R_{C_j}^{DS_i}$ is the importance rating of criteria j given by decision supporter i. For each $cd_{ij} \in \text{IFS}$, the $cd_{ij}\_w_{C_j}$ is defined as follows [25]:

$$cd_{ij}\_w_{C_j} = \left\{ < 1-(1-\mu_{A_i}(C_j))^{w_{C_j}}, (v_{A_i}(C_j))^{w_{C_j}} > \right\}. \tag{3.15}$$

After including the weight, the new weighted matrix is generated for consensus decision analysis.

Step 2. Determine the intuitionistic fuzzy positive ideal solution (IFPIS) and the intuitionistic fuzzy negative ideal solution (IFNIS).

The calculations of the IFPIS (A^+) and IFNIS (A^-) in this step are respectively defined as follows:

$$A^+ = \left\{ \max_i \bar{\mu}_{A_i}(C_j), \min_i \bar{v}_{A_i}(C_j) \right\} \text{ and } A^- = \left\{ \min_i \bar{\mu}_{A_i}(C_j), \max_i \bar{v}_{A_i}(C_j) \right\} \tag{3.16}$$

$$\bar{\mu}_{A_i}(C_j) = 1-(1-\mu_{A_i}(C_j))^{w_{C_j}},\ \bar{v}_{A_i}(C_j) = (v_{A_i}(C_j))^{w_{C_j}}. \tag{3.17}$$

Step 3. Calculate the distance between the alternative and the IFPIS and between the alternative and the IFNIS.

The following measurement definitions [111] will be used to determine the Euclidean distance. The $\text{ED}(A_i, A^+)$ and $\text{ED}(A_i, A^-)$ respectively denote the Euclidean distance between alternative A_i and IFPIS A^+ and between alternative A_i and IFPIS A^-.

$$\mathrm{ED}(A_i, A^+) = \sqrt{\sum_{j=1}^{n}\left[\left(\bar{\mu}_{A_i}(C_j) - \mu_{A^+}(C_j)\right)^2 + \left(\bar{v}_{A_i}(C_j) - v_{A^+}(C_j)\right)^2 + \left(\bar{\pi}_{A_i}(C_j) - \pi_{A^+}(C_j)\right)^2\right]}; \quad (3.18)$$

$$\mathrm{ED}(A_i, A^-) = \sqrt{\sum_{j=1}^{m}\left[\left(\bar{\mu}_{A_i}(C_j) - \mu_{A^-}(C_j)\right)^2 + \left(\bar{v}_{A_i}(C_j) - v_{A^-}(C_j)\right)^2 + \left(\bar{\pi}_{A_i}(C_j) - \pi_{A^-}(C_j)\right)^2\right]}. \quad (3.19)$$

Step 4. Calculate the relative closeness coefficient (CC) and rank the preference order of all the alternatives.

The relative closeness coefficient of each alternative with respect to the intuitionistic fuzzy ideal solutions is calculated as:

$$CC_{A_i} = \frac{\mathrm{ED}(A_i, A^-)}{\mathrm{ED}(A_i, A^+) + \mathrm{ED}(A_i, A^-)}, \text{ where } CC_{A_i} \in [0,1], i = \{1, 2, ..., m\}. \quad (3.20)$$

The greater closeness coefficient value indicates that the alternative is simultaneously closer to IFPIS and farther from IFNIS. Hence, the ranking list of all the alternatives can be determined according to the descending order of closeness coefficient values. Finally, the alternative with the highest ranking is the most preferred alternative.

3.2 Experiments

3.2.1 Experiment Source

In order to evaluate the proposed social appraisal support mechanism, we construct experiments on both search goods and experience goods in the Plurk micro-blogosphere. According to the report from InRev Inc. [7], the Plurk micro-blogosphere is very popular in Taiwan, the Philippines, Indonesia, and the United States. Based on the statistics of May 18, 2010, almost 50% of Plurk users are teenagers and 30% of users are aged 20~30. Because Plurk is predominently used by youths and young adults for information sharing, we believe that it is an excellent platform for soliciting social appraisal support when users face a purchase decision.

Construction of the friend network. In the experiments, a total of 113 active Plurk users are invited to be support requesters. All these qualified support requesters have undertaken at least one purchasing activity in the last three months. Besides, to ensure that a support requester has sufficient time to evaluate the satisfaction degree of the purchased product, the latest purchase decision of a support requester should have been more than one week ago. We construct the friend network as initiated and expanded from these support requesters. Data descriptions of the experiments are outlined in Table 3.2. In the experiments, a total of 161 purchase decisions (88 for search goods and 73 for experience goods) are evaluated. A typical decision support request contains 3-5 alternatives and on average 16 friends (decision supporters) reply to a request with their opinions. For the purpose of analyzing the companionships of the decision supporters who respond, we collected the post and response activity records in the last 6 months from the participants' public Plurk interface. Figure 3.7 shows the visualization of the collected friend network.

Table 3.2 Data descriptions of the experiment

Statistics of the experiment data	
Number of invited participants	113
Number of available social appraisal requests	161
Average number of decision supporters per social appraisal request	16
Average number of friends per participant	83
Average number of interactions per participant (6 months)	2,967
Average number of requests released per participants	1.6
Average number of alternatives per social appraisal request	4.2

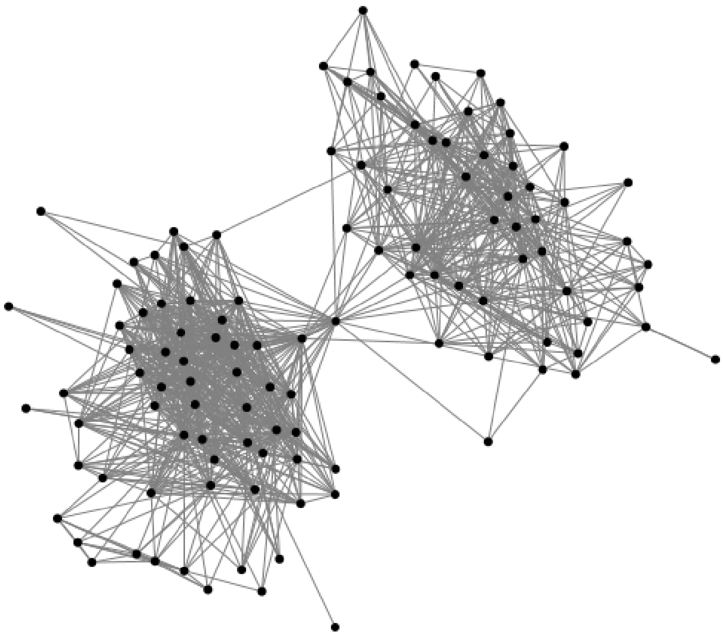
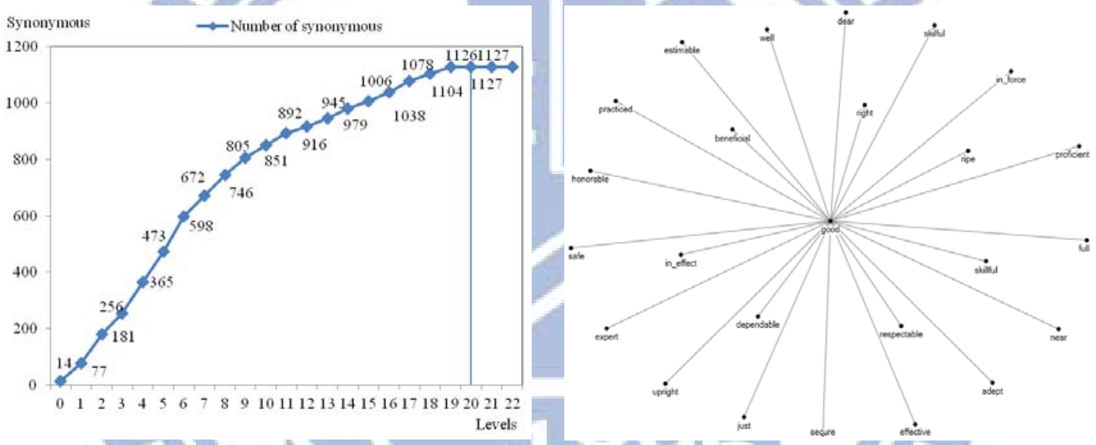


Figure 3.7 Visualization of collected social appraisal network

Table 3.3 Features of products in different categories

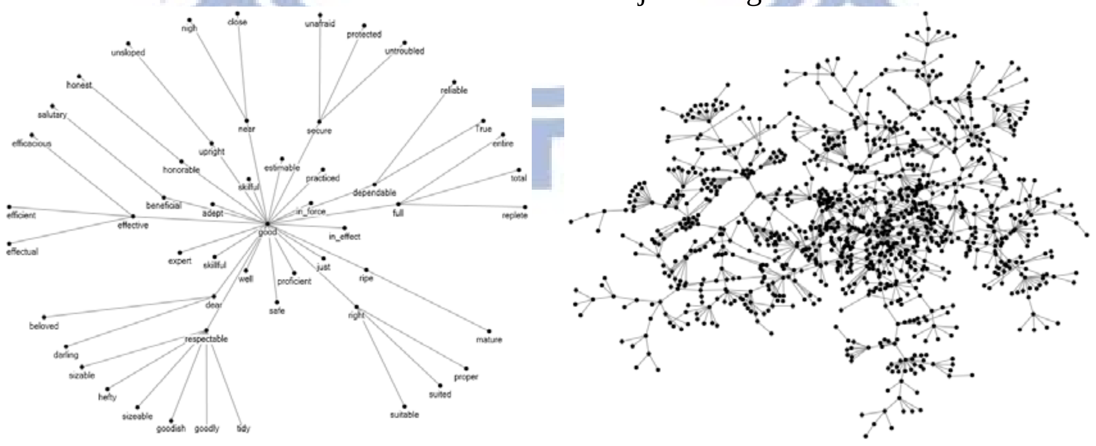
Digital Camera	**Computer**	**MP3 Player**	**Cell Phone**
Resolution	Processor	PC interface	Cellular tech.
Price	Memory	Flash memory	Specific absorption rate
Lens	Video graphic	Dimension	Band/mode
Storage	Size of case	Weight	Wireless interface
Interfaces	Storage	Resolution	Weight
Exposure controls	Warranty	Battery tech.	Memory
Focus controls	Network	Battery life	Battery life
Flash modes	Audio		

<u>*Construction of the decision criteria*</u>. Four kinds of search goods, “digital camera,” “computer,” “MP3 player,” and “cell phone,” and three kinds of experience goods, such as “restaurant,” “movie,” and “peripheral products” are analyzed in the experiments. Note that “peripheral products” mainly refers to the peripheral products of mobile devices (e.g. case, headset of tablet or smartphone, etc.). As the features and characteristics of search goods can be explicitly evaluated by the customers before purchasing, we pre-collect product features as the appraisal criteria from the buying guide of the CNE product review site. The pre-collected product categories and features of search goods are listed in Table 3.3. The participants were asked to initiate a request for decision support and disseminate it over their own social networks on the Plurk platform. For experienced goods, we use semantic analysis of the microblog messages to extract the implicit decision criteria, described in subsection 3.1.2.1.



(a) The synonymous adjective expansion

(b) The first-level expansion of the adjective “good”



(c) The second-level expansion of the adjective “good”

(d) The final expanded synonymous adjective graph

Figure 3.8 Synonymous adjective graph creation

<u>*Construction of the adjective word graph*</u>. Figure 3.8 depicts the evolving process of the word set expansion. We can observe that the expansion of the word set is marginally diminishing from Figure 3.8-(a). Altogether 1,127 non-duplicate adjectives are included in the word set used for synonymous adjective graph building. In Figure 3.8-(b-c), an example of two-level synonymous adjective expansion of the adjective "good" is shown. The word "good" has synonymies of "full," "estimable," "beneficial" etc. in the first-level expansion according to WordNet. These extracted synonymies are used as the seed words for further extracting the second-level synonymies of "good" in the second-level expansion, and so on. The final expanded synonymous adjective graph is shown in Figure 3.8-(d).

<u>*Selection of the polar adjectives*</u>. As explained in section 3.1.2.2, the semantic orientation of an adjective is calculated by the comparison of the shortest paths between this adjective and the positive polar adjective and between this adjective and the negative polar adjective. In this research, we use 27 words (19 words of high popularity and 8 words of low popularity) selected from the list of adjective words used by Vegnaduzzo [118] to evaluate whether the orientation identification mechanism could deal with the user's daily used adjectives. These words are included in the synonymous adjective graph created as the evaluation word set. These 27 words are sequentially fed into the proposed evaluation extraction process to estimate the semantic orientation identification accuracy. However, these words are without orientation or polarity information. A group of 10 human judges (consisting of 2 doctoral students and 8 master students) was invited to pre-identify the semantic orientation (positive or negative) using the majority voting method. If an adjective is identified as having a positive orientation and a negative orientation with an equal number of votes, it would be marked as a vague orientation.

We experimented with various polar pairs such as (*good*, *bad*), (*positive*, *negative*), and (*excellent*, *poor*) to study the impact on the accuracy of semantic orientation identification. The experimental results and the two-paired sample t-test at the 95% significant level are respectively shown in Figure 3.9. As we can observe, the accuracy rate of adjective semantic orientation identification using the polar pair of (*good*, *bad*) is significantly higher than that of other pairs. Hence, it is used for the semantic orientation identification process in the experiments.

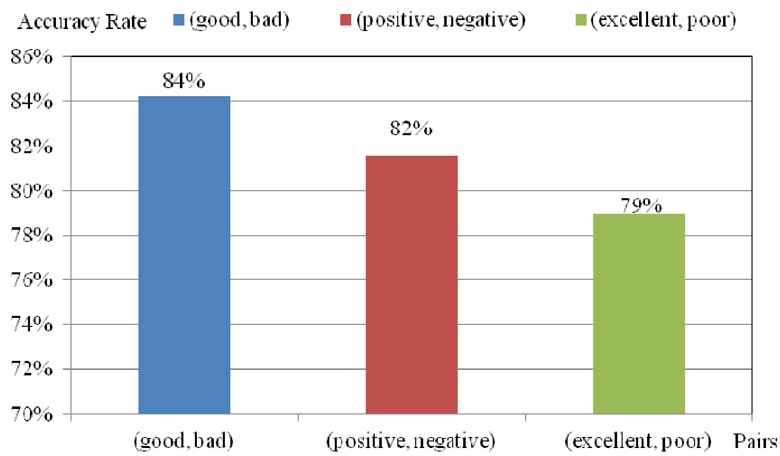


Figure 3.9 Accuracy comparison between different polar word pairs

3.2.2 Experiment Design

In the experiments, we asked the participants to recall their original decision-making process and report (1) the product they bought and the alternatives they took into account, (2) the criteria they considered, and (3) whether the product purchase decision was satisfactory.

First, we have to know which product they bought because different products have different criteria for decision making. The alternatives together with the suited criteria set were sent to their friends through Plurk. A friend becomes a decision supporter when he/she replies to the message with his/her criteria evaluation.

Second, although we pre-collected a general criteria set (i.e. product features) of products, in order to make the criteria set closer to participants' considerations, the collective criteria for each product could be additionally collected from the participants. For search goods, the system would respond with the pre-collected criteria set (as shown in Table 3.3) according to the product category mentioned in the social appraisal request. The decision supporters could give their evaluation ("G," "B," or "U") to each criterion of the alternatives. For experience goods, the system analyzes the opinions posted by decision supporters to extract possible criteria and evaluations.

Third, after gathering the evaluation and building the collective decision matrix, the proposed social appraisal mechanism will output a ranking list of all the alternatives to support the originator's decision-making on product purchasing. In order to evaluate the efficiency of the proposed social appraisal support mechanism, it is necessary to know whether the participants are satisfied with their product purchase decision. In our mechanism evaluation process, the item ranked in the first place is selected as the purchasing target and it is used to evaluate the effectiveness of the proposed mechanism.

We illustrate the system process in the following example:

User *A* wants to buy a camera. According to self-survey or other recommendations, he/she has narrowed the choice to three camera alternatives but it is hard to decide which one is most suitable. He/she initiates a support request in the micro-blogosphere. The request message is formed as "[Digital camera]: [camera1, camera2, camera3]." The extracted criteria set for the digital camera would be posted in the form of "[Criteria]: [resolution, price, lens, storage, interfaces, exposure controls, focus controls, flash modes]." Then, the decision supporters (the friends of *A*) reply with their criteria evaluation of each alternative in the following form "[ans]: [G, B, U, G, G, B, U, G], [U, G, G, B, B, B, U, G], [G, G, G, G, U, G, G, B], [1, 3, 8, 4, 2, 7, 5, 6]." After the consensus decision analysis, the system produces a list of ranked cameras for *A* in the form of "[Rank]: [camera2 > camera3 > camera1]," which indicates that *A*'s friends think that "camera2" is the most suitable camera.

Another example considers experience goods. User *B* initiates a support request for restaurant selection as "[Restaurant]: [restaurant1, restaurant2, restaurant3]. For a family dinner, which one is the best?" Suppose that friend1 gives his opinion as "[ans]: [the service is great and the food is delicious but the price is expensive], [the distance is too far but food and service are good], []". After collective opinion analysis, the system respectively transformed the sentences into the criteria set as "[Criteria]: [service, food, price, distance]" and the criteria evaluation as "[ans]: [G, G, B, U], [U, G, U, B], [U, U, U, U]" for these three restaurants and feed into the consensus decision analysis. Notice that the system would post the current criteria set to the support request message and allow other friends to give their opinions according to these criteria. Then, if friend2 mentioned other features of the restaurants, like "[ans]: [the service is great but I do not like their food and the price is a little bit expensive, distance is ok to me], [service and food are great], [very nice background music]," the criteria set would be expanded automatically as "[Criteria]: [service, food, price, distance, music]" and the evaluation of the criterion "music" of friend1 would be set as "U" and the evaluations updated as "[ans]: [G, G, B, U, U], [U, G, U, B, U], [U, U, U, U, U]" for consensus decision analysis. Finally, after the consensus decision analysis, the social appraisal system would reply with the restaurant ranking to *B* as "[Rank]: [restaurant2 > restaurant1 > restaurant3]," which means that *B*'s friends think "restaurant2" is the most suitable restaurant for *B*.

3.3 Results and Evaluations

The effectiveness of social decision support is determined by the recipient's subjective judgment [39], so the results recommended by the proposed mechanism should be compared with the support requester's self-evaluation. The detailed comparison rules are listed in Table 3.4.

Table 3.4 Evaluation rule table

		User evaluation	
		Satisfied	Unsatisfied
System recommendation	Purchasing	CSS	$1-CSU$
	Not purchasing	$1-CSS$	CSU

There are two major evaluation rules to judge the effectiveness of the social support mechanism:

(1) Do recommend the user to buy the product they are satisfied with; if the support requester feels satisfied with the product and the social appraisal mechanism also recommends purchasing it (i.e. it is placed in the first ranking by the system), a mark "CSS," which means correct social support is made.

$$CSS = \frac{|S \cap R|}{|S|}, \tag{3.21}$$

where S stands for the set of satisfactory products purchased and R stands for the set of products recommended for purchasing.

