A Study on Decision Support System to Enhance Notification in a Mobile Market Place Environment

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by

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CERTIFICATE

This is to certify that the thesis entitled "A Study on Decision Support System to Enhance Notification in a Mobile Market Place Environment" submitted by Amer Ali Sallam Farea bearing Reg. No 07MCPC21 in partial fulfilment of the requirements for the award of Doctor of Philosophy in Computer and Information Sciences is a bonafide work carried out by him/her under my/our supervision and guidance.

The thesis has not been submitted previously in part or in full to this or any other University or Institution for the award of any degree or diploma.

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DECLARATION

I Amer Ali Sallam Farea hereby declare that this thesis entitled "A Study on Decision Support System to Enhance Notification in a Mobile Market Place Environment" submitted by me under the guidance and supervision of Dr. Siba K. Udgata, Department of Computer and Information Sciences, University of Hyderabad, Hyderabad is a bonafide research work. I also declare that it has not been submitted previously in part or in full to this University or any other University or Institution for the award of any degree or diploma.

Date: Amer Ali Sallam Farea

DEDICATION

I would like to dedicate this Ph.D thesis to My Family and Friends.

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Amer A. Sallam Farea

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ABSTRACT

Electronic Market Place refers to the field of marketing, selling, buying and distributing different products or services over the internet but still lacks flexibility and convenience. This type of Market Place is limited according to convenience, diversity of accessibility, as well as in the personalization where the personal computer (PC) is often shared across multi-user. However, the huge increase in wireless technology increases the number of mobile device users and provides an opportunity for the rapid development of Mobile Market Place (MMP) using these devices. Hence, MMP, defined as the traditional Electronic Market Place (EMP) combined with mobile devices, Internet technology and wireless communications. Somehow, MMP has the capability of allowing users to conduct EMP activities on their mobile devices (such as Mobile phone, smart phone, Personal Digital Assistant, laptop, etc.): receiving/gathering sales information, selecting, making a purchase decision, paying for it, obtaining the service or product and delivering the right information to the right place at the right time without location and time constraints. These qualities make MMP prevalent in our daily life, and mobile users are more willing to do business on their mobile devices more readily.

Meanwhile, the internet technologies continue to develop, popularity of mobile terminals to increase, and the quantity of information on the internet is immense and increasing each day. Therefore, the mobile users are in need for a recommender system that can help them in their decision-making while interacting with large of information space among MMP. Hence, How to recommend the mobile user with the information that meets user/group needs, based on his/her/their profile and location is the core of this research. In fact, this thesis aims at presenting such aspects and

areas. It begins with introducing a general integrated architecture for Mobile Market Place (MMP) for efficient transaction and marketing using mobile devices and related infrastructure. This architecture describes the functionality of the different components of MMP in a single framework.

This thesis aims at improving the decision support system to enhance the quality and accuracy of the notification among mobile market place environment. Thus, this study searches the notion of recommending the useful information that fits each individual needs, as well as satisfying the group users desire. It is also desired that the recommendations that made to mobile user must be justified, in the sense that an explanation is to be provided as to why that particular item/service is of interest to the user. However, this recommended information not only helps in getting the items having high degree of interest with reasonable justification, but also considers the combination of user preferences, item features, recommendation reasoning and geographic location for both user/group and items.

Chapter 1

This chapter deals with a brief introduction to the research, and define the term of improving the decision support system to enhance the quality and accuracy of the notification among MMP environment through recommending the mobile user with the information of interest and based on location. Then we review the research issues in this context followed by the scope and the significant of the study, we list contributions in the summary.

1.1 Introduction

The huge increase in wireless technology increases the number of mobile device users and provides an opportunity for the rapid development of *Mobile Market Place (MMP)* using these devices. Hence, MMP, defined as the traditional *Electronic Market Place (EMP)* combined with mobile devices, Internet technology and wireless communications. The Internet technologies continue to develop, popularity of mobile terminals is also increasing, and the quantity of information on the Internet is immense and increasing each day. Somehow, MMP has the capability of allowing users to conduct EMP activities on their mobile devices (such as Mobile phone, smart phone, Personal Digital Assistant, laptop, etc.): receiving/gathering sales information, selecting, making a purchase decision, paying for it, obtaining the service or product and delivering the right information at the right place in right time without location and time constraints. These qualities make MMP prevalent in our daily life, and mobile users are more willing to do business on their mobile devices. Thus, MMP not only extends Internet-based EMP, but also provides many ways of information exchange and purchases methods, and it is likely to become a major business model in the near future. In fact, the essence of MMP revolves around the goal of reaching mobile users and suppliers, and satisfies whatever the users' demands by fitting the preferences of the users in combination with time and location whenever they want. In addition, MMP offers a unique business opportunity characterized by some unique attributes that equip it with certain advantages against traditional EMP (Ding X., et al.; 2004). These attributes can be summarized as follows:

- *Ubiquity and Accessibility*: Ubiquity is the main feature of MMP. It involves the delivery of services in the physical world and allows the mobile user to avail these services and carry out transactions in real time anywhere. This feature can be useful in many situations, viz. to access any interested information or conducting transactions while standing in a supermarket or while the move through different access modes of mobile devices whenever such a need arises. The immediacy of transaction helps capture mobile users at the moment of intention so that sales are not lost in the time between the point of intention and that of actual purchase.
- *Localization:* Positioning technologies such as the Global Positioning System (GPS), helps to achieve great success of providing information about mobile user's physical location at a particular moment, which can attract many service providers in particular time to offer goods and services- those services include information about price and location about the item of interest, nearest hotels, restaurants, travel information, etc. - to the user based on his current location. Thus, location-based services add significant value to MMP while EMP cannot offer such services.
- *Personalization*: It seems clearly that Mobile Devices are configured for a

single user where PC is often shared across resources and multiple users. This makes it possible to adjust a mobile device to the user's needs and interest via MMP applications. These applications can be personalized to obtain information or provide services in ways appropriate to a specific user rather than to search for that among huge number of information that are available on the internet.

- *Convenience*: the features of mobile devices and their ubiquity and accessibility make them a preferable tool for performing personal tasks. Thus, users are using their mobile devices more often than PCs and that is considered important clue to extend the way of interacting with people from EMP to more attractive way of conducting business like MMP. Moreover, MMP extends the current traditional sales channel of EMP into the more immediate and personalized mobile environment.
- *Dissemination*: MMP offers an efficient means to targeting large number of mobile users by disseminating data to all mobile users within a specific geographical region.

Accordingly, MMP should bring many benefits to mobile users, service providers, and telecommunication operators. From the customer point of view, he/she can access on-demand, at the point of purchase and obtain best prices that are available in the MMP domain. This can happen via mobile applications. Although MMP provides a technology to increase merchants' sales, it enhances management efficiency for service providers, as companies exchange product information with mobile users on time according to their personalized preferences. And that can be done via a web page promotion or a mobile alert to increase their willingness to buy a product. Also there is some portion on the part of telecommunication operators; viz. the more the MMP's services are used by mobile users through mobile devices; the more revenue can be achieved by telecommunication operators.

Meanwhile, MMP services are presently under transition with a record of many "tried and failed" solutions and a promising future but uncertain possibilities with a potential new technology innovation. Accordingly, MMP working over mobile agent technology has attracted a considerable attention, and a relevant body of literature has been published on the issue. However, there are still quite a lot of issues that have to be addressed and revolved for different factors, such as, improving the quality of publishing and advertising, increasing security, enhancing the delivering processes along with payment transaction, reducing search costs and locational efficiencies, in order to have an efficient MMP. Moreover, this agent should take into consideration the institutional infrastructures such as legal standardization and regulatory frameworks.

Somehow, the market place agent can be simply defined as an agent that acts on behalf of a user and moves through a network of heterogeneous machines. Its main functions (Ibrahim *et al.*, 2001) are: matching the requirement of buyers with available goods or services, then facilitating the exchange of information, and payments associated with market transactions. However, such agent needs to continually collect and integrate data distributed among huge set of users, sites and applications. As a result, it would help users in gathering relevant information of interest and enabling users to decide in timely manner. In addition, within this system, data would be exchangeable through a very large number of devices and heterogeneous type of information resources (Kaasinen 2003). This may lead to server resource contention, network overload and congestion. Therefore, such agent has to select appropriate methods of data delivery and use the most intelligent recommender system to serve user to meet his/her potential needs.