(2) Do not recommend the user to buy the product they are unsatisfied with. If the support requester feels unsatisfied with the product and the social appraisal

mechanism does not recommend purchasing it, a mark “CSU” is given, which means that wrong social support is avoided.

$$CSU = \frac{|\bar{S} - R|}{|\bar{S}|}, \tag{3.22}$$

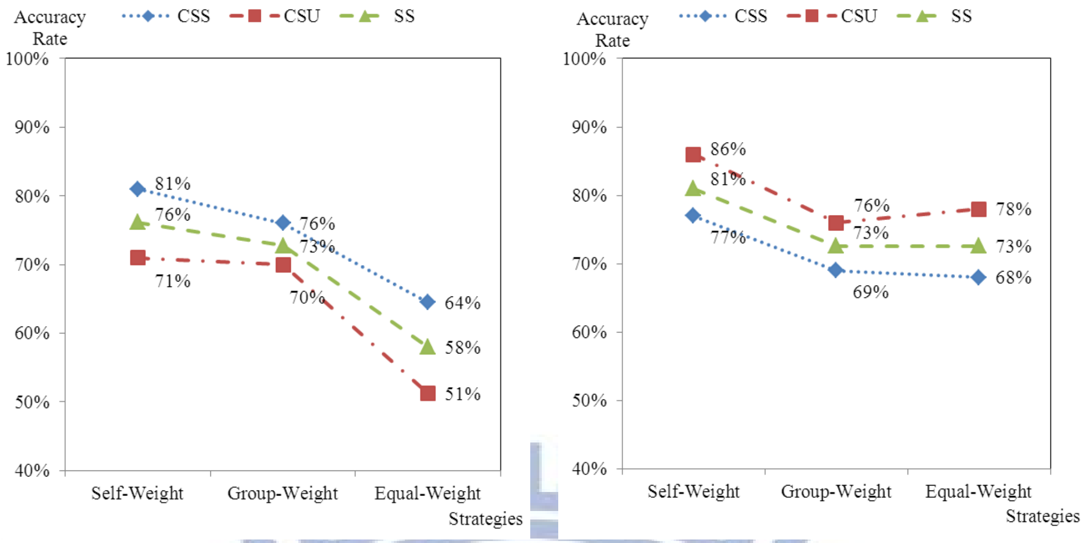
where $\bar{S}$ stands for the set of unsatisfactory products purchased. For enterprises, these two rules could enhance customers’ degree of satisfaction and create more business opportunities.

Finally, the overall successful support is measured as:

$$SS = \frac{|S \cap R| + |\bar{S} - R|}{|S| + |\bar{S}|}. \tag{3.23}$$

3.3.1 Comparisons of Criteria Weighting Strategies

We construct three experiments and compare the results with respect to the self-weighting, group-weighting, and equal-weighting strategies. The criteria importance of self-weighting and group-weighting strategies is respectively obtained from the decision requester and the group of decision supporters. For the equal-weighting strategy, the criteria importance would be set to 1. The results shown in Figure 3.10-(a) and -(b) reveal that the self-weighting strategy is more effective than other strategies for both search goods and experience goods. It is because when making a purchasing decision, the decision maker most clearly knows his/her individual needs. Besides, as our close friends might know us better, the group-weighting strategy has better performance than the equal-weighting strategy. Therefore, it is suitable to use group-weighting strategy as the default criteria weighting if the support requester did not give their own criteria importance settings.



(a) Search goods (b) Experience goods

Figure 3.10 Accuracy rates of different criteria weighting strategies

Table 4 and 5 shows the results of the 95% significant level two-paired sample t-test. The results verified that the self-weighting strategy significantly outperforms the other strategies.

Table 3.5 Statistical verification of the decision analysis results with different weighting methods for search goods

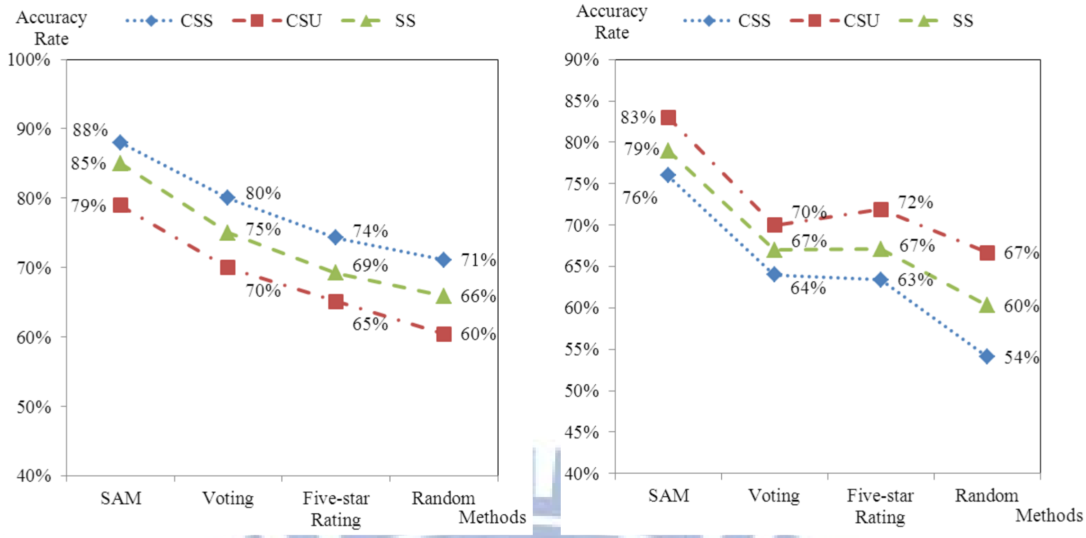
Paired Group		**Mean**	**Std. Deviation**	**Std. Error Mean**	**T value**	**Sig. (2-tailed)**
Self V.S.	**Group**	-0.063	0.358	0.020	-3.138	0.002
	Equal	-0.036	0.394	0.022	-1.670	0.003
Group V.S.	**Equal**	0.026	0.389	0.021	1.198	0.011

Table 3.6 Statistical verification of the decision analysis results with different weighting methods for experience goods

Paired Group		**Mean**	**Std. Deviation**	**Std. Error Mean**	**T value**	**Sig. (2-tailed)**
Self V.S.	**Group**	0.099	0.370	0.023	4.306	0.000
	Equal	0.083	0.376	0.024	3.535	0.000
Group V.S.	**Equal**	-0.017	0.381	0.024	-0.699	0.001

3.3.2 Comparisons of Support Effectiveness

We construct and compare the results of three experiments with three different product selection approaches: the proposed social appraisal mechanism (SAM), the majority voting (voting) method, the five-star rating method, and the random selection method (random). The majority voting method is one of the baseline social support methods allowing users to aggregate friends' opinions. For example, Facebook developed a simple social support function, "Questions." In this scenario, the support requesters are asked to re-post their social appraisal request, then the decision supporters vote directly for which candidate is most suitable without criteria and evaluations. The five-star rating method is one of the baseline product evaluation methods for gathering the collective opinion of public users' opinions. In this scenario, the decision supporters are requested to reply their opinions by using five stars scaling for each alternative. The random selection method is used to simulate the scenario that there is no social support mechanism. In this scenario, the participants do not know which product is the most suitable and pick one to buy randomly. Figure 3.11 indicates that the proposed mechanism is more effective than other baseline social support methods. Measures "CSS" and "CSU" respectively indicate the performance that the support requester indeed buys the most suitable product and the performance that the support requester indeed avoids buying an unsuitable product.



(a) Search goods (b) Experience goods

Figure 3.11 Accuracy rates of different methods

As we can observe, the performance of our proposed SAM is better than that of the other approaches. First, the SAM, majority voting, and five-star rating methods achieve better performance than the random approach. This indicates that soliciting external appraisement from the social network is helpful for supporting customers' online shopping behavior. Second, both the SAM and the majority voting method aim to provide social appraisal support for support requesters, but the majority voting method does not consider the relative importance of decision supporters. This shows that considering social companionship could improve the social appraisal mechanism. Third, the result of the five-star rating method is very similar to the voting method. From the purchasing purpose, the buyer would like to buy the product which is the most suitable. While a decision supporter gives the highest star to a product indicates that he/she feels the product is the most appropriate. Similarly, he/she will vote the most suitable product in the voting method.

Due to the difficulty of complex nature language analysis and heterogeneity of user tastes, the extracted criteria and evaluations using semantic analysis for experienced good might not perfectly represent the characteristics of a product. So that, the CSS evaluation values of experience goods are lower than search goods. And, the CSU is greater than CSS in the evaluations of experience goods.

Finally, the result of the overall performance of different approaches is further evaluated by two-paired sample t-test and shown in Table 3.7 and 3.8. At the 95%

significant level, all the test results show that the proposed social appraisal mechanism significantly outperforms the other product selection approaches.

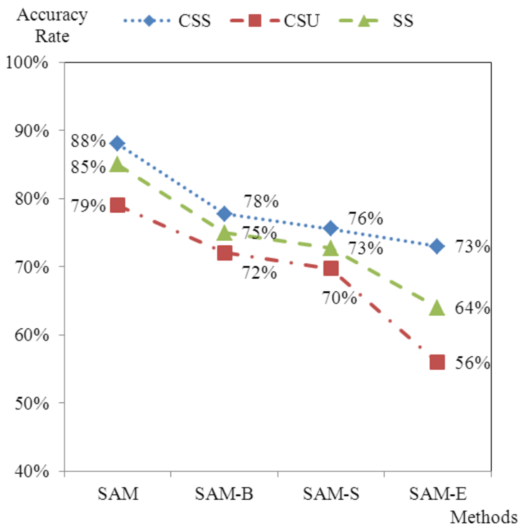
Table 3.7 Statistical verification of the decision analysis results with different selection approaches for search goods

Paired Group		Mean	Std. Deviation	Std. Error Mean	T value	Sig. (2-tailed)
SAM V.S.	Voting	-.01904	.38157	.02140	-.890	.003
	Five-star	.02918	.39352	.02207	1.322	.002
	Random	-.04526	.39169	.02197	-2.061	.000

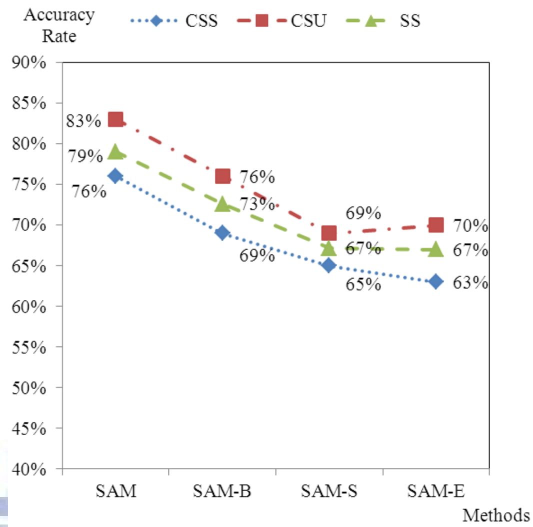
Table 3.8 Statistical verification of the decision analysis results with different selection approaches for experience goods

Paired Group		Mean	Std. Deviation	Std. Error Mean	T value	Sig. (2-tailed)
SAM V.S.	Voting	0.051	0.406	0.017	3.025	0.003
	Five-star	0.027	0.392	0.016	1.620	0.000
	Random	0.097	0.386	0.016	6.002	0.006

We further compare the effectiveness of various appraisal mechanisms using different social companionship measures: (1) the proposed social appraisal mechanism (SAM), which considers the behavioral and structural tie strengths, (2) an appraisal mechanism using only behavior weighting (SAM-B), (3) an appraisal mechanism using only structural weighting (SAM-S), and (4) an appraisal mechanism using equal weighting (SAM-E). The alternatives are ranked by these different appraisal mechanisms.



(a) Search goods



(b) Experience goods

Figure 3.12 Accuracy rates of different companionship measures

Figure 3.12 reveals that using both the behavioral and the structural characteristics to evaluate the importance of friends can significantly improve the appraisal effectiveness. The results of the two-paired sample t-test are shown in Table 3.9 and 3.10. At the 95% significant level, all the test results show that the proposed companionship evaluation approach significantly outperforms the other approaches. This implies that it is beneficial and essential to consider the behavioral information and the structural information together while developing a social support mechanism.

Table 3.9 Statistical verification of the decision analysis results with different models for search goods

Paired Group		**Mean**	**Std. Deviation**	**Std. Error Mean**	**T value**	**Sig. (2-tailed)**
SAM V.S.	**SAM-B**	-.06406	.36091	.02024	-3.165	.002
	SAM-S	-.04501	.37700	.02114	-2.129	.003
	SAM-E	-.04043	.39475	.02214	-1.826	.000

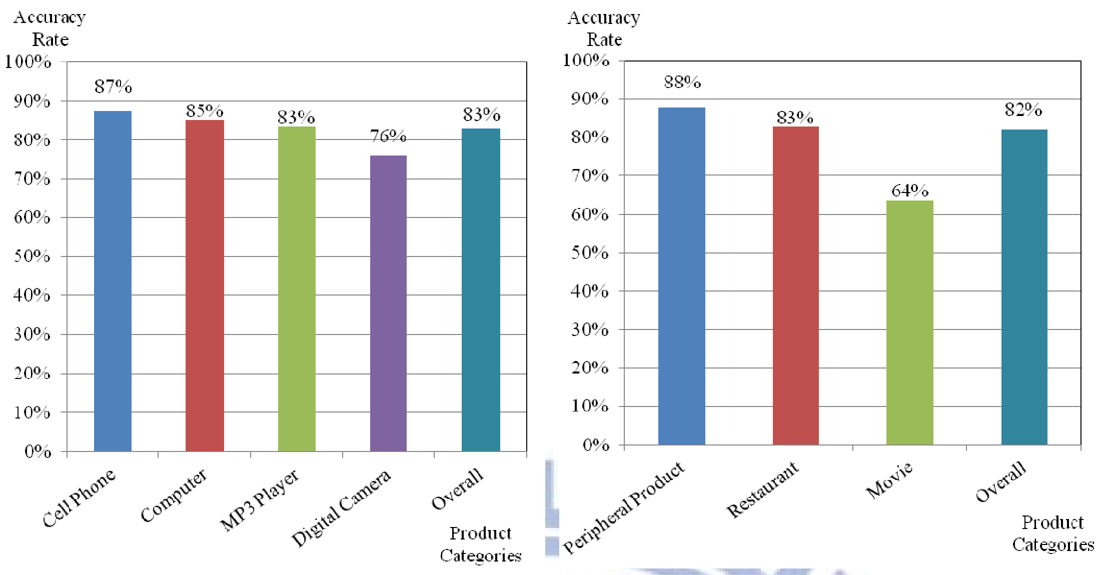
Table 3.10 Statistical verification of the decision analysis results with different models for experience goods

Paired Group		Mean	Std. Deviation	Std. Error Mean	T value	Sig. (2-tailed)
SAM V.S.	SAM-B	.09978	.37075	.02317	4.306	.000
	SAM-S	.08013	.37909	.02369	3.382	.001
	SAM-E	.08312	.37627	.02352	3.535	.000

3.3.3 Comparison of Search and Experience Goods

The accuracy rates with respect to different products are shown in Figure 3.13. The proposed mechanism achieved an overall 83% accuracy rate. The accuracy rate for search goods and for experience goods is 83% and 82%, respectively. Among the search goods, cell phones have the highest accuracy rate (87%). Among the experience goods, peripheral products have the highest accuracy rate (88%). Mobile devices, such as smartphones and tablets, are trendy products and most of the decision supporters invited to take part in the experiments already have one or more mobile devices and peripheral products. Respectively, 21% and 32% of the requests for social appraisal support are related to peripheral products and mobile devices (cell phones and computer categories). Therefore, the social support has relatively sufficient basic knowledge to judge whether a product is good or bad and provide more appropriate product opinions and criteria evaluations.

As Figure 3.13 shows, movies have the lowest rate (64%). The result can be explained by two reasons. First, movies are highly dependent on individual preferences, so 11 (about 7%) appraisal requests are released. The number of decision samples might be insufficient to evaluate the performance accurately. Second, there are too many "unknown" criteria evaluations in the movie category. Besides, as watching a movie is a costly activity (time and price), comparatively few friends have watched all the alternatives of a movie appraisal request and respond with their opinions. However, the proposed mechanism still received approximately a 64% support accuracy rate in the movie category.



(a) Search goods (b) Experience goods

Figure 3.13 Accuracy rates for different products

3.4 Chapter Summary

In this chapter, a social appraisal mechanism, which is composed of social companionship analysis, collective opinion analysis, and consensus decision analysis, for online purchase support in the micro-blogosphere was proposed. To measure the social companionship of decision support, this study constructed an interaction network based on the interactions of posts and responses in micro-blogs to measure the behavioral tie strength of the social relationship and measured the structural tie strength of the social relationship by analyzing the friend network. To analyze the collective opinions, a text-mining technique with semantic orientation identification was developed for criteria and evaluation extraction. Besides, to resolve the inherent issue of information incompleteness in the collective opinions, IFS is applied to model the vague or incompletely known opinions from the micro-blogosphere. Finally, to consolidate the evaluations from various decision supporters and the support requester's decision criteria preference, TOPSIS was applied to rank the final alternative. Our experimental results show that the accuracy of the proposed social appraisal support mechanism outperforms that of other benchmark approaches. The proposed social appraisal framework soliciting opinions from trustable friends can thus be effectively applied to support individual decisions, such as online purchasing.

CHAPTER 4 SOCIAL DIFFUSION

Social media are gaining importance as a component of marketing strategies. Many of them, such as social networking sites, blogospheres, and micro-blogospheres, have been seeking business opportunities and establishing brand expression in recent years. Online marketing information diffusion is becoming the critical business model for online social networks. Marketers attempt to diffuse advertisements to potential customers through the Internet. However, most of the current marketing research discovers potential influencers but does not appropriately support them to diffuse advertisements. In this research, a diffusing path planning mechanism for advertisement is developed to support influencers in propagating marketing information and to support marketers in evaluating the possible rewards under different marketing strategies

4.1 Advertisement Path Planning Mechanism

The procedures for conducting information diffusion over social media are described as follows. A marketer propagates marketing information by distributing ads to the starting endorsers, who could be selected according to some evaluation criteria such as influence or active strength. For each starting node, we recommend the diffusion path that is generated based on the aggregate reward, which is measured by information influenceability and ad reachability. In the mechanism, a diffusion path is generated for the purpose of aggregated reward maximization. A starting node is only aware of the first node in the planned diffusion path and decides whether to forward the ad to the node spontaneously. If a node breaks the planned diffusion path (does not pass the marketing information to the next node as planned in the diffusion path), the proposed system would replan a diffusion path from the breaking node.

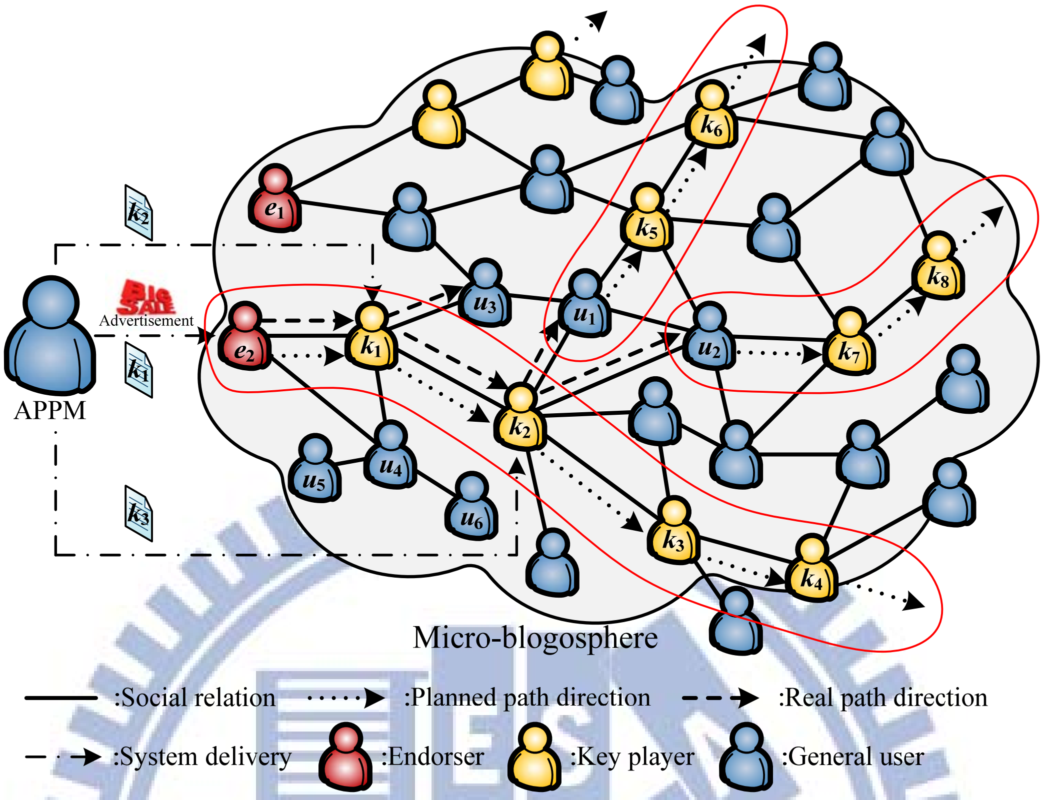


Figure 4.1 Information diffusion path

As shown in Figure 4.1, e_2 is one of the marketer's identified starting endorsers and the APPM would like to plan a diffusion path for supporting information propagation. At first, as users have higher tendency to share with friends the information they feel interested in, the preference fitness analyzing module use the previous post contents to analyze the preference fitness with the marketing information of k_1 and u_5. It evaluates who has higher probability to forward the information. Secondly, the transition flow inferring module respectively infer the transition probability of the possible information forwarding between e_2 and k_1 and between e_2 and u_5 based on daily post and reply behaviours. It evaluates who has higher probability to receive the information. Thirdly, the customer value evaluating module respectively calculates the diffusion value of k_1 and u_5 from the social network structure to evaluate how many people they could be influenced and reached. Finally, the diffusion path planning module plan the path based on the above modules. A diffusion path for supporting e_2 to propagate marketing information is planned as $e_2 \rightarrow k_1 \rightarrow k_2 \rightarrow k_3 \rightarrow k_4$. The system will first deliver the information to e_2 and suggest the next key player (k_1) to forward it to. If k_1 receives the information, then the system will suggest him/her to forward the information to k_2 and so on. If k_2 receives the information but k_2 breaks the planned diffusion path (i.e. does not forward to the suggested k_2) and passes the marketing information to u_1 and u_2, the APPM respectively replans a diffusion path $u_1 \to k_5 \to k_6$ and $u_2 \to k_7 \to k_8$ for u_1 and u_2 to continue the marketing information diffusion process.

Table 4.1 Symbols used in advertisement path planning mechanism

Symbol	Description
$sim(KV, PV^i)$	Cosine similarity between keywords vector (KV) and i^{th} post vector of user
$pw(t_i)$	Preference weighting function for article i, which is decreasing by time t
$PF(u)$	Preference fitness of user u to the product
$P_r(\overrightarrow{u_i u_j})$	Transition probability between users
$ec(u_i)$	Eigenvector centrality of u_i
$IA(u_i)$	Influenceability of u_i
$asn(u_i)$	Total number of active social nodes with respect to u_i
$RA(u_i)$	Reachability of u_i
$F(n,u_i)$	Number of nodes which can be reach by u_i at n steps
$sb(u_i)$	Degree of daily sharing behavior of a social node
$wts(u_i)$	Tendency of willing-to-share of u_i
$DR(u_i)$	Diffusion reward of u_i
$Neighbor\_DR(s,i)$	Reward coming from neighbor node i to starting node s
$Path(s)$	Planned optimal path which is started from node s
$TR(s)$	Total reward from diffusing information through $Path(s)$
CTR	Click-through rate
EA	Exposure ability
ER	Egoism ratio
AR	Altruism ratio

Figure 4.2 depicts the framework of the proposed system framework and the symbols used in the proposed mechanism are listed in Table 4.1. The proposed framework is comprised of three main components: the preference fitness analysis module, transition flow inferring module, customer value analyzing module, and diffusion path planning module:

(1) Preference fitness analysis module: preference fitness analysis is used to measure the fitness degree between a user's preference and the marketing information. The latent semantic indexing (LSI) based methodology is exploited to estimate the preference fitness of a user to the marketing information by analyzing their daily micro-blogging messages.

(2) Transition flow inference module: the purpose of transition flow inferring analysis is to infer the transition probability of the possible information forwarding between two users based on the daily social interactions among the users within the social network. We apply the concept of the Markov chain to derive the transition probabilities of information forwarding.

(3) Customer value evaluation module: the aim of customer value evaluation is to estimate the diffusion value of the nodes that are included in the social network according to their interaction intensity. The directed interaction relations are transformed into an adjacency matrix and the diffusion effectiveness factors, influenceability and reachability, are considered to derive the information diffusion value of a node.

(4) Diffusion path planning module: the objective of diffusion path planning is to identify the optimal diffusion path starting from a seed endorser node, which could be recommended by the influencer discovery mechanisms [21,59,126]. The path that maximizes the aggregate diffusion reward is generated by integrating the propagation tendency (transition probabilities between social nodes) and propagation reward (information diffusion value of social nodes).

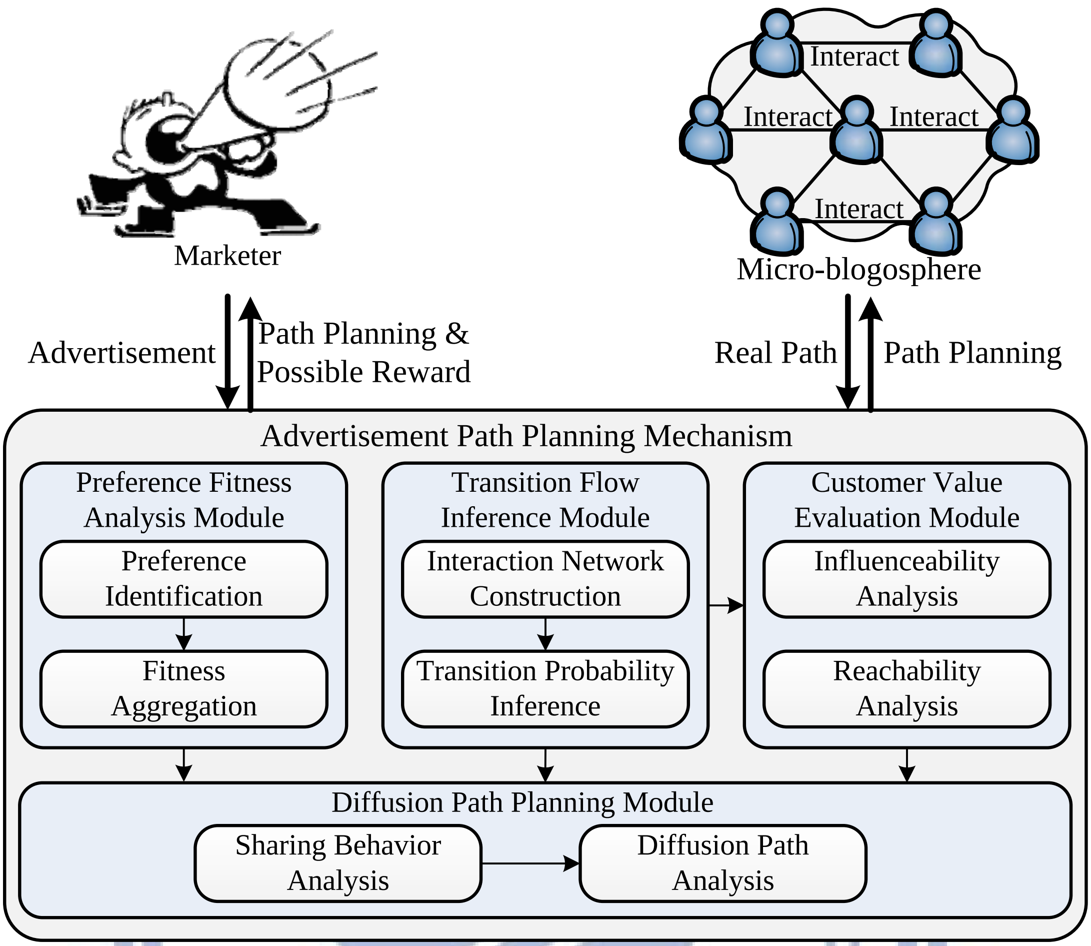


Figure 4.2 The framework of the advertisement path planning mechanism

4.1.1 Preference Fitness Analysis Module

As users have a higher tendency to share with friends the information they feel interested in, it is essential to analyze the matching between the preference of a user and the information to diffuse. The preferences of users could be discovered according to the information that they share on social media. For example, a preference of a user would be represented by the micro-blogging messages he/she has posted on the micro-blogosphere.

4.1.1.1 Preference Identification

In this research, the latent semantic indexing technique (LSI) [26] is used to model the user's preference for a specific product. LSI, one of the well-known information retrieval algorithms, is a process to map keywords to a vector and find the most relevant documents from a group of documents. In practice, the marketer could provide some keywords that can most represent their products to promote and users' preferences can be implicitly discovered from their daily sharing behaviors, so LSI would be an appropriate method for identifying preferences in this research. The procedures of LSI-based preference identification are described as follows:

Step 1. Construct the term-post matrix and keywords of product column matrix.

For each user, the micro-blogging messages posted in the last six months are gathered to represent his/her preference. Then, each post included in the corpus is tokenized and the stop words in the post are removed to extract the terms. A term-post matrix (TD), which consists of m terms and n posts, can be expressed as:

$$TD = \left[tf_{ij} \right]_{m \times n}, \tag{4.1}$$

where tf_{ij} denotes the term frequency of term i in post j of the corpus and it is simply defined as the total occurrence of term i in post j.

To estimate the LSI-based product–user similarity, the representative keywords for the product are required and could be given by the marketer. The product keyword column matrix (KC) can be expressed as:

$$KC = \left[ko_{ij} \right]_{m \times 1}, \tag{4.2}$$

where ko_{ij} denotes the occurrence of keyword i in term j. If keyword *i* hits term *j*, $ko_{ij} = 1$, otherwise $ko_{ij} = 0$.

For example, a user posted three micro-blogging messages and the product keywords given by the marketer are as follows:

p1: *Wow~It's really sunny today~Summer is coming~!*

p2: *Sunburned! I should use the high SPF sunblock lotion and I would not get sunburned again.*

p3: *I've been looking for good sunscreen that will work even while I'm sweating.*

keywords: *sunblock, suncreen, lotion, sunburned, SPF*

Matrices TD and KC can be constructed and represented as:

$$
\begin{array}{c}
\textit{terms} \\ \textit{good} \\ \textit{high} \\ \textit{lotion} \\ \textit{spf} \\ \textit{summer} \\ \textit{sunblock} \\ \textit{sunburned} \\ \textit{sunny} \\ \textit{sunscreen} \\ \textit{sweating} \\ \textit{today} \\ \textit{work} \\ \textit{wow}
\end{array}
\quad
TD = \begin{array}{c}
\begin{array}{ccc} p1 & p2 & p3 \end{array} \\
\begin{bmatrix}
0 & 0 & 1 \\
0 & 1 & 0 \\
0 & 1 & 0 \\
0 & 1 & 0 \\
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 2 & 0 \\
1 & 0 & 0 \\
0 & 0 & 1 \\
0 & 0 & 1 \\
1 & 0 & 0 \\
0 & 0 & 1 \\
1 & 0 & 0
\end{bmatrix}
\end{array}
\quad
KC = \begin{array}{c}
\textit{keywords} \\
\begin{bmatrix}
0 \\ 0 \\ 1 \\ 1 \\ 0 \\ 1 \\ 1 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0
\end{bmatrix}
\end{array}
$$

Step 2. Compute the similarity between micro-blogging message and keywords of product.

In this step, singular value decomposition (SVD) [17,35], a well-known matrix factorization technique, is used to decompose the TD into three matrices. Because the SVD method provides the lower rank approximations of the matrix, it is very useful for our application. SVD can produce a low-dimensional representation of the TD and the original matrix can be obtained through following matrix multiplication.

$$TD = U \cdot \Sigma \cdot V^T, \tag{4.3}$$

where matrices U and V^T are two orthogonal matrices and Σ is a diagonal matrix having all the singular values of matrix TD as its diagonal entries. All the entries of matrix Σ are positive and stored in decreasing order of magnitude.

LSI retains only the first k singular values together with the corresponding rows of U and V, which induce an approximation to TD. The dimensionality reduction obtained by performing SVD reduces matrix Σ to only k (a tuned parameter) largest diagonal values (Σ_k). Accordingly, while matrix U and matrix V are both reduced, the reconstructed matrix $TD_k = U_k \cdot \Sigma_k \cdot V_k^T$ is the closest rank-*k* matrix to TD. In other words, the dimensionality reduction in the SVD method projects large dimensions (there may be thousands of dimensions) into much smaller dimensions (k dimensions). Each row of U_k represents a term as a *k*-dimensional vector and each row of V_k

represents a post as a k-dimensional vector. From the matrix V_k^T, we can obtain that this matrix must contain n number of rows holding eigenvector values for n posts. Each of these rows then holds the coordinates of individual post vectors (PV). Each PV represents an individual post.

However, the selection of k value, which is the reduced dimensional representation, is an active open research area. It is difficult to find the best one and it is usually determined through sequential experimental tests [19]. According to previous studies [19,26,35,63], the k value around 100 would give better performance. Therefore, the value of k is set to 100 in this study.

Step 3. Incorporating the product keywords and computing the preference similarity

In order to incorporate the keywords of the product, we use the definition described by Berry et al. [10] to obtain the keywords vector (KV) for computing the similarity to the user's preference; it is defined as:

$$KV = KC^T \cdot U_k \cdot \Sigma_k^{-1}. \qquad (4.4)$$

After we obtain KV, we compute the cosine similarity [105] between KV and each PV of users as:

$$sim\left(KV, PV^i\right) = \frac{\sum_{j=1}^{k}\left(KV_j \times PV_j^i\right)}{\sqrt{\sum_{j=1}^{k} KV_j^2}\sqrt{\sum_{j=1}^{k}\left(PV_j^i\right)^2}}, \qquad (4.5)$$

where PV^i denotes the i^{th} post vector of user (each post vector represent a micro-blog post) and KV_j and PV_j^i respectively indicates the j^{th} element of KV and PV^i.

4.1.1.2 Fitness Aggregation

Although the user preference could be observed from the posts, the importance levels of these posts should differ when they are used for evaluating the user preference fitness to the product. For example, two articles that are highly correlated with the product were posted yesterday and three months ago. The former means the user is focusing on the related product information now, so that the user would be more willing to adopt and share the product information. However, the latter might reflect that the user had once surveyed the related information, but might not still be interested in the related product information if his/her focus has changed recently. A preference weighting function for article *i*, which is decreasing by time, is defined as:

$$pw(t_i) = \frac{1}{t_i}, \tag{4.6}$$

where t_i is denotes the time periods since article *i* was posted. For example, $t_i = 1$ indicates that the article was posted within one recent month. Finally, the preference fitness of user u to the product is formulated as:

$$PF(u) = \frac{\sum_{i=1}^{n} pw(t_i) \times sim(KV, PV^i)}{n}, \tag{4.7}$$

where n is the total number of articles posted by user U.

4.1.2 Transition Flow Inference Module

The basic concept of the Markov model is to determine the transition probability of transitions from one state to another. In the context of a social network, a state stands for a user and the transition between two states is interpreted as interaction between two users. Specifically, the transition probabilities between possible states are estimated according to social interactions.

4.1.2.1 Interaction Network Construction.

We leverage the social interaction data from online social networks to obtain the set of active social nodes with respect to a specific user and use the identified nodes as the possible transition states from the current state (the specific user). When the circle of people's friendship grows, there is an increasing need for friend management. Research by Dunbar [30] indicates that there is an approximate natural group size in which everyone can really know each other. Though one can have hundreds of online friends, most of them are just a name in one's friend list and do not incur any social interaction. A recent study also shows that social media users have a very small number of offline friends compared with the number of online friends they declare [48]. We construct a network of social interactions to filter out the active friends of a user and use these nodes as the possible information transition states. Specifically, the directed interaction network of a specific user is constructed by analyzing the social interaction data collected from his/her micro-blogosphere. The edge direction of the interaction network represents the direction of the interaction flow. When a user posts a micro-blogging message, he/she is likely to expect some responses. In the current paper, we define a micro-blogging message poster and replier as “interaction requester” and “interaction provider,” respectively. For example, as illustrated in Figure 4.3, u_A, u_B and u_C post message in the micro-blogosphere, which means u_A, u_B and u_C are interaction requesters. u_D replies to all of them, implying that u_D is an interaction provider. Consequently, there would be “interaction” flowing from u_D to u_A, u_B and u_C.

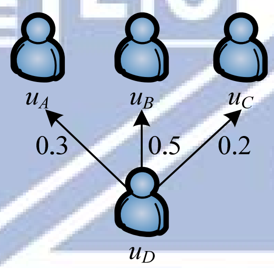


Figure 4.3 Directed interaction network

4.1.2.2 Transition Probability Inference

After obtaining the set of active social nodes (possible transition states), the following formulation is used to determine the transition probability between states.

$$P_r\left(\overrightarrow{u_i u_j}\right) = \frac{\left|\Phi_{\overrightarrow{u_i u_j}}\right|}{\left|\bigcup_j \Phi_{\overrightarrow{u_i u_j}}\right|}, \tag{4.8}$$

where $\left|\Phi_{\overrightarrow{u_i u_j}}\right|$ stands for the number of interaction flows from u_i to u_j, $P_r\left(\overrightarrow{u_i u_j}\right)$ is the interaction transition probability from u_i to u_j, and $\left|\bigcup_j \Phi_{\overrightarrow{u_i u_j}}\right|$ denotes the total number of interactions flowing out from u_i. As shown in Figure 4.3, the $P_r\left(\overrightarrow{u_D u_A}\right)$, $P_r\left(\overrightarrow{u_D u_B}\right)$ and $P_r\left(\overrightarrow{u_D u_C}\right)$ are obtained as 0.3, 0.5 and 0.2 respectively. Finally, the interaction network is represented as a transition matrix (TM):

$TM = \left[P_r\left(\overrightarrow{u_i u_j}\right)\right]_{m\times m}$, where m denotes the total number of active social nodes.

4.1.3 Customer Value Evaluation Module

The purpose of this module is to evaluate the network-structure-based measurements: influenceability and reachability. In this module, the friendship network constructed by the friend list in the micro-blogosphere is used to obtain the eigenvector centrality and reach centrality to evaluate the influenceability and reachability, respectively.

First, the friend network is represented as a bipartite graph $G=(V,E)$, where V denotes the vertices in the network and E denotes the edges between V. Next, for the influenceability and reachability analysis, G is transformed to an adjacency matrix $A=(a_{v,t})$, if vertex v and vertex t are connected, $a_{v,t}=1$, otherwise $a_{v,t}=0$. In this research, we use UCINET to compute the following two measurements of centrality.

4.1.3.1 Influenceability Analysis

For business, the greatest interest of the marketers is to know how many purchase intentions of potential consumers could be stimulated by the marketing information they receive. In this respect, the influence of a node plays an important role in enhancing the diffusion effectiveness of marketing information for the purpose of seeking business opportunities. Kiss and Bichler [62] compare plenty of measures of influence including different centrality measures in customer networks and suggest that the eigenvector centrality is one of the effective measures for estimating the influence of a node in a network. In the current research, the eigenvector centrality is used to compute the influenceability of the users. Conceptually, different neighbors may have different values contributing to the eigenvector centrality. That is, the eigenvector centrality of user u_i is contributed to by the eigenvector centrality of the connected neighbors of u_i. The eigenvector centrality of u_i is determined as:

$$ec(u_i) = \frac{\sum_{j \in SN_i, j \neq i} a_{i,j} \times ec(u_j)}{\lambda}, \tag{4.9}$$

where SN_i denotes the social network of u_i and λ denotes the eigenvalue of matrix A.