This thesis focuses on the issue of recommending the mobile user/group with the information that meets user(s) needs, based on the profile and location of the intended user(s). Technically speaking, the MMP offers a business model of buying and selling millions of goods and services. Among so many options, choosing is challenging for the user. Increasing choices, however, also increased the amount of information that users must process before they are able to select which items meet their needs. Thus, browsing and making decisions for buying an item in some MMP environment, considered as time-consuming and frustrating task. To address this information overload, a notification system integrated with a recommender system can tackle this problem and make it easier and more efficient through suggesting items for users that are likely to fit their needs, and to provide users with information to help them decide what to buy, and to decide where to buy from.

The goal of recommender systems is to help users in their decision making while interacting with large information space. They recommend data of interest to users based on their preferences they have expressed, either explicitly or implicitly. The ever-expanding volume and increasing complexity of information on the wired and wireless networks have therefore made such systems the essential tools for users in a variety of information seeking for MMP activities. Based on what kind of recommendation techniques is used, personalized recommender systems are usually classified into three categories (1) *Collaborative Filtering* (CF): recommending items to users that other users with similar tastes liked in the past (2) *Content Based* (CB): providing recommendations by comparing representations of content describing an item to representations of content that interests a user (3) *Hybrid Methods (*HM): combining the both techniques of CF and CB.

Several recommender systems have been proposed in the literature which makes use of the above techniques with different strategies like (Xue G. et al., 2005; George T. et al., 2005; Michael J. Pazzani, 1999; Schafer *et al.,* 2003; Dietmar *et al.,* 2010; Bharat *et al.,* 2010). However, these techniques fall into the category of CF algorithms and the problem with pure CF is that it treats all users and items as atomic units, where predictions are made without regard to the specifics of individual users or items.

There have been also several hybrid approaches which are proposed to combine the CB and CF. A general framework for CB/CF is proposed in (Prem et al., 2002; Abbar et al., 2009; Cantador et al., 2008; Adomavicius et al., 2005) where CB predictions are applied to convert a sparse user ratings matrix into a full ratings matrix, and then a CF method is used to provide recommendations. In (Salter J. et al., 2006; Jin R. et al., 2006; Chen 2005; Manouselis et al., 2007, George *et al.*, 2008; Yoshii *et al.*, 2008), CF is used to compute the predicted rating values and then CB is applied to generate recommendation list. These techniques are mainly aimed to improve the quality of recommendations and reduce the effect of the traditional CF cold-start problem but they have not consider the quality of group recommendation and the mobility attributes like location was apparently missing.

Likewise, as EMP and MMP communities have increased exponentially, and the need for *a group recommendation system* has also become more and more imperative. So we need systems for recommending items (books, movies, websites etc.) that take into consideration our own as well as group's interests. These systems are generally divided into two categories namely *personal recommender system* and *group recommender system* wherein the former is effective in filtering useful information that fits each user's needs, the latter provides suggestions for group decisions and satisfy individual user's needs in group activities. However, most of the previously published studies in recommender systems focus on the technique of building personalized recommender systems and hence, are not suitable for supporting group decisions making. They assume that the input of the system is comprised of item's ratings given by individuals and the group recommendation is obtained by combining or aggregating the individual recommendations of the members in the group. The problem with this approach is that (1) the ratings are combined without considering the interaction of group members which may lead to incorrect recommendations for a group. (2) It is difficult to specify the additional information which may be required from the user to determine the exact combination/aggregation strategy and (3) A lot of time will be required even if opinions from domain experts are sought after to guide the combination process.

Moreover, the recommendation techniques as cited above have mainly aimed to enhance the accuracy of recommendations by fine-tuning the respective algorithms. At the same time, it is also important to note that the acceptance of a recommender system is increased when users receive along with a recommendation the *reasoning* behind it. Such recommendations are called *justifiable recommendations.* They help improve customer attraction/retention and sales boosting because mobile users can evaluate the provided recommendations more easily and accept them if satisfactory. High quality justifications can be provided by combining the *content influence* of item's features along with rating data of user on items. The content and rating data are able to disclose the information of features influence among user interests. However, it should be kept in mind that though some of the existing recommender systems combine *content* with *ratings* and provide accurate recommendations, they cannot adequately justify them. This happens because (1) most of these systems are hybrid in nature wherein the technique of collaborative filtering (CF) and content based (CB) are run separately (J. Salter *et al.*, 2006; Markov*al.*,1997) thereby missing the dependence between user ratings and item features which in turn can be used for justifying a recommendation (Adomavicius G. *et. al.*, 2005). (2) Most existing hybrid systems cannot detect partial similarity of the user's preferences because similarity between two users is measured on the entire set of items they have rated. Therefore, partial matching cannot be used for justifying their grouping. (3) Most of the current hybrid systems focus only on accuracy wherein they have objective metrics for accuracy (Bilgic *et al.*, 2005; Jonathan *et al.*, 2004) but lacks metrics to evaluate the quality of recommendation.

Another important feature which most of the previous studies in recommender systems do not address is regarding *location* profile of an item/user. It is very important for a good recommender system to help users find the closest place that surely contains his/her items of interest. Nowadays location features are becoming a fundamental part of different mobile devices. Such features played important roles in enhancing the mobile location service, thus supplying the recommender system with an accurate transition towards context-aware and utilizing location based features can enhance the potential of user satisfaction towards the quality of recommendation that reveals user needs. It makes it possible to find and recommend items for user/group operating mobile devices based on his/her/their location. However, a user's preferences and item's features are also assumed to be directly related to recommendation quality. Though there has been a lot of work on location sharing applications wherein either people explicitly request another person's current location or where people broadcast their location to friends through social networks (Tang *et al.*, 2010), but a combination of user/item/explanation/ location based recommendation is still missing.

1.2 Thesis Scope and the Significant of the study

This study relies on introducing an integrated architecture for MMP and defines such architecture, by focusing on the heterogeneous nature of the components. It is intended to figure out the different components, their relationship, and importance in MMP, which realizes interaction between mobile users and merchants. We begin with proposing an integrated architecture for mobile marketplace for efficient transaction and marketing using mobile devices and related infrastructure. We have highlighted the main components that supposed to be addressed all together in single framework in order to have an efficient mobile market place. It is our belief that this architecture paves the way for future research in which more general modular approach can be explored to build more robust architecture for MMP environments.

The significance of this study lies in investigating a general robust integrated architecture and to show how decision support system can improve the quality of recommendation in a mobile market place environment. It searches the notion of recommending the mobile user with the information that meets user/group needs, based on his/her/their profile and location. In fact, the thesis, aims at presenting such aspects and areas. To achieve this goal, recommender systems can be applied to the domain of mobile marketplace. More precisely, in this thesis, a recommender system using individuals/group profile and location-based model for efficient recommendation is presented. The user/group preferences and item-features information provided as a series of numeric values. These values provide information about the characteristics of the items and give coherent clue about user/group interest. Such information used to make strong recommendation and provide reasonable justification. This system considers the combination of user preferences, item features, recommendation reasoning and geographic location for both user/group and items. As a result, the proposed method obtained a significant role in providing efficient and effective means for recommendation to enhance the quality of notification in MMP environment.

1.3 Contributions in Summary

The thesis can be summarized as below:

1. This study intends to introduce a general integrated architecture of MMP as discussed in chapter 3. This architecture integrates the main components of mobile market place and describes their functionalities through integrated architecture that facilitates the transaction process among the heterogeneous components of mobile marketplace (MMP). It analyzes a general integrated architecture that supports MMP rather than treating various technical aspects in isolation. Out of this architecture, our aim is to focus on how to provide mobile user/group with the information that meets such user/group needs, based on the profile and location of the intended user/group.

2. This work aims to propose an effective recommender system that can help mobile individuals /group formulate better decision-making by incorporating user/group profile preferences as well as the geographical location. Thus, it should subdivide a mobile marketplace into distinct subsets of users where any subset may be selected as group or individual target. This can lead to the creation of distinct recommendations according to the preferences of a specific users/group. To

achieve this, user profiles have been constructed and processed based on information related to users' ratings and item features. Such process reflects dependencies among items and users, thus disclosing user's rating behaviour. The next step is to assign weight on user's profile in order to show the features that are more interesting and peculiar to each user. Thereafter, grouping users and items into clusters based on the most coherent rating. A subsequent step is using neighbourhood technique- Cosine Similarity- to find the clusters that contain the partial matching with the target user/group. This is, in fact, carried through observing ratings/features patterns of users/items for the target user/group vs. the available clusters. Hence, items are identified based on similarity of their features that are selected together by a sufficient number of users. Then, a list of recommended items is generated along with reasonable justification.