For the purpose of comparisons within a graph, it is appropriate to use the eigenvector centrality with maximum normalization [104], which is derived as:

$$ec_{norm}(u_i) = \frac{ec(u_i)}{\max_j ec(u_j)}. \tag{4.10}$$

From the network structure, a person with higher centrality could influence more other nodes in a social network. Besides, a person is influenced by another through the social interactions between them. Therefore, the influenceability of u_i is measured as:

$$IA(u_i) = ec_{norm}(u_i) \times asn(u_i), \tag{4.11}$$

where $asn(u_i)$ is the total number of active social nodes with respect to u_i

4.1.3.2 Reachability Analysis

In relation to establishing brand expression, determining how many potential consumers can be reached during the marketing information diffusion process is what marketers care about most. Hanneman [42] suggest the m-step reach centrality [13] to measure the reach efficiency (e.g. the portion of all others whom one can reach in a network). In the current research, the m-step reach centrality is used to evaluate the reachability of u_i. The m-step reach centrality measures the number of reachable nodes within m steps from a given social node. That is, reachability indicates how many users u_i could reach on average per step. The reachability of u_i is measured as:

$$RA(u_i) = \frac{\sum_{n=1}^{m} F(n, u_i)}{m}, \tag{4.12}$$

where m denotes the number of steps and $F(n, u_i)$ is the number of nodes that can be reached by u_i in n steps. The value of m could be set according to the needs of marketers. According to the small-world effect [92], the value of n is no need to be greater than 6.

4.1.4 Diffusion Path Planning Module

4.1.4.1 Sharing Behavior Analysis.

The expected value of the diffusion reward is impacted on by the willingness-to-share of social nodes. Despite a node obtaining higher influenceability and greater reachability than others, he/she might just like to engage in daily chat and specific conversations with someone but may not like to share information in the micro-blogosphere. If the diffusion path plans to pass through him/her, it will be easily interrupted. Due to the small character limit (140 characters) in the micro-blogosphere, a URL is frequently used to conduct information sharing behavior. On the other hand, a message is external information sharing from other sources, if it contains a URL in a micro-blogging message. The degree of daily sharing behavior of a social node is measured as:

$$sb(u_i) = \frac{|\mathrm{M}_{http}|}{|\mathrm{M}_{post}| + |\mathrm{M}_{reply}|}, \tag{4.13}$$

where $|\mathrm{M}_{post}|$ and $|\mathrm{M}_{reply}|$ denote the total number of messages posted and the total number of message replied to others by u_i respectively. $|\mathrm{M}_{http}|$ denotes the total number of messages containing at least a URL in $|\mathrm{M}_{post}|$ and $|\mathrm{M}_{reply}|$.

According to previous survey [46], egoism and altruism are two significant motivations of users who are willing to share information. Egoism refers to users who would like to share the information for which they have preferences with their friends because they expect the sharing behavior to enhance their personal reputation. Altruism referred to users who are willing to increase the welfare of their friends without expecting returns, so users would like to share information with friends because they might know their friends' preferences. The tendency of willingness-to-share of u_i is defined as follow:

$$wts(u_i) = PF(u_i) \times sb(u_i)\,. \tag{4.14}$$

4.1.4.2 Diffusion Path Analysis

In the proposed APPM, we have combined the probability of state transition, the tendency of willingness-to-share, and the diffusion reward function as treatments to explore the diffusion path with the highest diffusion reward. First, we define the diffusion reward function as:

$$DR(u_i) = \alpha \times IA(u_i) + (1-\alpha) \times RA(u_i)\,, \tag{4.15}$$

where α is the information diffusion strategy weighted to balance the performance of influenceability and reachability, which is determined by the focus of marketing strategies (business opportunity seeking or brand awareness). The direct reward coming from neighbor node i to starting node s can be formulated as:

$$Neighbor\_DR(s,i) = P_r\left(\overrightarrow{u_s u_i}\right) \times wts(u_i) \times DR(u_i)\,. \tag{4.16}$$

The total reward generated from diffusing the information through the planned optimal path, which starts from node *s*, is defined as :

$$TR(s) = \max_{i \in SN, i \notin Path(s)} \left(Neighbor\_DR(s,i) + TR(i)\right),\ Path(s) == \{s\} \cup Path(i)\,, \tag{4.17}$$

where $TR(i) = 0$ and $Path(i) = \varnothing$ for $Neighbor\_R(s,i) = 0$ or $Path\_Length(s,i) \geq \hat{l}$.

$Path(s)$ consists of a sequentially selected key endorser node in the social network. $Path\_Length(s,i)$ denotes the path length between node s and node $\hat{l}$ stands for the maximal length of a planned path. Notice that $TR(s)$ is the conservatively estimated reward of the diffusion process along the path starting from node *s*. That is, if the marketing information could be disseminated by following $Path(s)$, the marketer could gain the diffusion reward at least as $TR(s)$. If some of the nodes who are included in $Path(s)$ are additionally willing to pass the marketing information to other people who are not included in $Path(s)$, the real diffusion reward will be greater than $TR(s)$.

Note that the model could be easily extended to multiple paths starting from node *s*. For example, in Figure 4.1, if we can revise the reward function to use the maximal and sub-maximal values at the same time to plan the path, the path of e_2 would be extended to multiple paths (starting from k_1 and u_4, respectively), as shown Figure 4.4. However, the diffusion reward would be greater than that in the single path planning. Generally, the choice of the number of neighboring nodes to forward to is determined by the total cost of the incentive to induce message forwarding, which increases as the number of endorsers becomes larger.

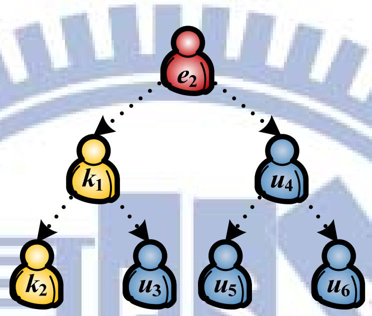


Figure 4.4 Example of multiple path planning

4.2 Experiments

4.2.1 Experiment Source

In this section, we apply the proposed mechanism to the micro-blogging system to examine its effectiveness. Micro-blogging services are one of the top tools for social media marketing. We use Plurk, one of the most popular micro-blogging services, as the platform for conducting experiments. Currently, Plurk is very popular in Asia and the United States [7]. It allows users to send and respond to messages in short sentences (with a limitation of 140 characters). Besides, it attracts users to communicate with each other and share external information by embedding URLs. Because Plurk is popular and predominantly used for communicating and sharing, it is an excellent platform for marketers to conduct information diffusion while conducting social media marketing.

In the experiment, 131 active Plurk users were invited to be participants, and they were also the candidates for the start point of a diffusion path. Firstly, for the purpose of constructing the interaction network to obtain the transition probability, we collected the last 6 months' micro-blogging messages (including post and response data) from participants' public Plurk interface. Then, with the purpose of constructing the friendship network to obtain the information influenceability and reachability, we recursively expanded friendships from the participants' friend list. Finally, there were 4,832 social nodes included in the friendship network. The information on the collected social network data is outlined in Table 4.2. Figure 4.5 shows the visualization of the collected friend network.

Table 4.2 Data descriptions of the experiment

Statistics of the experiment data	
Number of invited participants	131
Average number of friends per participant	37
Average number of active social nodes per participant	11
Average number of monthly interactions per participant (6 months)	2,147

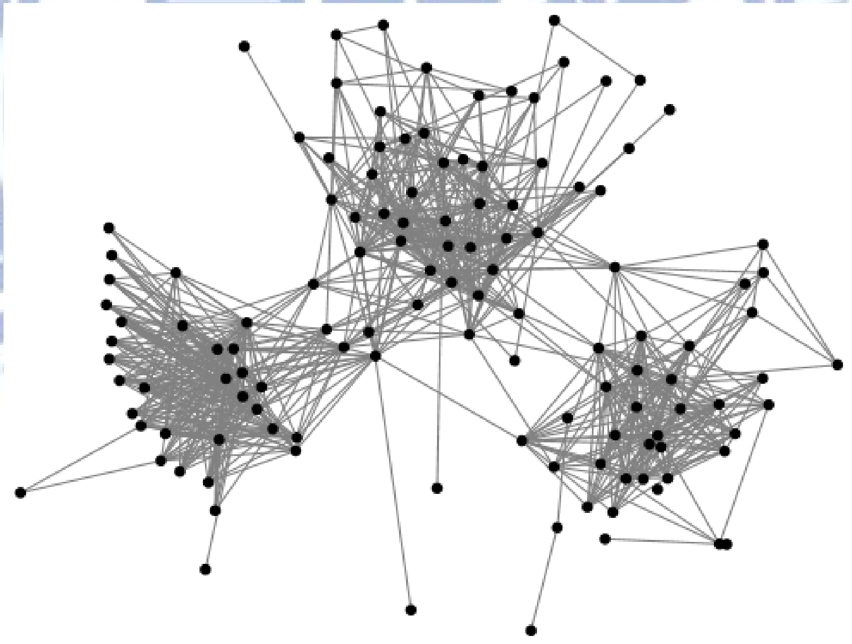


Figure 4.5 Visualization of collected social diffusion network

4.2.2 Experiment Design

In the experiment, we diffused 40 pieces of marketing information in total via 2 different marketing strategies: (1) seeking business opportunities and (2) establishing brand expression. According to previous studies, coupon promotions could cause an increase in product sales [8] and the product reviews from third parties might spread good news/impressions of brands so that it can increase the effectiveness of firms' advertising [18]. There were in total 20 product deals/coupon advertisements for seeking business opportunities and 20 product evaluation review articles for establishing brand expression. The former marketing information was collected from Yahoo! Shopping, which is one of the largest online shopping sites, and the latter was collected from Epinions, which is one of the most professional and famous product review platforms allowing users to share their product experiences and opinions. In order to perform the preference fitness analysis, the keywords that can best represent the product are needed. In our experiments, the keywords of marketing information were provided by an expert group made up of six senior graduate students and four doctoral students in business colleges. The advertisements were delivered with an online 5-star rating questionnaire for the marketing information receivers to feed back their acceptance and diffusion path tracking (Which friend was the marketing information received from?).

We evaluated our proposed mechanism by comparing with the following benchmark approaches: (1) random advertising without a path planning mechanism (Random), (2) random advertising with a path planning mechanism (Random+Path), (3) influencer advertising without a path planning mechanism (Influencer), and (4) influencer advertising with a path planning mechanism (Influencer+Path). According to Kiss and Bichler [62], out-degree centrality produces better performance in influencer identification, so we used out-degree influencer selection to select the starting point of information diffusion. Besides, the random advertising method randomly selects participants whose $sb(u) > 0$ as the starting point of the information diffusion process. For each advertising method, we selected five participants as starting points for diffusing the marketing information.

4.3 Results and Evaluations

In order to evaluate the performance of different advertising methods, we use the click-through rate (CTR) of the advertisements and the receivers' five-star acceptance rating feedback on the received marketing message as the evaluation indicators. The former is a popular practical indicator of advertising efficiency; the latter could evaluate the users' impression of the marketing message received.

Intuitively, for the purpose of seeking business opportunities, it is expected to seek the potential customers with high ($\geq$ four-star) acceptance of the product advertisement, and for establishing brand expression, it is expected to seek the potential customers with not the lowest ($\geq$ two-star) acceptance of the product advertisement. We compare the performance using CTR with different star rating conditions.

4.3.1 Seeking Business Opportunities Strategy

Generally, business opportunities exist in the potential customers with high acceptance of product advertisement, which means that they have a higher chance of buying products. The CTR with the acceptance condition formula is defined as:

$$CTR = \frac{|\Phi_{click}| \cap |\Phi_{4-star}|}{|\Phi_{ad}|}, \tag{4.18}$$

where $|\Phi_{ad}|$ denotes the total number of delivered advertisements, $|\Phi_{click}|$ denotes the total number of clicked/read advertisements, and $|\Phi_{4-star}|$ denotes the total number of receiver rating $\geq$ four-stars acceptance.

Figure 4.6 shows the CTRs of each step with respect to the different benchmark methods. After 4 steps forward, the 20 advertisements in "Random" and "Random+Path" respectively diffused 583 and 776 times in total and received 0.120 and 0.216 CTR, which means that our path planning mechanism improved by approximately 10% the chance for seeking business opportunities. The advertisements in the "Influencer" and "Influencer+Path" respectively diffused 852 and 1,067 times in total and received 0.264 and 0.347 CTR, which means that our path planning mechanism improved by approximately 8% the chance for seeking business opportunities.

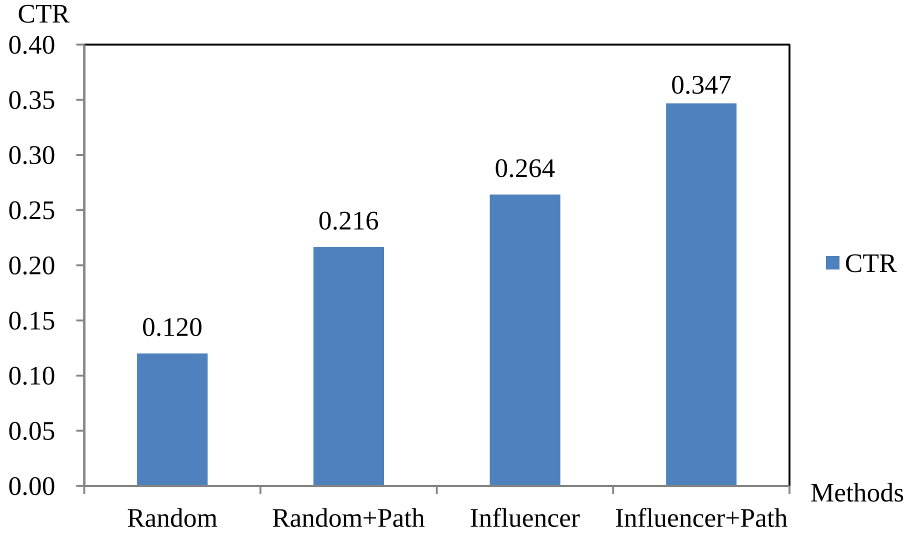


Figure 4.6 CTR in seeking business opportunities.

Furthermore, a 95% significance level two-paired sample t-test is used to evaluate the overall performance of different advertising strategies. The results are shown in the following Table 4.3. First, the test results show that the proposed path planning mechanism significantly improved the benchmark advertising methods. Besides, the diffusion effectiveness was also significantly improved if the path planning started from qualified starting points.

Table 4.3 Statistical verification of the CTR under seeking business opportunities strategy

Paired Group	Mean	Std Deviation	Std Error Mean	T value	Sig. (2-tailed)
Random+Path V.S. Random	0.098	0.123	0.027	3.604	0.002
Influencer+Path V.S. Influencer	0.109	0.202	0.045	2.392	0.027
Influencer+Path V.S. Random+Path	0.172	0.224	0.050	3.433	0.003

4.3.2 Establishing Brand Expression Strategy

The purpose of this marketing strategy is to enhance (four to five stars) or reverse (two to three stars) the brand expression of customers. However, it is very hard to reverse the brand expression of antis (zero to one star). It might even have the opposite effect in marketing strategies. The CTR with the acceptance condition formula is defined as:

$$CTR = \frac{|\Phi_{click}| \cap |\Phi_{2-star}|}{|\Phi_{ad}|}, \tag{4.19}$$

where $|\Phi_{ad}|$ denotes the total number of delivered advertisements, $|\Phi_{click}|$ is the total number of clicked/read advertisements, and $|\Phi_{2-star}|$ denotes the total number of receiver ratings $\geq$ two-star acceptance.

The Figure 4.7 shows the CTR using different benchmark methods. The 20 advertisements in “Random” and “Random+Path” diffused in total 985 and 1,243 times and received 0.160 and 0.221 CTR, which means that our path planning mechanism improved by approximately 6% the chance for establishing brand expression. The advertisements in the “Influencer” and “Influencer+Path” respectively diffused 1,601 and 1,887 times in total and received 0.252 and 0.321 CTR, which means that our path planning mechanism improved by approximately 7% the chance for establishing brand expression. Finally, the result of the overall performance of different approaches is further evaluated by two-paired sample t-test and shown in Table 4.4. At the 95% significance level, all the test results show that the proposed path planning mechanism significantly improves the other advertising approaches.

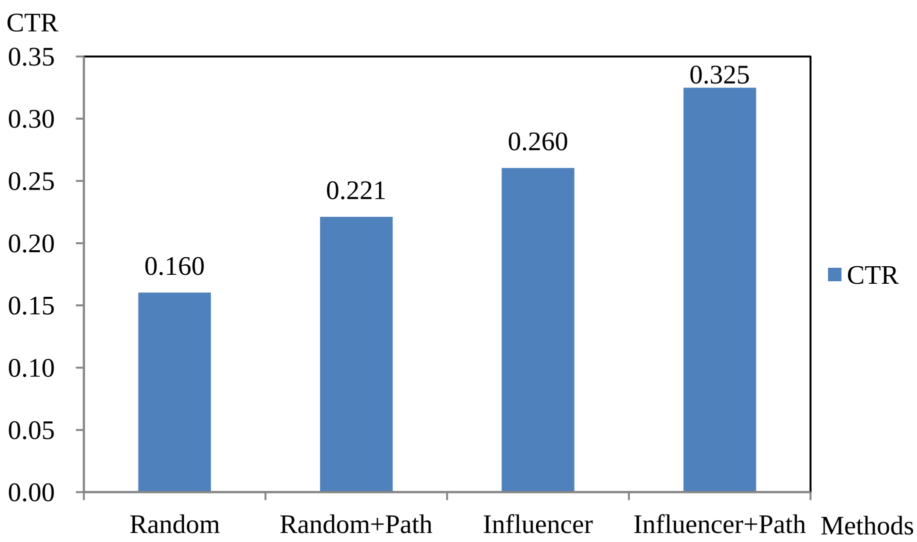


Figure 4.7 CTR in establishing brand expression.

Table 4.4 Statistical verification of the CTR under establishing brand expression strategy

Paired Group	Mean	Std Deviation	Std Error Mean	T value	Sig. (2-tailed)
Random+Path V.S. Random	0.074	0.131	0.029	2.529	0.020
Influencer+Path V.S. Influencer	0.072	0.124	0.027	2.609	0.017
Influencer+Path V.S. Random+Path	0.076	0.106	0.023	3.206	0.005

4.3.3 Exposure Ability in Different Strategies

Advertisers are concerned about the effective exposure for their advertisements. The proposed APPM would plan a suitable diffusion path for advertisements following different strategies. In one of the diffusions, the total number of message receivers in addition to the people who are included in the planned diffusion path gives the message exposure range of path planning. For instance, as shown in Figure 4.1, the nodes u_1, u_2, u_3, and u_4 are the exposure range of the planned diffusion path. Because the path was broken by node k_2 (k_2 delivers the marketing information to nodes u_1 and u_2 rather than the planned node k_3) and the system respectively replans the diffusion path for u_1 and u_2, the planned diffusion paths of the diffusion would be adjusted as shown in Figure 4.8.

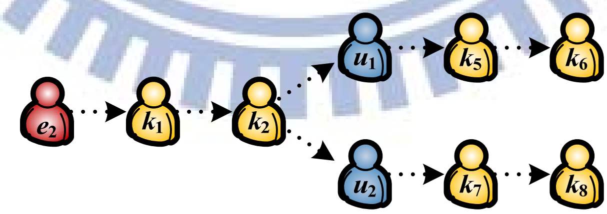


Figure 4.8 Adjusted diffusion path

However, the replanned diffusion paths still belong to the same marketing information diffusion process. The eventual number of message receivers of the diffusion is an important indicator for evaluating the performance of the planned diffusion path. The exposure ability (EA) is the average number of receivers of marketing information and it is formulated as follows:

$$EA = \frac{|\Phi_{receivers}|}{|\Phi_{mi}|}, \qquad (4.20)$$

where $|\Phi_{receivers}|$ is the total number of receivers in addition to the path nodes and $|\Phi_{mi}|$ denotes the total amount of delivered marketing information. EA is the average number of receivers per marketing information.

From Figures 4.9 and 4.10, we observe that the proposed APPM could enhance the exposure ability of product advertisements, if we ignore the acceptance of product advertisement. For the random advertising method, after forwarding for 4 steps, the APPM respectively improves by approximately 33% and 26% the exposure ability of the random advertising method in the seeking business opportunities strategy and in the establishing brand expression strategy. For the influencer advertising method, the APPM respectively improves by approximately 25% and 22% the exposure ability of the random advertising method in the seeking business opportunities strategy and in the establishing brand expression strategy.

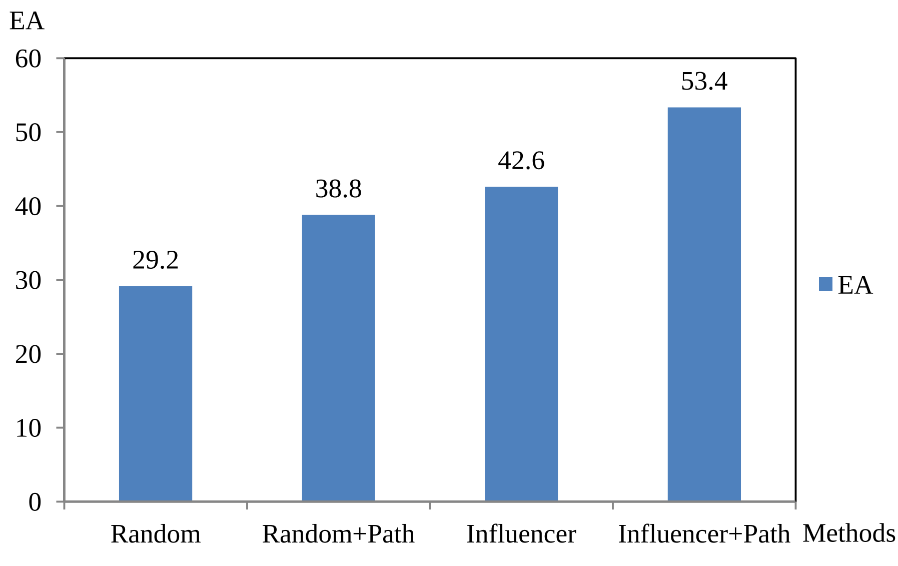


Figure 4.9 Exposure ability in seeking business opportunities strategy.

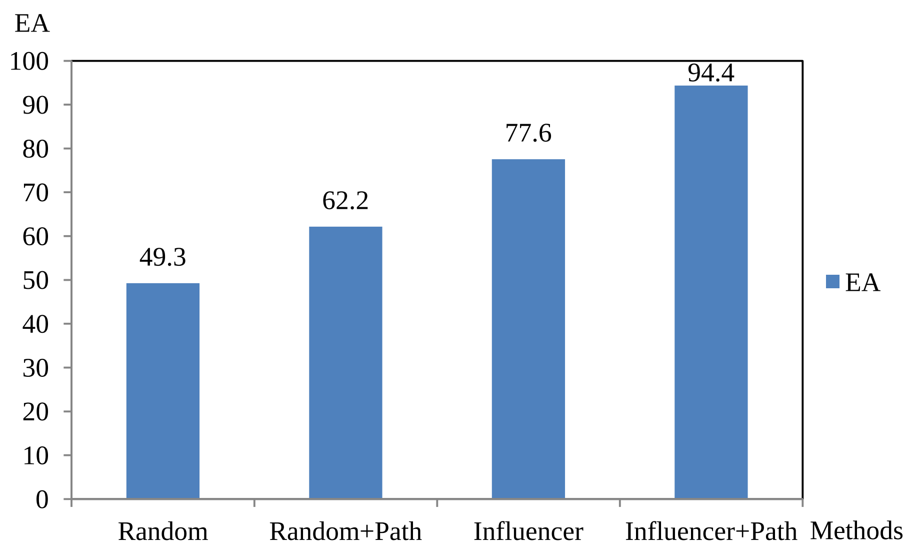


Figure 4.10 Exposure ability in establishing brand expression strategy.

Here, the paired sample t-test is also performed to provide further confirmation of the significant difference in the results of the benchmark approaches under different strategies, as shown in Table 4.5 and Table 4.6. At the 95% significance level, all the test results show that the advertising strategies with the APPM significantly outperformed the advertising strategies without the APPM. Therefore, they prove that our proposed strategy is the best compared with other strategies.

Table 4.5 Statistical verification of the EA under seeking business opportunities strategy

Paired Group	**Mean**	**Std Deviation**	**Std Error Mean**	**T value**	**Sig. (2-tailed)**
Random+Path V.S. Random	9.65	14.01	3.13	3.080	0.006
Influencer+Path V.S. Influencer	10.75	18.81	4.21	2.556	0.019
Influencer+Path V.S. Random+Path	14.55	17.36	3.88	3.748	0.001

Table 4.6 Statistical verification of the EA under establishing brand expression strategy

Paired Group	Mean	Std Deviation	Std Error Mean	T value	Sig. (2-tailed)
Random+Path V.S. Random	12.90	10.03	2.244	5.748	0.000
Influencer+Path V.S. Influencer	16.80	19.71	4.406	3.813	0.001
Influencer+Path V.S. Random+Path	32.20	20.06	4.487	7.176	0.000

4.3.4 Sharing Behavior Evaluation

This section further evaluates the sharing behaviors in different advertisement diffusion processes. As mentioned before, egoism and altruism are two of the significant factors of willing-to-share behavior. There are four delivery situations discussed, as shown in Table 4.7.

(1) Indicating that the forwarder expects to obtain positive recognition from receivers. It is the most beneficial to both the business opportunities seeking strategy and the brand expression establishing strategy.

(2) Indicating that the forwarder expects to influence the impression of receivers on a specific product/brand. It may be helpful to the brand expression establishing strategy.

(3) Indicating that the forwarder expects to inform the receivers of some promotion information of products. It is most beneficial to the business opportunities seeking strategy.

(4) Although this could also indicate that the forwarders expect to obtain negative recognition from receivers, it has no benefits to business. Furthermore, it is possibly just a blind delivery behavior. It is defined as ineffective propagation.

Table 4.7 Four delivering situations discussions

		Receiver	
		High preference	**Low preference**
Forwarder	**High preference**	(1) Egoism	(2) Altruism for establishing brand expression
	Low preference	(3) Altruism for seeking business opportunities	(4) Ineffective propagation

Then, we define the egoism ratio (ER), altruism ratio (AR), and ineffective delivery ratio (IR) for each advertisement diffusion process, as shown in Table 4.8, to evaluate whether the APPM could take advantage of the egoism and altruism sharing motivations. In the formulations, we simply define the high preference value (PF^H) as $PF \geq 0.5$ and the low preference value (PF^L) as $PF < 0.5$.

Table 4.8 ER, AR, and IR formulations of the experiment

	Seeking Business Opportunities Strategy	**Establishing Brand Expression Strategy**
ER	$ER = \frac{\lvert \Phi_{forwarder \cap PF^H} \cap \Phi_{receiver \cap PF^H} \rvert}{\lvert \Phi_{forwards} \rvert}$	
AR	$AR = \frac{\lvert \Phi_{forwarder \cap PF^L} \cap \Phi_{receiver \cap PF^H} \rvert}{\lvert \Phi_{forwards} \rvert}$	$AR = \frac{\lvert \Phi_{forwarder \cap PF^H} \cap \Phi_{receiver \cap PF^L} \rvert}{\lvert \Phi_{forwards} \rvert}$
IR	$IR = \frac{\lvert \Phi_{forwarder \cap PF^L} \cap \Phi_{receiver \cap PF^L} \rvert}{\lvert \Phi_{forwards} \rvert}$	

where $\left|\Phi_{forwards}\right|$ denotes the total times of forwarding of the advertisement, $\left|\Phi_{forwarder \cap PF^H}\right|$, $\left|\Phi_{forwarder \cap PF^L}\right|$ is the total number of forwarders who have high and low preference fitness, respectively, and $\left|\Phi_{receiver \cap PF^H}\right|$ and $\left|\Phi_{receiver \cap PF^L}\right|$ denote the total number of high and low preference fitness receivers who receive the advertisement from the forwarders.

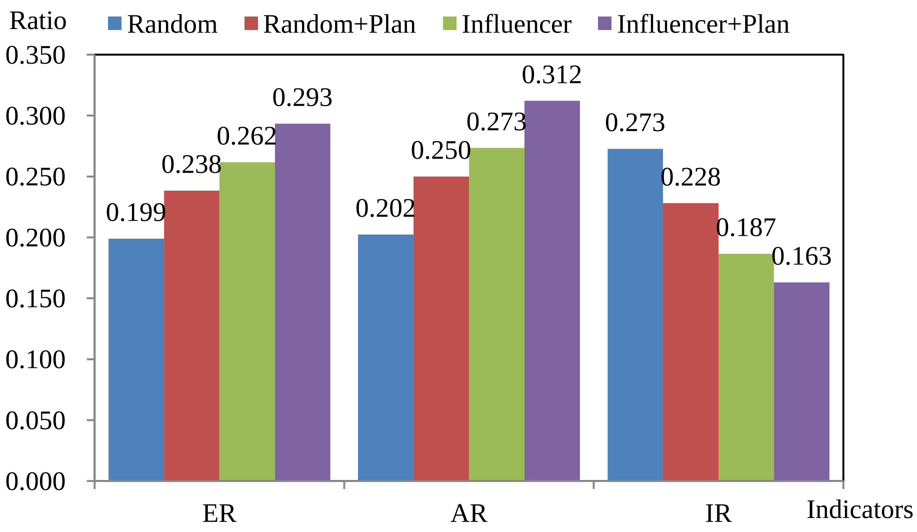


Figure 4.11 Sharing behavior evaluations in seeking business opportunities strategy

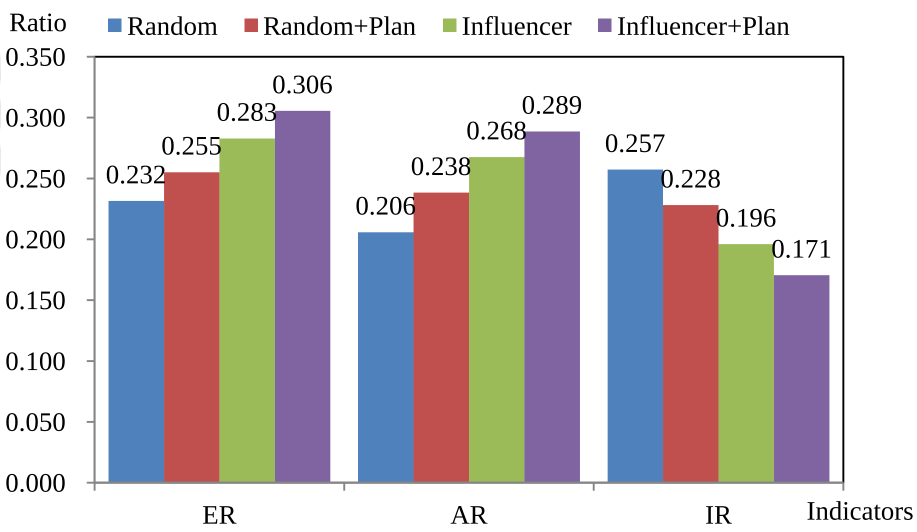


Figure 4.12 Sharing behavior evaluations in establishing brand expression strategy

From Figures 4.11 and 4.12, it is easily observed that the proposed APPM could take advantage of the egoism and altruism sharing motivations and decrease the ineffective delivery ratio in both strategies. Besides, we found that all of the ARs are higher than the ERs in the seeking business opportunities strategy. This indicates that the altruism-motivated users (with a higher value of $sb(\cdot)$) are helpful to business opportunity seeking. Because of that, if the altruism-motivated users do not have a preference for the information, they are still willing to share the information with friends who might like it. In the brand expression establishing strategy, all of the ERs are higher than the ARs, which means that the egoism-motivated users (with a higher value of $PF(\cdot)$) are more beneficial to establishing brand expression. Because the egoism-motivated users expect to obtain responses and reputations, they are willing to share the information that they know and are interested in.

4.4 Chapter Summary

In this chapter, an advertisement path planning mechanism, named APPM, which is based on probability and optimization models, is proposed to support marketers' online information diffusion process in micro-blogosphere. The mechanism treats the diffusion problem as a sequential optimization problem. It incorporate preference fitness analyzing, transition flow inferring, customer value evaluating, and diffusion path planning techniques to plan the optimal diffusion path for influential social nodes. To identify the transition probability of the possible transition states, we first construct an interaction network based on the daily social interactions within a social network. Then, in order to identify the personal preference fitness between the user and the product marketing information, the LSI-based methodology is applied to identify the preference fitness of users from their daily micro-blogging messages. The concept of the Markov chain is used to derive the transition probabilities between the active social nodes. To determine the diffusion value of social nodes, social network analysis based on the constructed interaction network is adopted to obtain the information influenceability and the reachability of social nodes. Finally, to plan the diffusion path for marketing information under different strategies starting from the social node that was previously recommended by the other influencer discovery mechanisms, a simple probability model consolidating the other sub-modules is utilized to calculate the expected value of path planning.

CHAPTER 5 SOCIAL TRUST

In this chapter, a Social Referral Mechanism (SRM) is proposed to help buyers refer to the reputations of possible sellers via their social networks. Buyers usually rely on online evaluation systems to select sellers to make transactions [36,90]. However, trust fraud issues still exist, as there are many ways to manipulate online evaluations. This increases online transaction risk for buyers. While a buyer would like to purchase a product from an online marketplace, he/she would search the possible sellers. Then, the buyer could sequentially feed target sellers into the social referring mechanism. The proposed seller referral mechanism will discover the possible referral candidates of the specific buyer. The referral candidate is defined as the one who have transaction experience and rating records of the target seller in the social network.

5.1 Social Referral Mechanism

Due to the trust fraud issues, those who want to make a transaction with a seller and mistrust the official evaluation system might rather rely on the evaluations of friends if they have made transactions with the same seller. Recently, most EC platforms have linked their services with other social networking services to drive more traffic to their marketplaces. For example, Yahoo! Auctions in Taiwan allow users to sign into the online marketplace using their Facebook accounts. Although most current EC platforms operate without social networking services, with the advantage of linking platforms, the proposed SRM could refer to a target seller's reputation from friends.

As shown in Figure 5.1, a buyer wants to make a transaction with s_1 and four connected and experienced users (rc_1, rc_2, rc_4, and rc_5) could be target referral candidates. Although rc_3 and rc_6 are also experienced users, they are strangers to the buyer because they not connected. The SRM would like to refer to the reputation of s_1 for the buyer to select a reliable seller. At first, the social analysis module analyzes the explicit (direct connection, e.g. the connection between the buyer and rc_1 and rc_2) and implicit (indirect connection, e.g. the connection between the buyer and rc_4 and rc_5) tie strength using daily interactions. Secondly, the expertise analysis module uses purchase histories to evaluate the expertise of rc_1, rc_2, rc_4, and rc_5. The ratings are more trustable if he/she has higher expertise in a specific product category. Thirdly, the referability analysis module derives the credibility of rc_1, rc_2, rc_4, and rc_5 according to their rating histories. Finally, the analyzed tie strength, expertise, and credibility of referral candidates is fed into the reference value analysis module to estimate the reliable reputation of s_1.

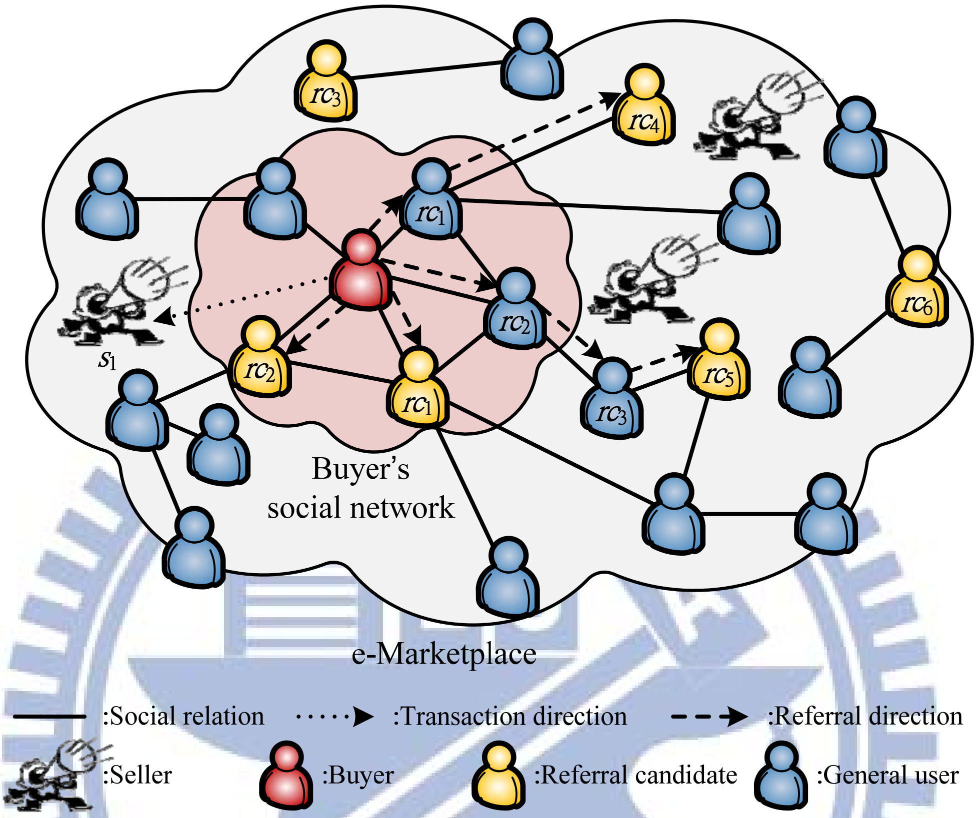


Figure 5.1 Illustration of social referral mechanism

Figure 5.2 briefly presents the concept and architecture of our proposed mechanism and the symbols used in the proposed mechanism are listed in Table 5.1. The proposed model comprises four main modules: the social analysis module, expertise analysis module, referability analysis, and reference value analysis module. Previous studies indicate that the tie strength between two people and the expertise of a person influence social trust [37,69]. The purpose of the social analysis module is to identify the tie strength between the buyer and each referral candidate. We apply the technique of social network analysis to derive social ties. The purpose of the expertise analysis module is to estimate the expertise of referral candidates. The RFM analytical model is used to derive the expertise of referral candidates. The purpose of the referability analysis module is to estimate the credibility of referral candidates. The statistical Z-scores and Pearson correlation coefficients are used to derive the rating tendency and co-orientation between the buyer and referral candidates. Finally, the trust scores of referral candidates are aggregated by using a linear combination method and the reference value estimated by using a weighted voting method in the reference value analysis module.