In the experimental setup of our recommender system, a bicluster may denote a group of users that prefer some specific features. Collective features can be extracted by using groups rather than individual users. As far as a group recommendation is concerned, we assume that the input data contain item's ratings given by both individuals and groups and instead of calculating similarity between one test user and each bicluster, we calculate similarity between a group of test users and each bicluster " considering the duality of content and rating data ". For instance, if we have a group of users G = $\{u_1, u_2, u_3\}$ and suppose we have ratings of a particular item I_a by users u_1, u_2, u_3, subgroup $\{u_1, u_2\}$ and subgroup $\{u_2, u_3\}$. To predict what rating group G would give on an item, most of the previous researches will make their predictions only based on the ratings from users' u_1, u_2 and u_3, while some of the researches would ask users provide additional information and some others would ask the help of domain experts. In our work, for example, if users u_1 and u_2 rate the item I_a as 1 and 5, respectively, but they as a whole rate the item I_a as 4, then we realize that user u_2 seems play more influential role in this group, which somewhat reflects the personalities of users u_1 and u_2. Hence, our approach is capable of taking into account the dependency of features influence among the preferences of the majority of users so as to come up with reasoning behind the justification that gives credibility to the recommendation.

3. This system not only recommends items for individual/group of users with applicable recommendations based on their interest, but is also capable of providing an explanation for the actual reasons behind the recommendations for individual and group users alike. Hence, reviewing the features of user profile against the features of recommendations list is essential to make the justification of recommendation more reasonable and understandable by service provider as well as by the mobile user. Thus, by exploring the features of items that recommended to the target 'individual user/group' with his/her/their user profile, the coherent match appears. This similarity is much closer among the recommended items that have highest values of influence. In contrast, the values revealing poor influence are evidence of the poor matching between the features of both those items and the tested user/group. Both the high and low values can be taken to interpret the significance of the role of influence among the features and user/group profile. Thus, the list of recommended items which contains the highest influence values actually meets the interest of the tested user/group by involving the most desirable features that user/group are looking for. Hence, the system was able to grasp the user/group needs and recommend items accordingly. Meanwhile, it should emphasize that the items that got poor influence value with

individual user are not supposed to be eliminated during building the recommendation for group. When these values have been eliminated less accuracy of recommendations has been observed. Therefore, those values play important roles to improve the accuracy and the quality of recommendations for the group. In other words, the influence of content data among users' profiles has strong effect on the quality of the group recommendations. The influence values may changes from case to case for the same user due to items/users influence among the different groups. However, that change does not affect the accuracy of recommended items or the justification for the target user. This can also be considered as another aspect of the system ability of filtering useful information that fits each individual needs, as well as satisfying the group users activities. Thereafter, the items that already have been rated by user could be excluded or kept the same 'if needed' to provide a recommendation to the specific user about the new generation of item that user got/rated it before.

4. Finally, we have constructed the users/items location profile; the system has been subjectively designed not only to generate reasonable recommendation in respect to user/group interest, but also to help users find the closest place that surely contains their item of interest. However, the location of users may continuously be updated due to user movement but the recommendation has to take place according to the last updates.

1.4 Thesis Outline

The outline of the thesis is as follows:

Chapter 1: Introduction: This chapter deals with a brief introduction to the research, and define the term of improving the decision support system to enhance the quality and accuracy of the notification among MMP environment through recommending the mobile user with the information of interest and location-based. Then we review the research issues in this context followed by the scope and the significant of the study, then we list the contributions in summary.

Chapter 2: Related Literature: In this chapter, we review the important literature related to our work. The reviews are discussed under the following headings(1) The different architectures of MMP (2) Notification Service, (3) Recommender Systems.

Chapter 3: The Main components of MMP: This chapter intends to introduce an integrated architecture for MMP and defines such architecture, by focusing on the heterogeneous nature of the components. It is intended to figure out the different components, their relationship, and importance in MMP, which realizes interaction between mobile users and merchants. It begins with proposing an integrated architecture for mobile marketplace for efficient transaction and marketing using mobile devices and related infrastructure. We have highlighted the main components that supposed to be addressed all together in single framework in order to have an adequate mobile market place.

Chapter 4: Recommender for MMP: This chapter deals with the design and implementation of the recommender system that can help mobile individuals/group formulate better decision-making by incorporating user/group profile as well as the geographical location. However, this system not only recommends items for individual/group of users with applicable recommendations based on their preferences and closest location, but is also capable of providing an explanation for the actual reasons behind the recommendations for individual and group users alike.

Chapter 5: Results and Discussions: in this chapter, we outline the proposed method and the formal underpinnings; thereafter we present the experimental results and validation of our concept.

Chapter 6: Conclusions and Future works: in this chapter, we conclude our work and the possible scope for future work.

Chapter 2

Related Literature

In this chapter, we review the important literature related to our work. The reviews are discussed under the following headings: (1) The different architectures of MMP (2) Notification Service, (3) Recommender Systems.

2.1 The Different Architectures of MMP

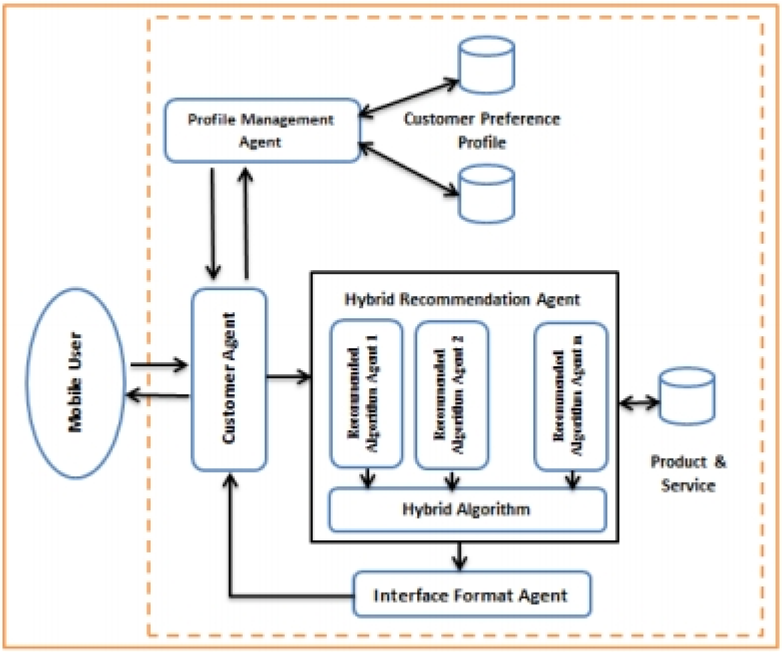
Several studies have proposed different architectures for different components of MMP to address some particular issue such as(improving the quality of publishing and advertising, increasing security, enhancing the delivering processes, improve the payment transaction, reducing search costs and locational efficiencies, etc.).

In (Karlene, C. and Upkar, V.; 2001) Karlene and Varshney proposed and discussed a product location framework for mobile commerce environment. Such framework serves as a guideline for facilitating interoperability among the diverse product location schemes. Karlene & Varshney have suggested that the knowledge and database engineering domain research should focus on the development of XML based ontologies which will facilitate an agent based product search and discovery which can be applied across heterogeneous location based systems adhering to this common ontology.

Another study describes a model for associating location scopes with services along with architecture to support the discovery of location-based services on the Internet (Sheng Hu, et at., 2006). Such model has also associate location-based guide, the map object handles one or more contact addresses. However, mobile user may choose different type of data results for output according his/her current need. Such study presented the Global Positioning System (GPS) Location Process, the structure of Location Based Service (LBS), and the architecture to support the discovery of location-based services on the Internet.

Chengzhi Liu and et al., in (Chengzhi Liu, et al., 2008) have proposed hybrid recommendation architecture for mobile commerce system as illustrated in Fig. (2.1).

Fig.(2. 1): Architecture of hybrid recommendation for mobile commerce (Chengzhi Liu, et al., 2008)



This architecture includes products and services database, customer and mobile device ontology, and cooperating agents. Based on the proposed architecture, a prototype system for restaurant recommendation has been presented. A test of the prototype system is implemented in the experimental atmosphere, the test shows that the system has a good feature of stabilization and the recommendation performance could be improved with time going by and experience increased.

In light of the resource constraints of mobile devices, security mechanisms for protecting traditional computer communications need to be revisited so as to ensure that electronic transactions involving mobile devices can be secured and implemented in a practical manner. Lam K., et al (Lam K., et al., 2003) has described a lightweight security mechanism for protecting electronic transactions conducted over the mobile platform. This scheme was designed to meet the security needs of security-sensitive mobile commerce applications including electronic financial services and electronic government services initiated over mobile handheld devices. The mobile commerce security architecture presented in this study provides a secure means for authenticating end users and transacting with them. The security architectures as illustrated in Figs.(2.2 and 2.3) provide a wireless protocol gateway to execute complex transaction protocols with the application server and at the same time allows mobile handheld devices to securely connect to the gateway using lightweight mechanisms.

Fig.(2. 2): System architecture of secure m-commerce application (Lam K., et al., 2003)

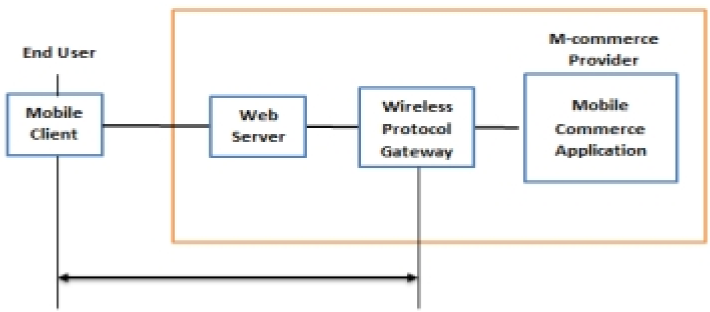
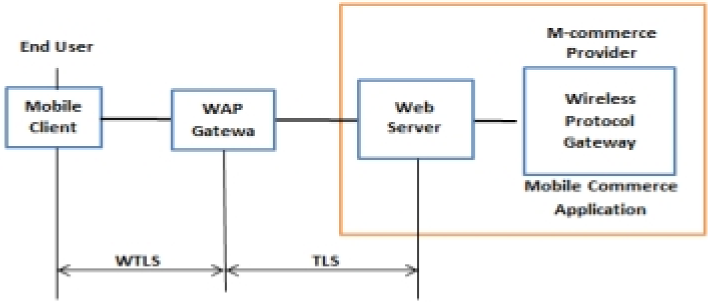
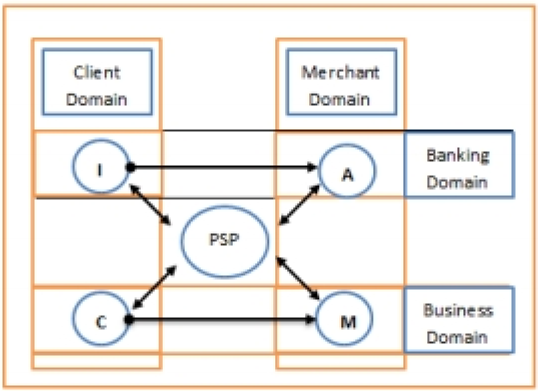


Fig.(2. 3): WAP-based system architecture of m-commerce application (Lam K., et al., 2003)



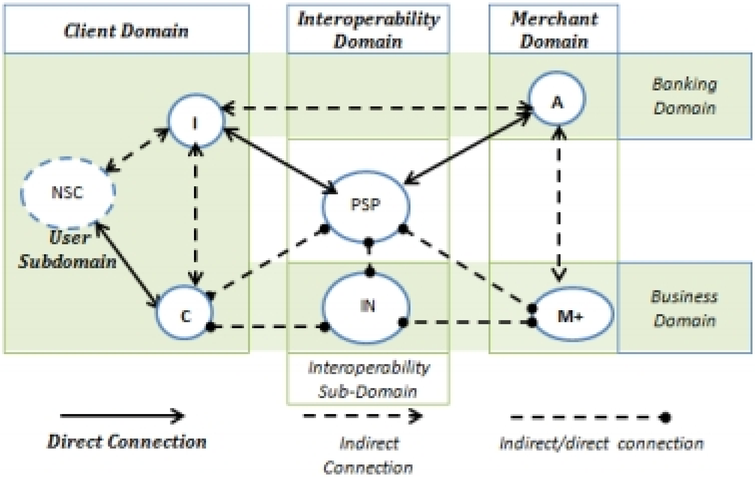
The classical e-payment model as illustrated in Fig.(2.4) shows the relationships among customers and merchants are established by means of business and banking domains, as well as, the transactions flows between entities. However, the security architectures based on this model are not sufficiently robust when new participants with their respective functionalities and particularities engage the e-payment system (Diego S., et al., 2007).

Fig.(2. 4): Classical e-payment model (Diego S., et al., 2007).



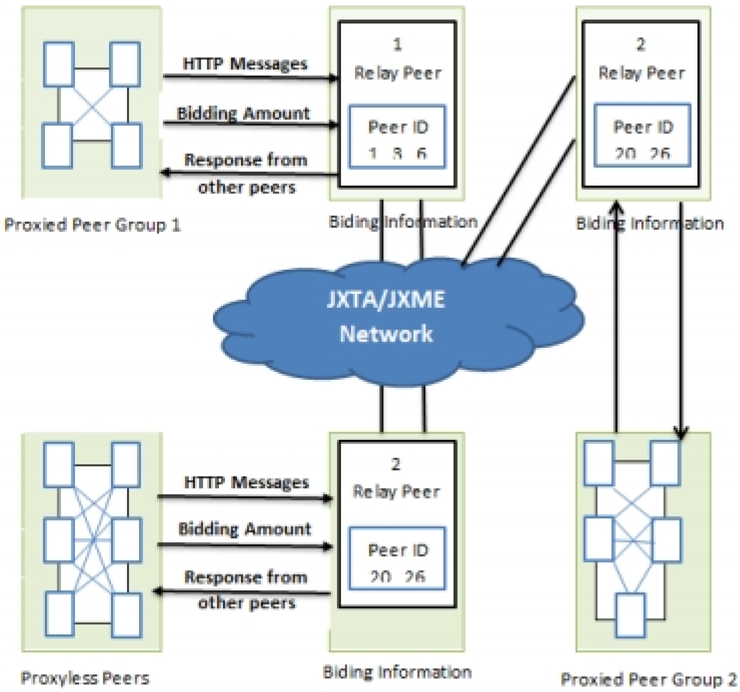
To address such problem, a domain-based payment model for emerging mobile commerce scenarios has been proposed by Diego S., and et al. 2007, in order to guarantee security robustness, and extend the payment model that allows more effective security solutions. In this work a domain-based e-payment model for mobile devices as shown in Fig.(2.5) has been introduced. Additionally, this work provides a security discussion and a set of requirements associated to their proposed model, with the goal of defining a robust across-domain security architecture.

Fig.(2. 5): New domain-based payment model (Diego S., et al., 2007).



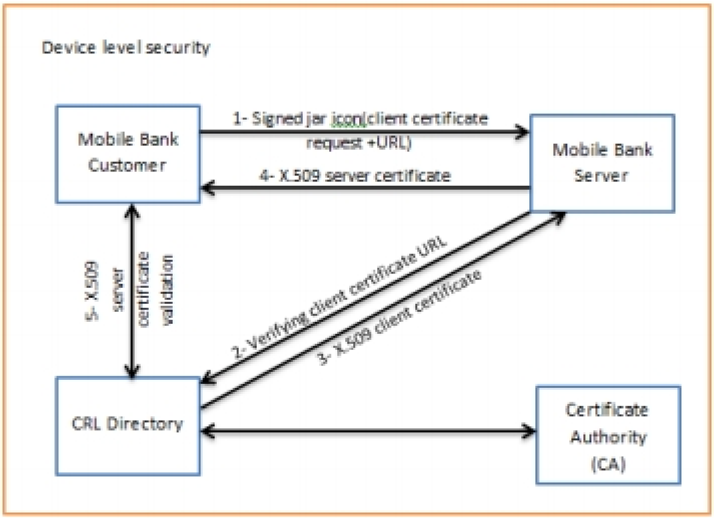
To get the items that a buyer wants in an Internet auction, user must search for the items through several auction sites. When the bidding starts, the buyer needs to connect to these auction sites frequently so that user can monitor the bid states and re-bid. In this regard, Rajkumar et al., (Rajkumar R., et al., 2011) have proposed architecture for mobile peer to peer auction using JXTA/JXME in M-Commerce as illustrated in Fig(2.6). This work presents architecture for mobile auction in consumer to consumer (C2C) fashion considering JXTA/JXME, as an environment which creates peer to peer applications in mobile constraint devices. Further they have discussed the pros and cons of using JXTE/JXME and its applicability to peer to peer (P2P) mobile auction system. Additionally they have concluded that proxy based P2P mobile auction would be good architecture to practically implement mobile auction process. Since JXTA and JXME are open source projects, and by considering the security aspects in mobile peer to peer communication, they have a plan to implement a P2P mobile based auction system in nearby future.