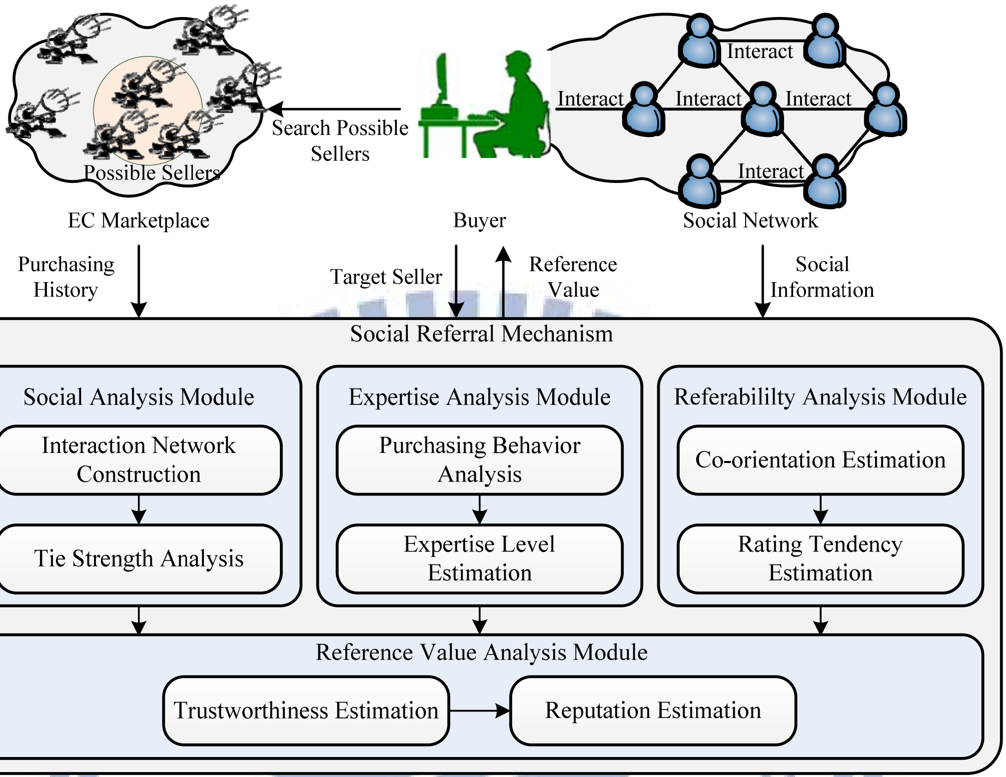


Figure 5.2 Seller referral mechanism

Table 5.1 Symbols used in social referral mechanism

Symbol	Description
$ts(i, j)$	Tie strength between referral candidates i and j
Recency	Last date of purchase in the product category
Frequency	Average products purchased in a certain time period
Monetary	Average amount money spent on one product
$el^c(rc_i)$	Expertise level of referral candidate (rc_i) under the category (c)
$co(b, rc)$	Co-orientation between buyer and referral candidate
$rt(rc)$	Rating tendency of referral candidate
$ref(b, rc)$	Referability of referral candidate for buyer
$tw(rc_i)$	Trustworthiness of a referral candidate
$td(d_p)$	Time decay rate for a specific time (d_p)
$rv(s_t)$	Reference value of a target seller (s_t)
$evaluation(s_t)$	Reputation evaluation of s_t

The procedures for conducting information diffusion over social media are described as follows. A marketer propagates marketing information by distributing ads to the starting endorsers, who could be selected according to some evaluation criteria such as influence or active strength. For each starting node, we recommend the diffusion path that is generated based on the aggregate reward, which is measured by information influenceability and ad reachability. In the mechanism, a diffusion path is generated for the purpose of aggregated reward maximization. A starting node is only aware of the first node in the planned diffusion path and decides whether to forward the ad to the node spontaneously. If a node breaks the planned diffusion path (does not pass the marketing information to the next node as planned in the diffusion path), the proposed system would replan a diffusion path from the breaking node.

5.1.1 Social Analysis Module

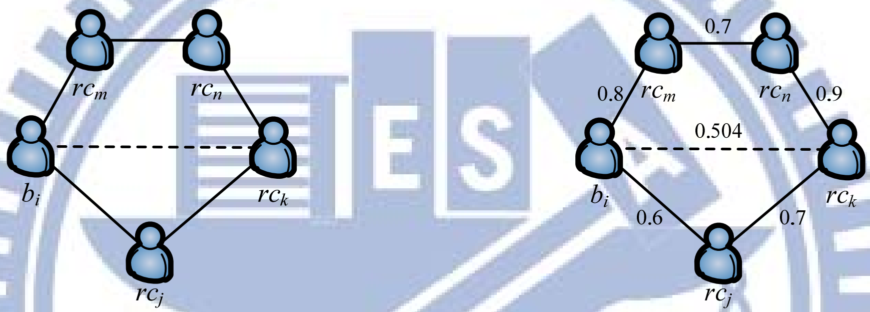
The purpose of this module is to identify tie strength based on the interactions between the buyer and referral candidates. If a person makes others favorable by making friendships or interacting with them, this person might recognize the extent to which the personal characteristics are attractive [14,102]. The influence of personal attractiveness on social networks can be extensively studied through life interactions [102].

Social interactions are used to construct a social network for identifying tie strength. Two social actors have a deeper acquaintanceship if there is stronger tie strength between them [98]. That is, the opinions or ratings given by these two social actors might be more trustable for each other than for others. Therefore, the goal of the social analysis module is to estimate the tie strength between the buyer and referral candidates in order to represent the degree of social acquaintanceship.

5.1.1.1 Interaction Network Construction

According to [28], social interaction tie strength is a combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services that characterize the tie. Intuitively, people would more frequently interact with friends with a stronger tie strength, which might have a greater impact on us.

On social media, social interactions can be captured from online posts and reply behaviors. For example, as shown in Figure 5.3-(a), buyer b_i has posted a message and referral candidate rc_j has replied to b_i. rc_j has posted a message and another referral candidate rc_k has replied to rc_j. There is a directly/explicit interaction connection between b_i and rc_j and between rc_j and rc_k. We can easily observe the indirectly/implicit connection between b_i and rc_k (the dotted line), because they are indirectly connected through rc_j (the friend-of-friend relationship). To construct the interaction network, we collect social interaction data from social media to discover stably maintained friendships. Then, we make an interaction network of referral candidates.



(a) Example for network construction (b) Example for tie strength estimation

Figure 5.3 Illustration of an interaction network

5.1.1.2 Tie Strength Estimation

After obtaining the interaction connections of the buyer and referral candidates, it can be easily observed that the explicit tie strength and implicit tie strength exist in the interaction network.

Explicit Tie Strength. In this study, the explicit tie strength, which is measured by the interaction frequency in a time period, is used to represent the acquaintanceship between the members of social media. The average number of interactions per week is used as the indicator of the explicit tie strength between nodes. The following formulation was used to determine tie strength (ts).

$$ts(i,j) = \frac{|si_{i,j}|}{|w|}, \tag{5.1}$$

where $|si_{i,j}|$ denotes the total number of social interactions between referral candidates i and j and $|w|$ denotes the number of data collection periods (weeks). Then the obtained tie strength would be normalized by min-max normalization as follows:

$$ts_{nor}(i,j) = \frac{ts(i,j) - \min_{ts}}{\max_{ts} - \min_{ts}}, \tag{5.2}$$

where the $\max_{ts}$ and $\min_{ts}$ respectively denotes the maximum and minimum tie strength in the whole network.

<u>*Implicit Tie strength.*</u> When a buyer is attempting to refer to a seller through their social network, the SRM would refer to the target seller from the buyer's direct and indirect friends who have experiences of making transactions with the seller. In practice, the explicit tie strengths among the social nodes can be directly observed through social interactions and the implicit tie strengths between two nodes indirectly evaluated from explicit connections. The calculation of the tie strength of an implicit connection such as b_i and rc_k in the above example is defined as follows:

$$ts_{nor}(i,k) = ts_{nor}(i,j) \times ts_{nor}(j,k) \tag{5.3}$$

Note that multiple connections between two nodes are likely to appear because people may connect to indirect friends via different paths. If implicit tie strength can be evaluated by multiple explicit connection paths, we use the maximum value as the implicit tie strength. For example, in Figure 5.3-(b), there are two explicit connection paths between b_i and rc_k. The implicit tie strength evaluated by $b_i \rightarrow rc_m \rightarrow rc_n \rightarrow rc_k$ (0.504) is greater than the strength evaluated by $b_i \rightarrow rc_j \rightarrow rc_k$ (0.42). The implicit tie strength between b_i and rc_k is thus evaluated as 0.504.

5.1.2 Expertise Analysis Module

The purpose of this module is to estimate the expertise of referral candidates. The RFM model is applied to provide a simple framework for quantifying customer behavior. A referral candidate with a higher RFM value in a specific category could infer that he/she has spent a lot of effort (i.e. time and money) on related products. This also implies that he/she might have more transaction experience with sellers and thus higher expertise. That is, his/her ratings are more trustable. This study adopts the RFM value of the referral candidate to represent his/her expertise in a product category. Here, we follow the treatment of Hughes [50] to perform the RFM analysis.

5.1.2.1 Purchasing Behavior Analysis

From the perspective of R (Recency), the buyer currently makes transactions in the product category, which means that he/she has the experience to confirm the current quality of the seller. In this research, the value of R is defined as the last date of purchase in the product category. From the perspective of F (Frequency), if a buyer has repeatedly made transactions in the product category, which means he/she might an experienced buyer, he/she can evaluate the sustained quality of the seller. The value of F is defined as the average number of products purchased in a certain time period. From the perspective of M (Monetary), this represents how much risk the buyer is willing to bear for making a transaction in the product category. For example, a buyer purchases a product with a price of 1,000 dollars and then gives the seller a rating; then, another buyer purchases a product with a price of 10 dollars and then gives the seller a rating. The effort for surveying a reliable seller and the risks associated with these two given ratings are greatly different. Buyers tend to carefully scrutinize and select sellers from which to purchase high-priced products but they might not carefully select sellers before purchasing products with a low price [129]. In this research, we modify the common definition of M (the amount of money spent of total purchases) as the average amount of money spent on one product.

The referral candidate's R, F, and M variable values under the category of buyer's target product are defined as follows:

$$Recency = \text{the last date of purchase in the category}, \tag{5.4}$$

$$Frequency = \frac{\text{total \# of purchased products in the category}}{\text{total \# of months}}, \tag{5.5}$$

$$Monetary = \frac{\text{total \# of spent money in the category}}{\text{total \# of bought products}}. \tag{5.6}$$

5.1.2.2 Expertise Level Estimation

The purpose of RFM scoring is to translate customer behaviors into numbers to be further analyzed. Generally, the most common RFM scoring method is the customer quintile method [49,50], which sorts the values of the R, F, and M variables in descending order and assigns them to five scoring intervals from 5 to 1. The top 20% is assigned the value of 5, while the value of 4 is given to the next 20% and so on. The customer quintile method has the advantage of convenience because it segments equal numbers of customers into different groups. However, it does encounter some scoring challenges in the area of F values [121]. In most marketplaces, a high percentage of customers have only ordered once. If more than 20% of customers only shop once, then the lowest frequency group cannot hold all of the customers with only one shopping behavior, and thus some of them will be segmented into the two score groups.

The mean scoring method, introduced by Miglautsch [84], overcomes the problem of frequency scoring mentioned above. While scoring the F value, one-time shoppers are first given a score of 1. Then, the scoring system averages the remaining customer records to determine the mean. If a customer's shopping frequency falls below the mean, he/she receives a score of 2. This process is repeated for scoring the remaining customers of 3, 4, and 5.

In this study, the customer quintile method is used for scoring R and M and the mean scoring method is used for scoring F. Then, we sum the scores of R, F, and M. A higher score indicates a higher expertise level. The expertise level (el) of referral candidate (rc_i) under the category (c) is defined as follows:

$$el^c(rc_i) = w_r \times Score(R_i^c) + w_f \times Score(F_i^c) + w_m \times Score(M_i^c)\,, \tag{5.7}$$

where the w_r, w_f, and w_m respectively indicates the scoring weightings of R, F, and M. The weighting strategies would be further discussed in Section 5.3.1.

Then, the obtained expertise level would be normalized by min-max normalization as follows:

$$el_{nor}^c(rc_i) = \frac{el^c(rc_i) - \min_{el}}{\max_{el} - \min_{el}}\,, \tag{5.8}$$

where the $\max_{el}$ and $\min_{el}$ respectively denotes the maximum and minimum expertise level among all of the referral candidates.

5.1.3 Referability Analysis Module

The purpose of this module is to estimate the referability of the referral candidate. It is common that biases exist when humans make rankings or assess the performances of others [81]. These biases could give referred sellers unfair advantages or disadvantages. In this section, the referability of referral candidates is analyzed by their rating tendency and grading standards (perceptions of criteria). If there is no special rating tendency (e.g. used to give higher or lower ratings) and grading standards are more fit in our mind, the referability of the ratings given by the referral candidate should be higher than others.

5.1.3.1 Co-orientation Estimation

Co-orientation, one of the factors of source credibility theory, is defined in Table 2.1. In this research, co-orientation is further depicted as having similar perceptions of criteria to evaluate a target such as a seller, product, service, and so on.

A seller rating (Positive, Neutral, or Negative) reflects the aggregation of the evaluations of decision criteria, such as item quality, a seller's service, and the shipping time of the transaction. Although everyone uses the same criteria to evaluate sellers, the perception varies from person to person for the decision criteria. For example, if the shipping time of a seller is 3 days, one buyer gives a negative rating to the seller because his/her perception of the shipping time is 1 day and another buyer gives a positive rating to this seller because his/her perception of the shipping time is 7 days. However, if the rating is given by the one who has similar perceptions of criteria to us, it is a more referable rating.

The perception similarity can be estimated by comparing the rating records of buyer (b) and referral candidate (rc) for co-rated sellers (s). That is, only rating records of the same seller by buyers and referral candidates can be used to estimate the co-orientation ($co(b,rc)$). The Pearson correlation coefficient [9], one of the most widely used coefficients in CF methods, is adapted as follows:

$$co(b,rc)=\frac{\sum_{i=1}^{n}\left(r_b^{s_i}-\overline{r_b^{s}}\right)\left(r_{rc}^{s_i}-\overline{r_{rc}^{s}}\right)}{\sqrt{\sum_{i=1}^{n}\left(r_b^{s_i}-\overline{r_b^{s}}\right)^2}\sqrt{\sum_{i}^{n}\left(r_{rc}^{s_i}-\overline{r_{rc}^{s}}\right)^2}}, \tag{5.9}$$

where the $r_b^{s_i}$ and $r_{rc}^{s_i}$ respectively indicates the rating of b and rc for the co-rated seller s_i, $\overline{r_b^{s}}$ and $\overline{r_{rc}^{s}}$ respectively indicates the average rating of b and rc for s. Note that, $s_i \in s$.

5.1.3.2 Rating Tendency Estimation

Leniency error indicates that a rater's tendency is to rate all alternatives at the high end of the scale or at the low end of the scale [81], which means that the rater over-emphasizes either positive or negative behaviors. Under the concept of rating tendency, if a rater tends to give higher or lower ratings, it means that the referability of these ratings from the rater should be decreased or increased.

By using the Z-score, more accurate relative preferences that reflect the tendency of a user's ratings can be acquired [40]. Here, we apply Z-score measures to calculate the rating tendency of a referral candidate. The rating tendency of referral candidate ($rt(rc)$) is measured by the average difference between the past ratings by a referral candidate and the average ratings of general users for the same sellers:

$$rt(rc)=\frac{1}{n}\sum_{i=1}^{n}\frac{r_{rc}^{s_i}-\overline{r_u^{s_i}}}{\sigma_{r_u^{s_i}}}, \tag{5.10}$$

where the $r_{rc}^{s_i}$ indicates the past rating of referral candidate for the co-rated seller s_i, $\overline{r_u^{s_i}}$ is the average ratings of the general users for s_i, $\sigma_{r_u^{s_i}}$ is the standard deviation of the ratings of the general users for s_i.

After analyzed the co-orientation and rating tendency, the following formulation is used to calculate the referability of referral candidate for buyer ($ref(b,rc)$).

$$ref(b,rc) = \begin{cases} co(b,rc) \times \left(1 - rt(rc)\right), \text{ if } rt(rc) > 0 \\ co(b,rc) \times \left(1 + |rt(rc)|\right), \text{ if } rt(rc) < 0 \end{cases} \tag{5.11}$$

Then, the obtained referability would be normalized by min-max normalization as follows:

$$ref_{nor}(b,rc) = \frac{ref(b,rc_i) - \min_{ref}}{\max_{ref} - \min_{ref}}, \tag{5.12}$$

where the $\max_{ref}$ and $\min_{ref}$ respectively denotes the maximum and minimum referability among all of the referral candidates.

5.1.4 Reference Value Analysis Module

The purpose of this module is to estimate the reference value of the target seller. Most online evaluation systems on EC platforms calculate the trust score of a seller by simply accumulating rating records. This means each rating record has an equal impact on a buyer selecting a seller. However, the ratings given by different raters should have different capacities and impacts on the evaluation of the buyers' seller search.

5.1.4.1 Trustworthiness Estimation

"Reputation" can be defined as a collective measure of "trust" based on the ratings assigned by the members in a community [55]. The tie strength and expertise level of a referral candidate are the two main factors that affect how trustable the ratings of the target seller are for the buyer. The linear combination method is used to estimate the trust scores of referral candidates as both tie strength and expertise level are positively correlated with trustworthiness. The trustworthiness of a referral candidate is defined as follows:

$$tw(rc_i) = el_{nor}^{c}(rc_i) + ts_{nor}(b, rc_i) + ref_{nor}(b, rc) . \tag{5.13}$$

The purpose of trustworthiness is to adjust the impact of the ratings given by other users on seller selection. The obtained trustworthiness is normalized to the interval of [0,2] by min-max normalization as follows:

$$tw_{nor}(rc_i) = \frac{tw(rc_i) - \min_{tw}}{\max_{tw} - \min_{tw}} \times 2 , \tag{5.14}$$

where the $\max_{tw}$ and $\min_{tw}$ respectively denotes the maximum and minimum trustworthiness among all of the referral candidates.

If the rater's trustworthiness is within the interval of (0,1), the impact of his/her rating on seller selection should be increased. If the trustworthiness of the rater is within the interval of (1,2], the impact should be decreased. Note that if trustworthiness is equal to 0 and 1, it indicates that the rating cannot be trusted and has no impact on seller selection. For example, for a positive rating given by a user with high trustworthiness, the impact on seller selection for the target buyer would be greater than 1. On the contrary, if it is given by a user with low trustworthiness, the impact would be smaller than 1. In addition, the impact of negative ratings should be adjusted by trustworthiness to make it greater or smaller than -1. Furthermore, the impact of a rating should be adjusted to 0 if it is given by a distrusted rater.

5.1.4.2 Reputation Estimation

Currently, most reputation systems provide sellers' e-marketplace reputations by simply accumulating buyers' ratings. Although sellers' reputations can be adjusted according to the obtained social tie strength and expertise level of raters, they should not only be adjusted based on the information of raters but also dynamically adjusted over time. For example, a rating given one month ago should have a greater reference value then a rating given six months ago because sellers might change their operation strategies or business partners. Thus, we introduce a simple time delay function for adjusting the reputation estimation. We utilize the basic power function to obtain the time delay ($td(\cdot)$) for a specific time as follows:

$$td(d_p) = \alpha^{-\left(\frac{d_c - d_p}{30}\right)}, \tag{5.15}$$

where d_c denotes the current date, d_p denotes the date when the rating was given by the referral candidate, $\frac{d_c - d_p}{30}$ is an estimate of the difference in months between d_c and d_p, and α is a constant of the time delay function. We are able to obtain different delay effects by adjusting the value of α. The value of α can be determined by iterative tests and practical experience. Figure 5.4 shows the delay effects of different values of α. The smaller the value, the slower the reputation delays and vice versa. The value of α can be adjusted according to the real situation of e-marketplaces.