Fig.(2. 6): P2P mobile auction using JXTA/JXME in proxied peer (Rajkumar R., et al., 2011).



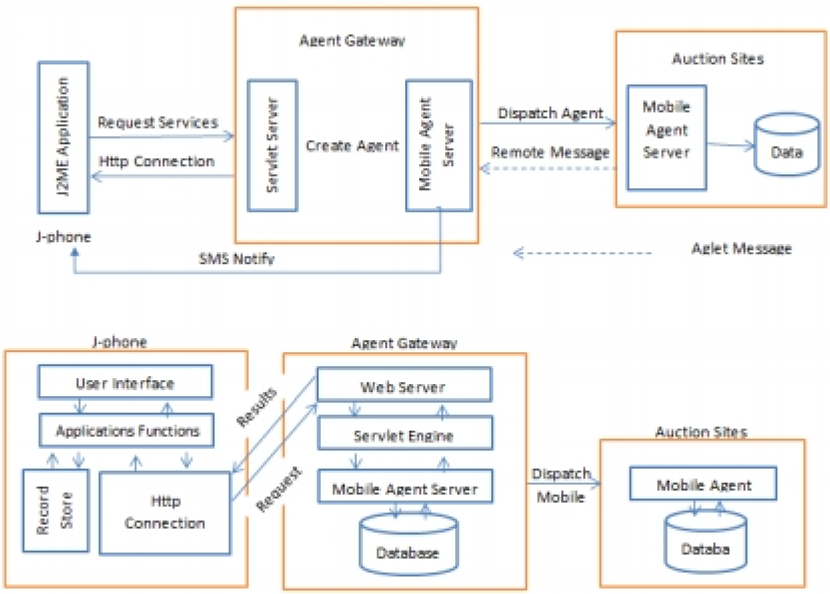
For any system based on asymmetric cryptography, using a public key infrastructure (PKI) can solve the basic problem that is related to signing the root certificate and maintains the required infrastructure. Performance evaluation on end-to-end security architecture using PKI for mobile banking system has been proposed in (Narendiran, C., et al., 2008) as illustrated in Fig.(2.7). This framework eliminates the use of browser by the mobile bank customer by transferring the data format through IP Packets in an encrypted format. According to their point of view, the security framework solution allows to provide strong customer authentication and non-repudiation by employing public-key cryptography for customer certificates and digital signatures. Encrypting messages that constitute mobile banking transactions provides confidentiality and message integrity.

Fig.(2. 7): Device authentication (certificate validation) (Narendiran, C., et al., 2008).



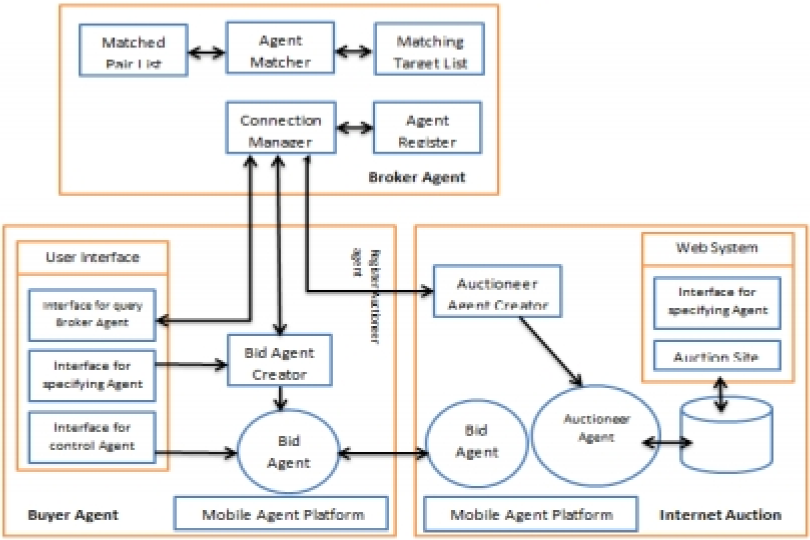
The mobile agent can greatly enhance the functionality of the system. For instance, agent can be designed to learn and store user preferences. This enhances the effectiveness of searching function such that user is easier and faster to find their favorable items and prices. Auction and bidding Strategies can be implemented to increase the wining probability and overcome the limitation of the mobile devices. In this regards, Calvin & Ronnie in (Calvin W., & Ronnie c., 2010) have proposed an auction agent architecture for mobile commerce as shown in Fig.(2.8). This work investigates the feasibility of using mobile agents from mobile wireless handheld devices. Calvin and Ronnie have developed J-phone auction agent architecture for mobile commerce. This approach overcomes low bandwidth wireless and network disconnection limitations by using mobile agents and dispatch agents. This approach also assists users to monitor bidding status and implements bidding decision at multiple auction sites. The security part of their system has not been implemented.

Fig.(2. 8): An auction agent architecture for mobile commerce (Calvin W., & Ronnie c., 2010).



In the wireless Internet environment, communication costs rise in proportion to a rise in network load. A mobile agent mechanism reduces user operations and network load by implementing the coordination of bids across multiple auction sites. In this regard, an auction agent system using a collaborative mobile agent and a brokering mechanism called (MoCAAS) Mobile collaborative auction agent system has been proposed in (Kwang Y., et al., 2003) as illustrated in Fig.(2.9). This collaborative mobile agent mediates between the buyer and the seller and executes bidding asynchronously and autonomously in order to reduce the network load, offer more intelligent bidding, and increase the clear ratio.

Fig.(2. 9): MoCAAS architecture (Kwang Y., et al., 2003).



Rapid technological evolution in E-Business leads to exist a competitive market for businesses such as hotels, restaurants, shopping malls and entertainment venues. A modern marketing system is needed for these kinds of businesses to stand out among competitors to be able to attract more customers. Customers require a system to inform them about points of interests and businesses special promotions. In this regard, Pantea in (Pantea K., et al., 2012) have illustrated results of a preliminary study to investigate user interests in location-based advertisement systems as shown in Fig.(2.10). This investigation describes how the proposed advertising system can improve the efficiency, robustness and reliability of E-Business in order to connect businesses to potential customers. Furthermore, the study describes how the proposed mobile advertisement application makes it more efficient for businesses as to advertise their products to mobile customers according to their current GPS location.

The location of the mobile user is tracked through GPS, and then the information of the query is sent through GPRS/3.5G based cellular network and Point of Interest (POI) information is tracked to make the system more efficient and reliable. Additionally, as illustrated in Fig.(2.11), the study shows how the proposed system assists businesses (e.g. hotels, restaurants, UNESCO and cultural sites, shopping malls and entertainment venues) to reach their potential customer. However, not all of the businesses will use the proposed system as a marketing tool, it can be a competitive advantage for them to attract more customers and offer their products and services.

Fig.(2. 10): Architecture of proposed location based system (Pantea K., et al., 2012).

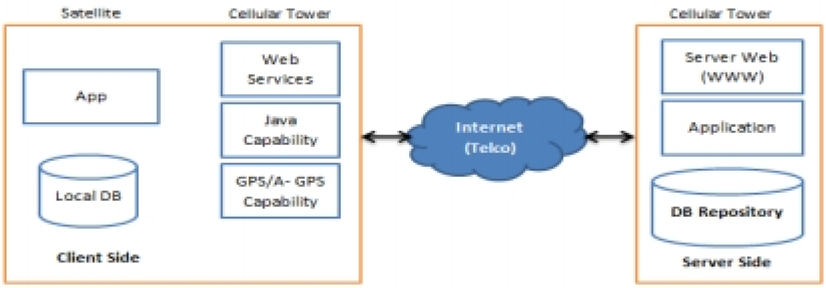
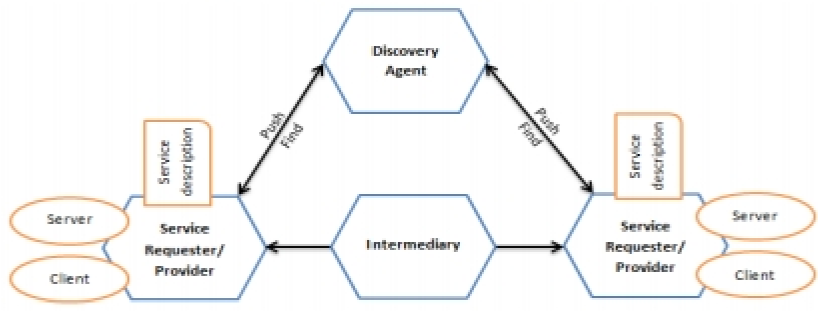


Fig.(2. 11): Location-based services & its features (Pantea K., et al., 2012).

Web Services using XML are being rapidly adopted as the standard infrastructure for large-scale distributed systems. In this regard, Yao-Chung C., et al., in (Yao-Chung C., et al., 2005) proposed a mobile commerce framework based on web services architecture technologies and mobile Internet functions as shown in Fig.(2.12). This framework concentrates on switching existing e-commerce applications from the wired Internet to the mobile Internet.

Fig.(2. 12): Web service architecture (Yao-Chung C., et al., 2005).

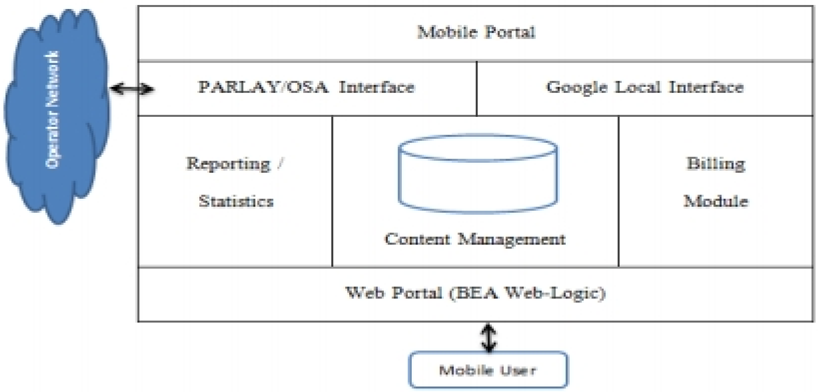


Ece K., et al. in their study (Ece K., et al. 2008) describe the efficient mechanisms, infrastructure, and automation that can enable sellers and buyers to take advantage of the relationship of the locations of retail offices to the routes of mobile buyers who may have another primary destination. The methods promote automated vigilance about opportunities to buy and sell, and to support negotiations on the joint value to buyers and sellers including buyers' costs of divergence from their original paths to acquire services and commodities. This study tried to extend the MC prototype and overall architecture to employ market-centric concepts. It presented methods and models used in the MC Market system and described its key components and extensions. Five main direction have been suggested by this study for future works: (1) enhancing means for eliciting preferences from buyers, particularly for multi-attribute items, (2) improving the current models to guarantee buyer truthfulness, (3) extending the market design to double actions, (4) achieving a strategy-proofness property in repeated transactions of MC market, and (5) applying more comprehensive cost-benefit analyses of opportunities that recognize promotions and daily pricing patterns.

However, the usages of M-Commerce services in commercial activities are expected to dominate the world and commercial activities through wireless are gradually changing the daily practice and future possibilities. This opens many new possibilities, opportunities and challenges in mobile commerce. Use of software agent technology by providing intelligence, autonomous, customized, adaptable and flexible services, can enhance M-Commerce activities. In this regard, Manvi and Bhajantri in their study (Manvi, S. S., Bhajantri L. B.; 2009) bring out various issues in M-Commerce and describe various agent-based product negotiation models in mobile commerce environment. In this study, the negotiation model has been discussed based on auctions, trade off and argumentation.

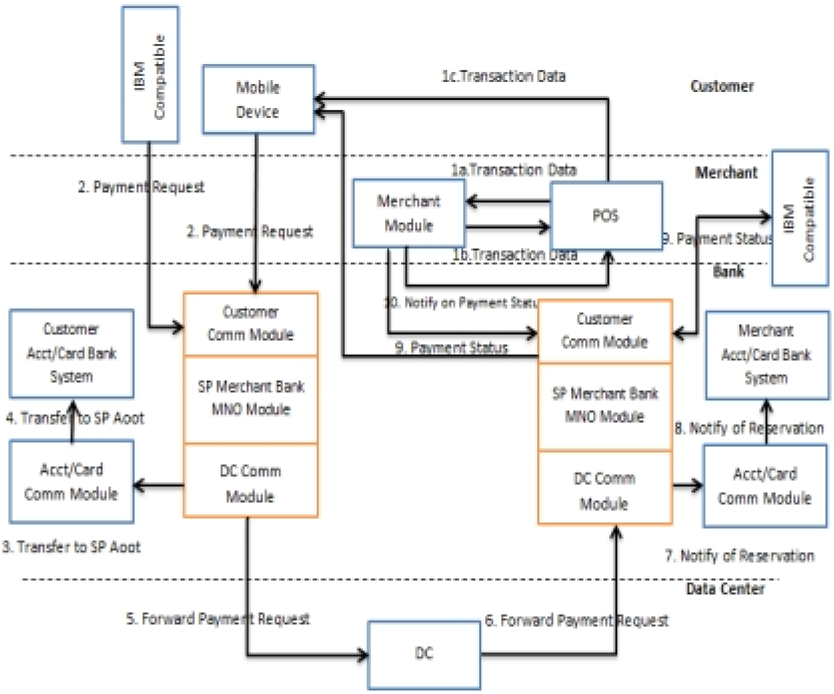
Another study has proposed UGetMobile End-user Mobile Publishing Platform (Tom P., et al., 2006) as shown in Fig.(2.13). This system has been developed with: a web portal, a mobile portal and core systems (content management, billing and payments) using Java2 technologies. Moreover, this project contains three major phases. (1) The core, creating the commercial-grade of UGetMobile Web 2.0 service for providing mobile web site creation and some value added service such SMS (Short Message Service), MMS (Multimedia Message Services), blogs, LBS (Location Base Services), video and e-mail. UGetMobile enhances these services by creating deep interconnections with mobile Operator's mobile portals and Service Delivery Platforms (SDP) via OSA/Parlay; and UGetMobile will leverage the growth of key emerging Web 2.0 mobile services such as Google Local, Google Base, Google Mobile, MSN mobile and Yahoo mobile. (2) The second phase is a full alpha trial with the project partners and their user-groups. This includes the core features required to enable the service getting generally available in the partner's countries including billing, payments and reporting, significantly enhancing the value added services offering. At the end of phase two a beta trial to be conducted with the project partners, followed by UGetMobile being made generally available in Ireland, the UK, Germany, Spain and Greece. (3) Phase three focus on the global launch of the service, improving the service based on end-user feedback and creating additional interconnections with a global SMS and MMS provider (such as mBlox) and also Google Local and Mobile, Yahoo Mobile and MSN Mobile. At the end of this phase the service will be launched in North America and handed over to a Campus Company for operation, support and role out to other countries.

Fig.(2. 13): UGetMobile Logical Architecture(Tom P., et al., 2006).