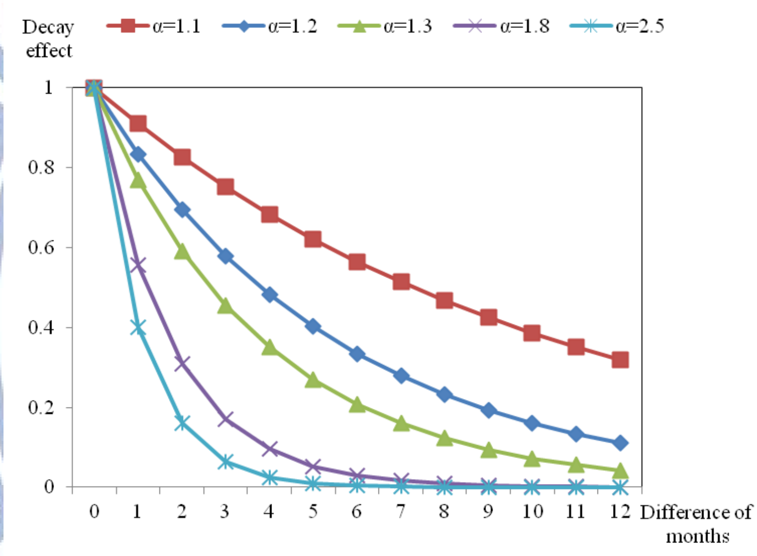


Figure 5.4 Time decay effects.

Finally, the weighted voting method is performed for estimating the reference value of the target seller. The reference value ($rv(\cdot)$) of a target seller (s_t) is defined as follows:

$$rv(s_t) = \sum_{i=1}^{n} \sum_{p=1}^{n} tw(rc_i) \times td(t_p) \times r_{rc_i}^{s_t, p} , \tag{5.16}$$

where the $r_{rc_i}^{s_t,p}$ denotes the rating of s_t which is given by rc_i in time period p. Note that, $r_{rc_i}^{s_t} = 1$ if rc_i gives a positive rating, $r_{rc_i}^{s_t} = -1$ if rc_i gives a negative rating, and $r_{rc_i}^{s_t} = 0$ if rc_i gives a neutral rating.

5.2 Experiments

In this section, we conduct experiments to evaluate the proposed SRM. To implement the mechanism, user information on the social network (e.g. social interactions) and online marketplace (e.g. purchase behaviors and seller ratings) is needed. However, most current social networking platforms, such as Facebook and Twitter, and EC platforms, such as Amazon and Yahoo! Shopping, are independently operated. The experimental data have to be independently collected. We constructed the experiment using Facebook, which is the most famous social networking site around the world for constructing social factors, and Yahoo! Auction, which is the largest online auction site in Taiwan for constructing marketplace factors.

Because of privacy issues, social interactions (wall postings in Facebook) and EC behaviors (purchase histories on Yahoo! Auction) are not allowed to be collected arbitrarily. In the experiment, the snowball sampling [37] method was used to collect experimental data. First, we invited six users willing to allow us to collect their social information and to provide their purchase histories to support the experiments. Then, we invited their friends and requested their friends invite friend-of-friends. Finally, 62 users participated in the experiment. There were totally 274 online transaction records in six categories (c1: cell phone and communications, c2: beauty products and makeup, c3: sports, c4: men's clothes and accessories, c5: women's bags and shoes, c6: women's clothes and accessories). These transactions were made with 81 sellers and each seller received an average rating of 3.38. There were totally 4,907 social interactions between participants. Data descriptions of the experiments are outlined in Table 5.2. Figure 5.5 shows the visualization of the collected friend network.

Table 5.2 Data descriptions of the experiment

Statistics of the experiment data	
Total number of invited participants	62
Total number of collected purchase histories	274
Total number of sellers for social referral	81
Average number of received ratings per seller	3.38
Average number of purchase behavior per participant (6 months)	4.42
Average number of interactions per participants (6 months)	79.14

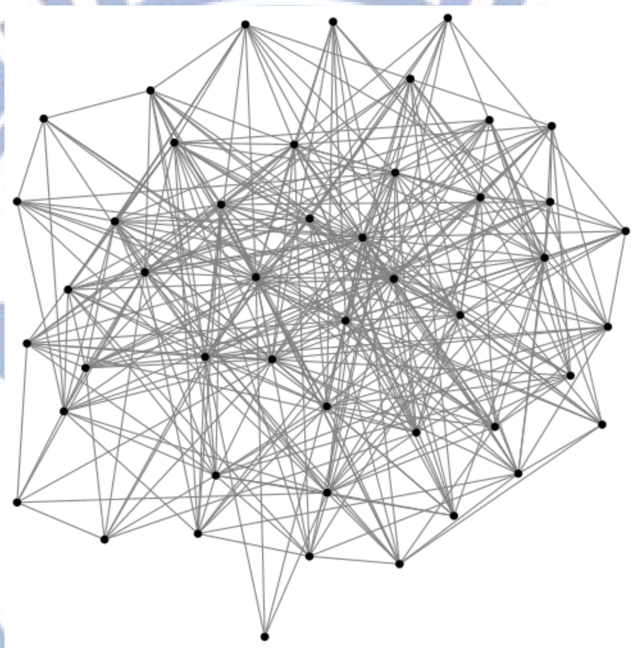


Figure 5.5 Visualization of collected social trust network

First, to construct the interaction network for analyzing tie strength, we collected and analyzed the past six months' wall postings, which is one of the most popular methods of user interactions [123] from Facebook. Second, to perform the RFM analysis for obtaining expertise level, we requested participants provide purchase history in the recent six months, including seller, purchase date, product name, product category, and seller's rating. After acquiring this social and historical information about participants, the experiment sequentially tested each transaction record, assuming that a buyer would like to make transaction with the specific seller. In addition, the buyer used the proposed mechanism to refer to the reference value of the seller from his/her social network.

5.3 Results and Evaluations

<u>Comparisons based on private evaluations.</u> The referral results are then compared with the real ratings of buyers on sellers. For example, if the seller referral result is positive and the real rating from the transaction record is positive, it means our mechanism can correctly refer to the evaluation of the online seller for the specific buyer. The accuracy rate of each category is calculated as the indicator. The tertile method in descriptive statistics is used to transform the reference values from numerical data to three-level ratings (Positive, Neutral, and Negative). The reference values are then sorted in decreasing order. Then, the threshold values of 0.88 (percentiles of 33%) and -0.62 (percentiles of 66%) are used for transforming. The evaluation of s_t ($evaluation(s_t)$) is set as following:

$$evaluation(s_t) = \begin{cases} 1, \text{ if } rv(s_t) \geq 0.88 \\ 0, \text{ if } 0.88 < rv(s_t) < -0.62 \\ -1, \text{ if } rv(s_t) \leq -0.62 \end{cases}. \tag{5.17}$$

The reference result is set to positive if $evaluation(s_t) = 1$, to negative if $evaluation(s_t) = -1$, and to neutral if $evaluation(s_t) = 0$. Finally, we utilize the following formulation to calculate the social referral accuracy rate according to the user ratings of the target sellers:

$$Accuracy = \frac{\text{total \# of seller referral results matching buyers' ratings}}{\text{total \# of seller referral results}} \times 100\% \tag{5.18}$$

5.3.1 Comparisons of Different Parameter Settings

In the proposed mechanism, the RFM scoring weightings and time delay function ($td(\cdot)$) are important factors for estimating the reference values of sellers. According to Hughes [50], each measure of R, F, and M has the same weight ($(w_r, w_f, w_m) = (1,1,1)$) when calculating a composite score. Libey [77] indicates that a different weight may be given to each measurement of RFM. This research points out that the scoring weighting set $(w_r, w_f, w_m) = (3,2,1)$ could show a better performance for computing a composite score. Furthermore, Miglautsch [84] states that $(w_r, w_f, w_m) = (9.9, 6.6, 3.3)$ is another scoring weighting setting for computing a composite score. The value of α in $td(\cdot)$ directly affects the delay effects. A suitable α value can be determined by practical experience or sequentially testing.

In order to determine the most appropriate values of factors with a better performance, we compare the performances of the experiments according to different combinations of RFM scoring weightings and values of α. Table 5.3 shows the mean absolute error (MAE) results under the six different word expansion levels and various trust delay rates. Here, we compare performance with the different settings of $(w_r, w_f, w_m) = \{(1,1,1), (3,2,1), (9.9, 6.6, 3.3)\}$ and α={1.1, 1.2, 1.3, 1.8, 2.5} . The effectiveness performance is evaluated based on the MAE (Mean Absolute Error):

$$MAE = \frac{1}{n}\sum_{t=1}^{n} | evaluation(s_t) - r_{b_i}^{s_t} |, \qquad (5.19)$$

where the $r_{b_i}^{s_t}$ indicates the real rating of buy b_i of seller s_t.

Table 5.3 Comparisons of appropriate factors

	α=1	**α=1.1**	**α=1.3**	**α=1.5**	**α=1.7**
(w_r,w_f,w_m)=(1,1,1)	0.511	0.453	0.401	0.394	0.504
(w_r,w_f,w_m)=(3,2,1)	0.453	*0.308*	0.646	0.730	0.796
(w_r,w_f,w_m)=(9.9,6.6,3.3)	0.434	0.438	0.668	0.745	0.799
	α=1.9	**α=2.1**	**α=2.3**	**α=2.5**	**α=2.7**
(w_r,w_f,w_m)=(1,1,1)	0.595	0.704	0.755	0.799	0.814
(w_r,w_f,w_m)=(3,2,1)	0.803	0.839	0.854	0.876	0.898
(w_r,w_f,w_m)=(9.9,6.6,3.3)	0.810	0.836	0.861	0.876	0.898

As a smaller MAE represents a more accurate result, we can observe that α=1.1 and $(w_r, w_f, w_m) = (3,2,1)$ has the best MAE performance in the experiments. Thus, in the following experiments, α=1.1 and $(w_r, w_f, w_m) = (3,2,1)$ are used. From the results, we can also observe that when $\alpha > 1.1$, the MAE values of each RFM scoring weighting becomes larger. This finding implies that the time impact of the seller's reputation for buyers might not delay very quickly (when α=1.1 the time delay rate approximates to 0.909 for each one-month period).

5.3.2 Comparisons of Referral Effectiveness

To evaluate whether the proposed SRM can help customers select superior sellers and prevent making transactions with fraudulent sellers in the online marketplace, we compare our mechanism with three benchmark methods. The four approaches used in the experiments are described as follows:

(1) SRM (our approach): The SRM considers factors from the perspectives of social, expertise, and referability to refer to a seller's reference value.

(2) EO: Expertise and co-orientation are two important factors for evaluating source credibility [43,106]. In this model, the EO model is treated as a basic referral method that exploits only the estimation of expertise analysis and co-orientation.

(3) CF: The basic concept of the CF model is that if the ratings are given by users that share similar tastes to us, these ratings would be more trustable [55]. In this model, only the interaction-based tie strength is taken into consideration to refer to the seller's reference value.

(4) Public: The current public seller's reputation extracted from the online marketplace.

Comparisons based on public evaluations. Here, the results are compared with the public evaluations of sellers given by the official evaluation system using the MAE method. In the experiment, the proposed SRM correctly referred to 204 of 274 seller evaluations. That is, as shown in Figures 5.6 and 5.7, the proposed mechanism showed a 79% accuracy rate and 0.308 MAE in the overall categories. The results verify that the seller evaluation based on the buyer's social network would be closer to the buyer's real evaluation than from the public evaluations.

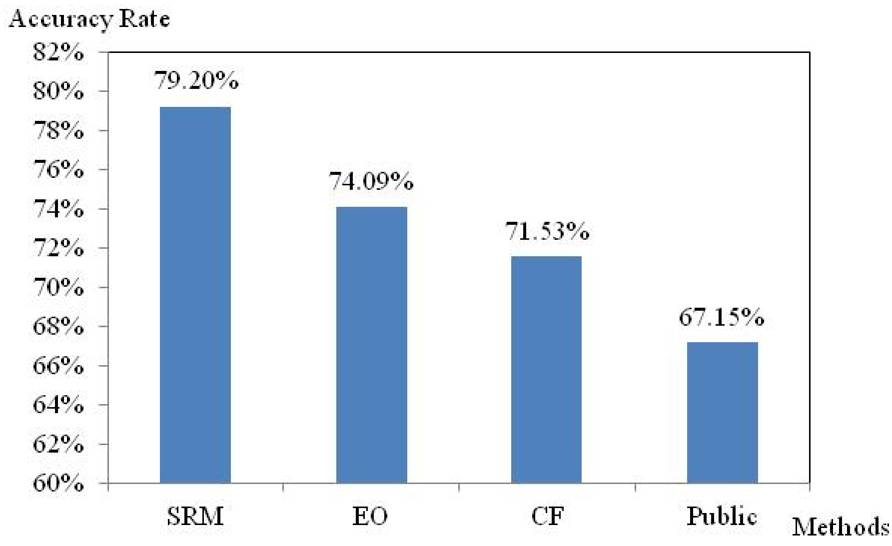


Figure 5.6 Accuracy rates in overall experiments

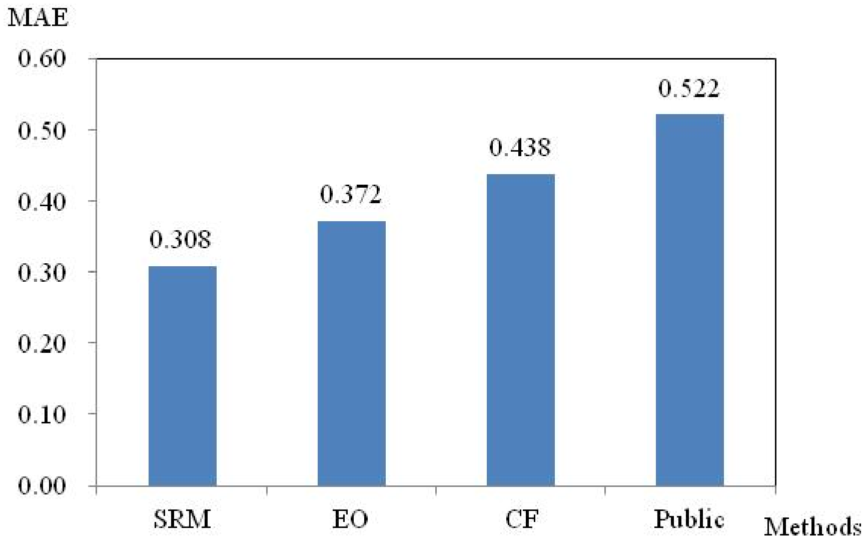


Figure 5.7 MAE rates in overall experiments

Table 5.4 Statistical verification of the referral results with different methods

Paired Group		Mean	Std. Deviation	Std. Error Mean	T value	Sig. (2-tailed)
SRM V.S.	EO	-.023	.987	.060	-.388	.031
	CF	-.010	1.051	.064	-.160	.013
	Public	-.731	1.040	.063	-11.635	.000

Finally, the result of the overall performance of the different benchmark methods is further evaluated by using a two-paired sample t-test, as shown in Table 5.4. At the 95% significance level, all the test results show that the proposed SRM significantly outperforms the other baseline seller referral approaches.

Detailed information is shown in Figure 5.8. In this figure, we can observe that the accuracy rate of c6 (women's clothes and accessories) is 83% and the accuracy rate of c1 (cell phone and communications) is 71%, which are the highest and lowest rates, respectively. According to our survey, around 38% of the collected purchase history records belong to c6. This might be attributed to fashion trends: most customers who bought similar products are likely to recommend sellers to their friends. As a result, the sellers in this category could be referred to by many more buyers than other categories and accuracy is statistically improved. In c1, most purchase records are one-time shopping trips for peripheral products for mobile devices. These kinds of products highly depend on personal preferences, so they are more difficult to make seller referrals. The MAE comparison results are shown in Figure 5.9. The results verify that the seller evaluation based on the buyer's social network is closer to the buyer's real evaluation than public evaluations.

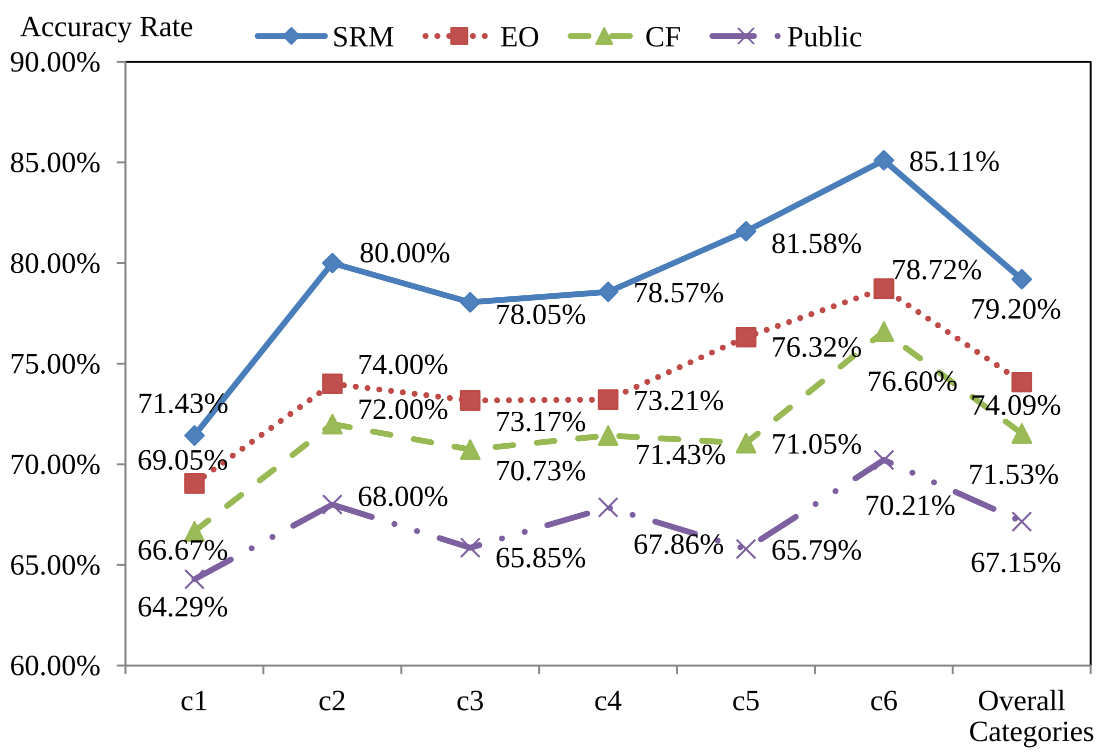


Figure 5.8 Accuracy rates in different categories

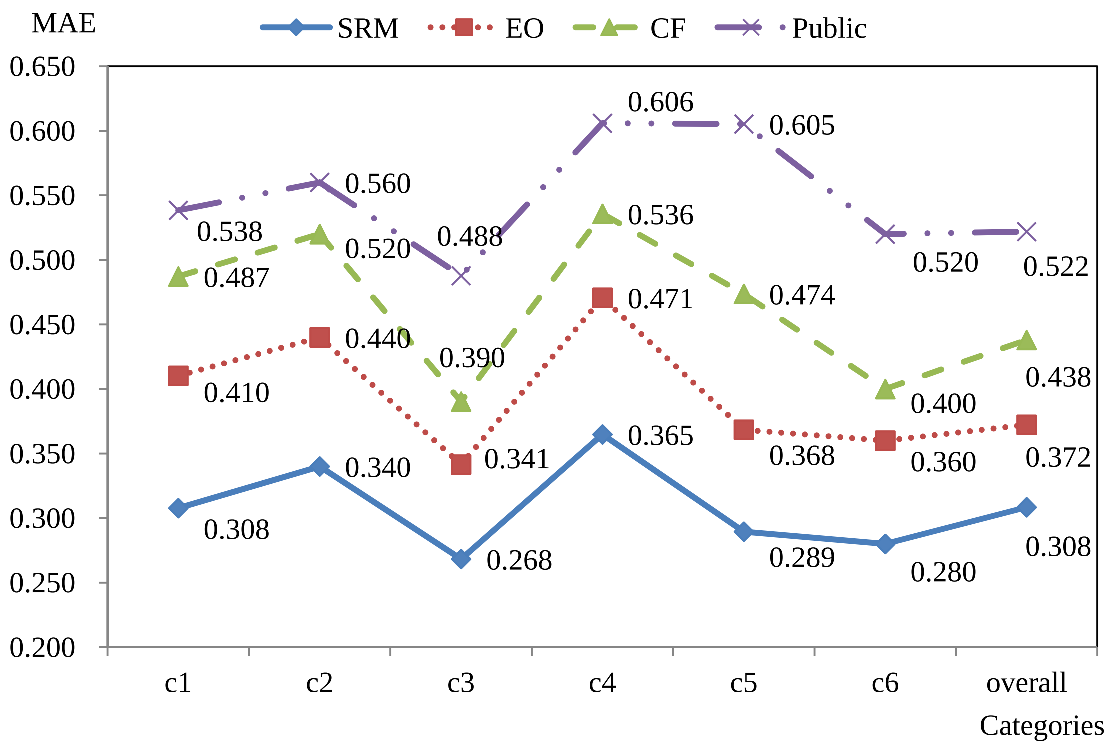


Figure 5.9 MAE rates in different categories

5.3.3 Additional Comparisons in Seller Recommendation

In this section, we build additional experiments in the seller recommendation scenario. The proposed SRM not only can be used to help the buyer refer to the reputation of a target seller via their social networks, but also can be used to recommend superior sellers to the buyer. We assume that the participating buyer does not know which seller's reputation he/she would like to refer to and make a transaction with. Then, the system recommends some sellers in a specific category to the buyer. Finally, the results are compared with the real purchase histories of buyers.