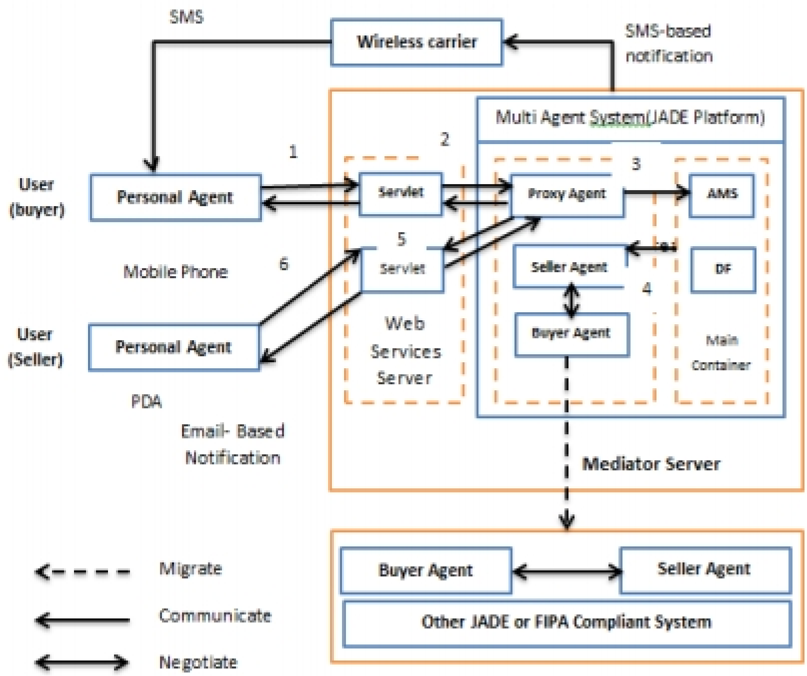
Mobile payment tries to kick-off the existing e- and m-commerce efforts and unleash the true potential of mobile business. Different approaches come to the market and try to address existing needs, but up to now no global solution exists. In this context, (Karnouskos, S., et al., 2003) proposed a secure mobile payment architecture and business model (SEMOPS) in order to develop a global mobile payment system as illustrated in Fig.(2.14) . This business model is based on two key concepts (a) that of cooperation of Banks and mobile network operators (MNOs) and (b) that of social trust relationships since each actor transacts only with his trusted bank or MNO. It is worth noting that SEMOPS features a distributed approach where banks/MNOs can dynamically join the system with their customer base and users do not have to register alone, something which will allow SEMOPS to grow fast and reach a the critical mass that may establish it as a global payment service. The SEMOPS business model is general and flexible enough to integrate future needs.

Fig.(2. 14): General architecture of SEMOPS (Karnouskos, S., et al., 2003).



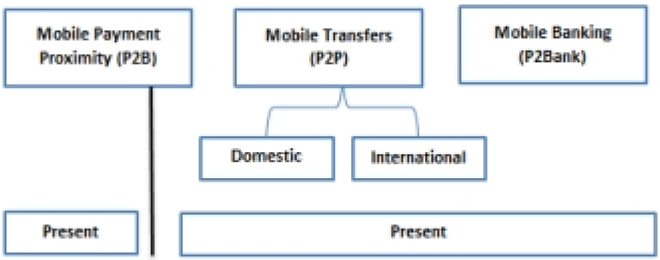
Zhiyong and Thomas (Zhiyong W., and Thomas T., 2007) have proposed a mobile intelligent agent-based e-business architecture that allows buyers and sellers to perform business at remote locations as shown in Fig.(2.15). This architecture proposed with hope that would be useful on a smaller scale and lead to new investigations that may result in new solutions to the problems that are related to mobile agent. This architecture aims at providing a convenience for traders as business can be conducted anytime and anywhere. The architecture tries to address the problem of limited and expensive connection time for mobile devices: A trader can disconnect a mobile device from its server after generating and launching a mobile intelligent agent. Later on, the trader can reconnect and call back the agent for results, therefore minimizing the connection time.

Fig.(2. 15): A Mobile Intelligent Agent-based Architecture for E-business (Zhiyong W., and Thomas T., 2007)



Cynthia in (Cynthia M., 2010) reviews the developments in mobile money transfers, the emerging ecosystem, and its participants and business models. The structure of the mobile financial services market illustrated in Fig.(2.16). It also examines the implications of payment systems roaming across geographic borders with their respective legal and regulatory jurisdictions, as well as the emergence of mobile airtime as an alternative currency. The risk environment for mobile money is examined in the context of both developed and emerging countries and in light of the participation of banks and nonbank telecom firms.

Fig.(2. 16): Structure of the mobile financial services market (Cynthia M., 2010)



Some of these architectures have shown more flexibility and increased the interoperability between mobile agents and provides high scalability design for swiftly moving across the network. However, such architectures involved with some particular problems and there was no architecture so far has covered all the components of the MMP in single framework.

2.2 Notification Service

Mobile notification service is becoming a very popular topic along with recommendation systems due to the growing diversity, availability and use of mobile information service. The challenge existing here is how to make information relevant to mobile user/group among MMP domain and automatically push interesting information to such mobile users.

In fact, traditional markets make available on the Internet electronic-catalogue that support lists of items or services, price information and commercial transactions. Depending on this, it returns a list of items or filtered services which meet the requirements specified by the buyer. According to the huge number of agencies, i.e. broker, auction, delivery, payment, supplier, buyer, etc. and overloaded information interacted and presented between them, Notification Service (NS) is considered the backbone of EMP and MMP.

Thus, in MMP paradigm, the notification service is responsible for publishing and advertising goods and services offered by the existing service providers, provides channels to communicate with other MMP components which assist to obtain useful information about location. In fact, there are two advantages of NS: first, effective personalized notification and efficient presentation of targeted notification to users that are likely to purchase items/services; thereby dramatically improves sales and businesses and makes more profit, and second, the more personalized the notification becomes; the more mobile users eventually regard this service not as an intrusive extra but rather as a helpful necessity.

Therefore, this type of service has also an impact factor on enhancing the finance capability of EMP and MMP. It increases the revenue and reduces the cost and time consuming, while searching for a particular item. NS designed for particular services has limited number of models (Engin *et al.*, 2007). Extensibility is not supported by the most of these models. Previous research has shown criteria that should satisfy the adaptive NS (Michael *et al.*, 1997; Demet *et al.*, 1999; Jon *et al.*, 2002; Ibach *et al.*, 2005; Adrian *et al.*, 2010) as:

- Take the mobility of users into account: manage highly model of users' interests (subscription, update, insertion, deletion).
- Manage changes in the underlying network topology that may occur in very dynamic setting like an ad hoc networking.
- Support multiple notification channels and multiple content formats: support heterogeneous notification channel (e-mail, internet protocols, fax, phone, WAP, etc.).
- Support large numbers of subscribers and publishers: continuously collect and integrate data distributed among a large set of users.
- Propagate notifications for thousands of information consumer simultaneously, which managing large amount of content sent to the system.
- Select the appropriate mode of communication: filtering and delivering relevant data to interested users and components in a timely manner with the help of middleware which gives filtered formation for potentially large set of users, gives their continuously changing location, their changing profiles.
- Support security and privacy of information: performing security functions, like subscriber and publisher authentication, secure content distribution, i.e. not all subscribers may be allowed to receive all publications that match their subscriptions.

In this regard, Many researchers ascertain that Notification Service (NS) has been investigated and implemented in different projects, protocols, and architectures for EMP but not for MMP, i.e. web services based event notification systems (Huang *et al.*, 2006), CORBA notification service (Gore *et al.*, 2001), and the publish/subscribe communication paradigm (Eugster *et al.*, 2003). However, such notification mechanisms still need some expansion with intelligent recommender system, in order to have adequate NS for MMP domain and anticipating changes, as foreseeable location updates.

Moreover, many studies have been conducted on Notification Service for providing information services in EMP domain such as personalized information to users (Wang *et al.*, 2010; Woerndl *et al.*, 2009; Abbar *et al.*, 2009; yap *et al.*, 2007). However, most of such systems still require users to reveal their preferences and input the keywords of their interest. This reveals a lot of problems on some mobile devices according to their limitation of information browsing and data input which are considered inconvenient. In addition, MMP can keep track of a user's preference, actions, location, etc. For this purpose, filtering user profile to deliver relevant information to mobile user could be a very pleasant and worthwhile solution in MMP environment.

No doubt that Internet and the wireless communication make an actual MMP all over the world without location and time restriction. These distinguished features give superiority to MMP to dominate the space of commerce instead of traditional EMP. Thus, these features play an important role to boost overall sales through targeting a huge number of mobile users based on their interests and locations. In addition, researchers assert that NS is one of the most important units in EMP and it provides the necessary information to various units of EMP (Minch *et at.*, 2004; Bazinette *et al.*, 2001). Undoubtedly, this unit will enhance the efficiency of MMP if it does consider the location and preferences for both user and service provider.

Notification Service was developed as a bridge between Mobile user and MMP environment. It can handle users' queries and push the data of interest to such users. The intelligent recommender system is built on the top of NS framework that incorporates user profile/location and item attributes and automatically pushes real time information that is considered relevant to mobile users.