The experiments recommend three sellers to a buyer according to the values of $rv(s_t)$ rather than the transformed three-level ratings. Sellers are ranked by the values of $rv(s_t)$ and the system recommends sellers ranked in the first three ranking positions. Then, the results are compared with the real seller selections that buyers decide to make transactions with and the ratings of sellers by buyers. For example, if the system recommends s_a, s_b, and s_c to the buyer and from the transaction records the buyer makes a transaction with s_b and gives him/her a positive rating, it means our mechanism can correctly recommend online sellers for a specific buyer. Detailed comparison rules are listed in Table 5.5.

Table 5.5 Evaluation rule table

		User evaluation	
		Positive rating	Negative rating
System recommendation	Recommended	*RP* (Recommended with positive rating)	*RN* (Recommended with negative rating)
	Not recommended	*NRP* (Not recommended with positive rating)	*NRN* (Not recommended with negative rating)

According to [97], the precision, recall and F_1 measure rates of the seller recommender are defined as follows:

$$precision = \frac{RP}{RP + RN}, \tag{5.20}$$

$$recall = \frac{RP}{RP + NRP}, \tag{5.21}$$

$$F_1 = \frac{2 \times precision \times recall}{precision + recall}, \tag{5.22}$$

The results in Figure 5.10 show that the proposed SRM is more effective than other benchmark methods. The SRM received approximately 70% precision, 58% recall, and 63% for the F1 measure rate in the seller recommender scenario. This is because the outputted reputation values by the SRM are adjusted according to the social, expertise, and referability factors that are the essential credibility factors of raters. If it recommends a seller using the current public seller's reputation, it received the lowest effectiveness because most sellers' reputations are similar and this makes the mechanism fail to recommend the correct sellers to buyers. Detailed information on each product category of the SRM is shown in Figure 5.11.

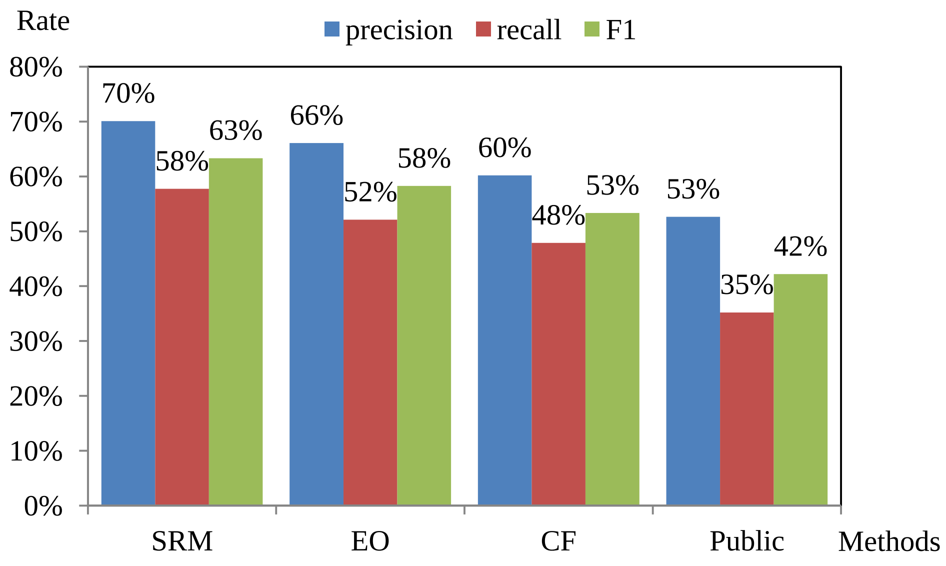


Figure 5.10 Additional comparison results in seller recommender scenario

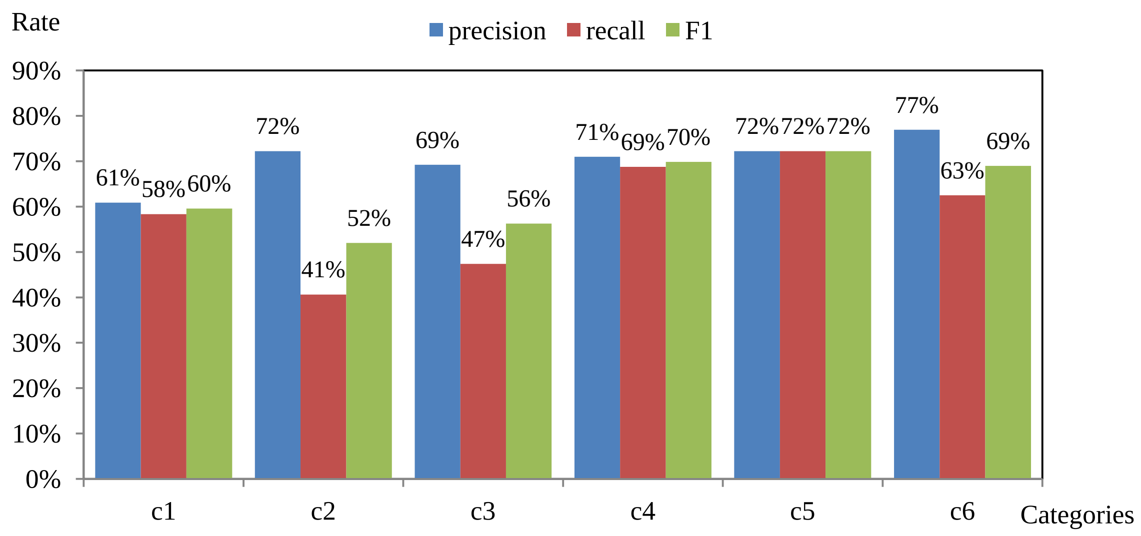


Figure 5.11 Detail comparison results in seller recommender scenario

Table 5.6 Statistical verification of seller recommender results with different methods

Paired Group		**Mean**	**Std. Deviation**	**Std. Error Mean**	**T value**	**Sig. (2-tailed)**
SRM V.S.	**EO**	.02054	.40736	.01421	1.446	.015
	CF	-.01158	.40785	.01423	-.814	.042
	Public	.51442	.28372	.00990	51.984	.000

Further, the results of the overall seller recommender performance of the benchmark methods are further evaluated by using a two-paired sample t-test, as shown in Table 5.6. At the 95% significance level, all the test results show that the proposed SRM significantly outperforms the benchmark methods in this scenario.

5.4 Chapter Summary

In this research, a framework of designing an SRM composed of a social network analysis, expertise analysis, referability analysis, and reference value analysis is proposed. In the social network analysis, the network is formed according to the message post and response interactions on social networking sites. We obtain the strength of explicit and implicit social ties to identify the attractiveness between the buyer and referral candidates. RFM analysis is utilized to estimate the expertise level of referral candidates from their purchase history records. In the referability analysis, the co-orientation and rating tendency is measured by Z-score to estimate the rating credibility of referral candidates. To successfully refer to the most trustable seller's evaluation from a buyer's social network, we aggregate the attractiveness, expertise, and referability of referral candidates to weight the evaluation of the seller that they gave. The experimental results show that the proposed SRM outperforms the other baseline benchmark methods.

CHAPTER 6 CONCLUSION

Social commerce is a term used to describe the online retail models or marketing strategies within the new digital economics which incorporate established social networks or interpersonal communications to raise sales. Many social network based applications were designed for business purposes. In this research, social appraisal mechanism, social path planning mechanism, and social reputation mechanism are proposed for collaboratively improving social commerce from the perspective of customer, vendor, and EC platform provider. This chapter concludes this research by discussing the contributions of the proposed mechanisms, identifying the limitations associated with the study, and offering recommendations for future research directions.

6.1 Discussion of Contributions

In the present research regarding the social appraisal mechanism from the perspective of customer, the methodological and practical contributions of this research are summarized as follows. First, from the perspective of system innovation, as online social intercourse and online shopping have become increasingly popular, the design of social appraisal systems becomes important. This research proposes a new and feasible mechanism seeking decision support from friends in the blogosphere. Second, from the perspective of methodology, the proposed framework appropriately integrates the techniques from various domains, such as social network analysis, text mining, fuzzy computing, and multi-criteria decision making, to resolve the decision-making problems of electronic commerce in the emerging social networking environment. Third, from the perspective of practice, through this proposed social appraisal support mechanism, users could treat their social networks as their own expert groups and leverage them for decision support. Although the aggregated public evaluations expressed on online review platforms (e.g. Amazon) are comparatively stable and objective, they may not really fit the preference and need of an individual decision requester. The proposed mechanism, which solicits and consolidates the comments from close friends, can better provide the more helpful and suitable support, and speed up the decision process.

In the present research regarding the social path planning mechanism from the perspective of vendor, the contributions and managerial implications of this research are summarized as follows. Firstly, from the perspective of system innovation, while social media marketing has become increasingly popular, little research has proposed a diffusion planning mechanism to support the influencers in boosting their advertising effectiveness for propagating information. We are one of the pioneers to treat the information diffusion problem as a sequential path planning optimization problem rather than a simple influential node recommendation issue. Secondly, from the perspective of methodology, we consider not only the individual preference and social influence (influenceability and reachability), but also behavioral factors (interaction transition probability and willingness-to-share) in the evaluation of the reward function to identify the path that could gain the maximum diffusion reward. Thirdly, from the perspective of performance, the evaluation results validate that the proposed mechanism can significantly improve the diffusion process of advertising messages and decrease the marketing uncertainty of marketers when they decide to deliver information for social media marketing. Even in the random influencer selection for choosing diffusion start points, the proposed path planning mechanism could support and improve the diffusion effectiveness and the mechanism would be able to achieve greater performance if combined with other influencer discovery mechanisms. Lastly, from the perspective of practice, the mechanism can support marketers in conservatively evaluating the possible information diffusion effectiveness under different marketing strategies and support the evaluated influencers in propagating information to specific individuals to continue the diffusion process. Furthermore, the proposed mechanism could take advantage of both the egoism and the altruism sharing motivations and decrease the ineffective delivery ratio under different marketing strategies.

In the present research regarding the social reputation mechanism from the perspective of EC platform provider, the contributions and managerial implications of this paper are summarized as follows. From the perspective of an EC platform provider, the proposed seller referral mechanism could help buyers prevent the trust fraud faced in the online marketplace and can effectively improve a healthy transaction environment. From the perspective of buyers, the proposed seller referral mechanism verifies the credibility of sellers according to the trustworthy ratings that could help buyers make transactions with the reliable sellers in the online marketplace. From the perspective of a seller, the system can reduce the risk of business transaction uncertainty, it could attract more buyers to be involved in the market platform and significantly increase the revenue of a seller. From the perspective of online marketplace, a more reliable reputation system is proposed that is helpful to deal with the online trust fraud issues. The proposed framework identifies those feedbacks given by trustworthy evaluators (i.e. friends) to evaluate the credibility of sellers and avoid the risk loss from purchasing a product from a bad seller, which may have a good public reputation. Besides, from the practical perspective, to our knowledge, most of the social network based EC mechanisms focus on products rather than sellers. So it would be helpful to consumers and expedite the EC activities if a more plausible seller evaluation mechanism could be equipped in the electronic market. In this paper, we aim to develop a seller referral mechanism to verify the credibility of sellers based on the experience of friends within a buyer's social network.

6.2 Limitations and Future Studies

There are several limitations and future studies to this research. First, due to the privacy issue, it is difficult to extract online personal data (e.g. social information and purchase histories etc.). Therefore, we invite participants to join in the experiments. If there are more users recruited and engaged, the accuracy of the proposed mechanisms will be more improved. Besides, in the current paper, the online postings in social media are used as social interactions for analyzing the strength of interpersonal relationships. In social media, there are many ways (e.g., messaging, applications, photo uploads, chat etc.) for users to interact with others. The analysis of relationship strength would be more comprehensive if more other interaction ways are considered.

Second, the essential concept of this research is that the closer friends might understand our preferences, habits, and needs better, so their opinions should be more reliable and suitable than others. Currently, the appraisal for purchase decision, key person for information deliver, and the reference values for seller selection are mainly estimated only by considering the evaluations given by close friends. However, there likely exist many good feedbacks contributed by people who are strange to us. How to further consider these trusty and referential evaluations and balance the impacts of opinions extracted from public and from friend should be a desirable extension direction.

Third, the mechanisms regard to analyze nature langue might not work with high effectiveness. As our observations, users used to express their opinions by short sentences in the social media. As a result, the information extracted from the online postings might not be sufficient to represent, for example, the criteria and evaluations of a product. Due to the problem of ambiguous nature langue (e.g. the user might tend to improvise new words and abbreviation) and they are a matter of taste, the semantic analysis might not well extract and represent the criteria and evaluations of a product. Besides, although the current adjective graph could satisfactorily identify most of the adjectives with high usage frequency, the adjective orientation might not be easily identifiable if users use words with low usage frequency. So that, the approach to extracting needed information from the online postings expressed in natural language could be elaborated.

Fourth, the directions of trustworthiness or social influence between users should be taken into considerations. It is one of important to the social advertising path planning issue. While determining the possible transition states and the transition probabilities, the concept of trust or the tie strength analysis between social nodes should be taken into account. The ratio based determination has possibility of data bias regarding the frequency of use under the period of data collection. Besides, in electronic marketplace, not only buyers could evaluate the reputations of sellers but also sellers could evaluate reputations of buyers. It would be also interesting to evaluate the trustworthiness of referral candidates from the perspective of sellers in the marketplace.

Fifth, the different social factors could be taken into consideration while building the social based mechanisms. The different social factor could be taken into consideration while formulating the diffusion reward function in the social advertising path planning mechanism. For example, if a social node located as a structural hole, the marketer might gain relatively great diffusion reward from him/her. In the social appraisal mechanism, in addition to the behavioral and structural dimensions, the method for measuring the importance or influence of the decision supporters might consider other factors. For example, the expertise or interest domain of the decision supporters could be considered.

Besides, the related thresholds should be taken into consideration while extending the social based mechanisms to a bigger scaled social network. For example, in the proposed advertisement path planning mechanism, if the mechanism would like to extend to multiple paths, the key players selection and the paths planning problems would increased the computational complexity. Only consider the nodes with transition probability higher than some threshold can exclude some nodes and speed up the computing process and increase the scalability of the mechanism.

Finally, social network based mechanisms generally investigate novel online services from many perspective, e.g. social structural and behavioral factors, personal and group characteristics, and public and private information. The impact of the different weighting methods of varied indicators in the mechanism could be further investigated. The effectiveness of designed mechanism might be improved if these indicators can be appropriately weighted.

APPENDIX

Publication List

Journal Papers

1. Yung-Ming Li, Chia-Hao Lin, and Cheng-Yang Lai, "Identifying Influential Reviewers for Word-of-Mouth Marketing," Electronic Commerce Research and Applications 9 (4) (2010), 294-304, 2010. (SSCI)
2. Yung-Ming Li, Cheng-Yang Lai, and Chien-Pang Kao, "Building a Qualitative Recruitment System via SVM with MCDM Approach," Applied Intelligence 35 (1) (2011), 75-88. (SCI)
3. Yung-Ming Li, Cheng-Yang Lai, and Ching-Wen Chen, "Discovering influencers for Marketing in the Blogoshpere," Information Sciences 181 (23) (2011), 5143-5157. (SCI)
4. Yung-Ming Li, Tzu-Fong Liao, and Cheng-Yang Lai, "A Social Recommender Mechanism for Improving Knowledge Sharing in Online Forums," Information Processing & Management 48 (5) (2012), 978-994. (SSCI)
5. Yung-Ming Li, Chun-Te Wu, and Cheng-Yang Lai, "A Social Recommender Mechanism for E-Commerce: Combining Similarity, Trust, and Relationship," Decision Support Systems 55 (3) (2013) 740-752. (SCI)
6. Yung-Ming Li, and Cheng-Yang Lai, "A Social Appraisal Mechanism for Online Purchase Decision Support in the Micro-Blogosphere," Decision Support Systems. (Under Revision 2nd) (SCI)

Conference Papers

1. Cheng-Yang Lai, and Yung-Ming Li, “A Social Referral Mechanism on e-Marketplace,” Proc. 15th International Conference on Electronic Commerce (ICEC 2013), Turku, Finland, August 2013.
2. Yung-Ming Li, and Cheng-Yang Lai, "A Diffusing Path Planning Mechanism for Marketing Information Propagation over Social Media," Proc. 46th Hawaii International Conference on System Science (HICSS-46), Maui, Hawaii, USA, January, 2013.
3. Yung-Ming Li and Cheng-Yang Lai, "Social Support Mechanism in Micro-blogosphere," Proc. 13th International Conference on Electronic Commerce (ICEC 2011), Liverpool, UK, August, 2011.

4. Yung-Ming Li, Cheng-Yang Lai, and Ching-Wen Chen, "Identifying Bloggers with Marketing Influence in the Blogoshpere," Proc. 11th International Conference on Electronic Commerce (ICEC 2009), Taipei, Taiwan, August, 2009.
5. Yung-Ming Li, Cheng-Yang Lai, and Chia-Hao Lin, "Discovering Influential Nodes for Viral Marketing," Proc. 42th Hawaii International Conference on System Science (HICSS-42), Manoa, Hawaii, USA, January, 2009.
6. Yung-Ming Li, Cheng-Yang Lai, and Chien-Pang Kao, "Incorporate Personality Trait with Support Vector Machine to Acquire Quality Matching of Personnel Recruitment," Proc. 4th International Conference on Business and Information (BAI 2008), Seoul, Korea, July, 2008.

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