The literature shows that notification models are designed to have high user interactivity and low user perceived latency. Real-time dynamic web data such as news headlines, stock tickers, and auction up-dates need to be propagated to the users as soon as possible. However, these applications still suffer from the limitations of the Web's request/response (pull-based) architecture which prevents servers from pushing real-time dynamic web data. Such applications usually use a pull style to obtain the latest updates, where the client actively requests the changes based on a pre-defined interval. It is possible to overcome this limitation by adopting a push style of interaction where the server broadcasts data change occurs on the server side. Both options have their own trade-offs (Bazinette *et al.*, 2001). However, data dissemination mechanisms involve the delivery of data from one or more sources to a large set of consumer (Afonso *et al.*, 2004). Many dissemination oriented applications have data access characteristics that differ significantly from the traditional notion of client/server as embodied in navigational web browsing technology (Emilio *et al.*, 2009). Table (2.1) illustrates the characteristics of dissemination oriented mechanisms.

Table (2. 1): Data delivery mechanisms characteristics

Pull	Request data when it is required, when request is received at server, the server locates the information of interest and sends it into the client.
Push	Data delivery involves sending information into a client population in advance of any specific request.
Periodic	Is performed according to some pre-arranged schedule, this schedule may be fixed or may be generated with some degree of randomness.

Aperiodic		Is event driven while data request for pull according to any user action, or transmission for push regarding to data update by server.
Unicast		Data items are sent from a data source (e.g., single server) to another machine.
1-N	Multicast	Data sent to specific subset of clients (recipients is known).
	Broadcast	Send information over a medium on unidentified and unbounded set of client can listen.

The client server dissemination application has the following attributes (Michael F., and Stanley Z. 1997): (1) there is a huge number of users who want to access the data. (2) There is an enormous degree of overlap among the interests of the users. (3) Some users are only interested in new data and changes taking place in the existing data. Therefore, if each user sends a request to the server, the large audience for a popular event can generate huge load at servers, resulting in long delays and server crashes. In addition, the use of unicast data delivery likewise causes problems in opposite direction (from server-to-client) with unicast the server is required to respond individually to each request. By considering these characteristics, it becomes clear that the -request/ response- unicast method of data delivery may alone lead to undesirable results.

Scalability is also considered as an elaborate problem in MNS, which can occur as a result of mismatch between the data access characteristics of the application and the technology. Furthermore, some of the mobile devices natures still suffer from the limitation in keyboard and display and the ability of processing. Hence, MNS needs to use appropriate mechanism of data delivery to enhance the performance of such system. These limitations force researchers to pay special attention to build a flexible system. Notwithstanding, with data push mechanism, the transmission of data to user is initiated without requesting the users to explicitly request it, users do not have to pull servers for new and update, the number of user requests that must be handled by server can be reduced dramatically. However, the battle of data push standards is well underway, and the changing from data-pull to data-push does not solve all the problems, and there is not yet data delivery approach that can provide adequate support (Ibach *et al.*, 2005) for the wide variety of data dissemination.

2.3 Recommender Systems

As mentioned earlier, the goal of recommender systems is to help users in their decision making while interacting with large information space. They recommend data of interest to users based on their preferences they have expressed, either explicitly or implicitly. The ever-expanding volume and increasing complexity of information on the wired and wireless networks have therefore made such systems essential tools for users in a variety of information seeking for MMP activities. Based on what kind of recommendation techniques is used, personalized recommender systems are usually classified into three categories (1) Collaborative Filtering (CF), (2) Content based Recommending (CB), (3) Hybrid Methods (HM): combining the both techniques of CF and CB.

However, CF and CB techniques are widely used and have become the most preferred methods. *Memory-based* and *Model-based* algorithms which are subdivisions of CF and CB methods have been extensively studied in this regard. In *memory-based* CF technique a subset of users are chosen based on their similarity to active user and a weighted combination of their ratings is used to produce predictions for this user. Similarity measures like Pearson correlation, cosine similarity, Spearman rank correlation, Kendall's correlation, mean squared differences, entropy and adjusted cosine similarity have been used (Xiaoyuan *et al.*, 2009; Herlocker *et al.*, 1999). It was shown that the conventional *memory-based* CF algorithms do not scale well when applied to millions of users and items due to the computational complexity of the search for similar users. To overcome this drawback Linden *et al.* (Greg Linden *et al.*, 2003) proposed *item-to-item* or *Model-based* technique where rather than matching similar users, they match a user's rated items to similar items. It was shown that this approach leads to faster online systems, and often results in improved recommendations (Badrul *et al.*, 2001; Greg *et al.*, 2003). In 2006, Wang *et al.* (Wang J. *et al.*, 2006) proposed the *similarity fusion* between the *user-based* and *item-based* methods by treating the individual user-item ratings as predictors of missing ratings and estimating the final rating by fusing predictions. This model shows that a fusion framework is effective in improving the prediction accuracy of collaborative filtering and dealing with the data sparsity problem. Other remarkable extensions to similarity-based Collaborative Filtering include weighted majority prediction in which both row similarity and column similarity are used for prediction (Atsuyoshi *et al.*, 1998), and imputation-boosted CF (Xiaoyuan *et al.*, 2008) here, imputation methods frequently used to deal with missing data in the tables and fill it up to create a pseudo rating matrix, then providing predictions based on this imputed data anticipating more accurate predictions then using traditional Pearson correlation-based CF (Sarwar, B.M., *et al.*, 2001) to produce the final recommendations.

As far as *model-based* CF algorithms are concerned Latent Factor (LF) and Matrix Factorization (MF) models (Robert *et al.*, 2009) have emerged as the state of the art methodology in this class. In LF model, similarity between users rating and items content is assumed to be induced by some lower-dimensional structure in the data. For instance, the rating that a user gives to a movie might be assumed to be dependent on few implicit factors such as the user's taste across various movie genres. On the other hand, MF techniques are a class of widely successful LF models where users and items are jointly represented as unknown feature vectors along with k latent dimensions. These feature vectors are learnt so that inner items approximate the known preference ratings with respect to some loss measure. For instance, in settings where only implicit preferences are available as opposed to explicit like-dislike ratings as in recommending TV shows based on watching habits of users. Here, preferences are implicit in what the users choose to see without any source of explicit ratings. Recently in (Rong *et al.*, 2009) it has been shown that matrix factorization techniques have been advanced to handle such problems.

Xue *et al.* (Xue G. *et al.*, 2005) proposed a cluster-based smoothing method wherein clusters are created and predictions for a target user are made by averaging the opinions of the other users in the cluster he/she participates and is weighted by the degree of participation. Another clustering algorithm put forward in (Jin R. *et al.*, 2006) uses the decoupled model wherein user preferences from its rating is decoupled but allows user/item to be in multiple clusters and performs separate clustering of users and items. In (George T. *et al.*, 2005) bi-clustering is used in CF to build a system that incrementally updates the bi-clusters as new users and new ratings are continuously entered. The main aim of this model is real-time efficiency.

All the methods discussed above fall into the category of CF algorithms and the problem with pure collaborative filtering recommenders is that it treats all users and items as atomic units, where predictions are made without regard to the specifics of individual users or items. Whereas many pure CB systems have tried to provide explanations by knowing more about a user, such as demographic information (Michael *et. al.*,1999), or about an item, such as the genre of a movie (Prem *et al.*, 2002). Billus and Pazzani (D. Billsus *et al.*, 1999) used pure CB to recommend news articles to users, and also provided explanations for the reasoning behind their recommendations. They have also exploited a user's feedback to improve the recommendation process. A method for recommending books based on pure CB was proposed in (Mooney R. *et al.*, 2000) wherein a machine learning algorithm was used for text categorization and explanations were provided for the recommendations made.

In order to leverage the strengths of content-based and collaborative recommenders, there have been several hybrid approaches which are proposed to combine both CF and CB. A general framework for content-boosted collaborative filtering is proposed in (Prem *et al.*, 2002) where content-based predictions are applied to convert a sparse user ratings matrix into a full ratings matrix, and then a CF method is used to provide recommendations. In (Salter J. *et al.*, 2006), CF is used to compute the predicted rating values for movies and then CB is applied to generate recommendation list. A web recommender system is proposed in (Jin X. *et al.*, 2005) in which collaborative and content features are integrated under the maximum entropy principle. In fact, hybrid recommendations were extended to contain knowledge-based techniques for the purposes of improving the quality of recommendations and reducing the effect of the traditional CF cold-start problem. More recent approaches (Werner *et al.*, 2008) allow users to create their own profile by crafting a list of their own questions/topics. Such system differs from the traditional recommender system ones, since it recommends content for users to create, rather than consume. They deploy two different algorithms (Network-based and Content-based), with the aim of recommending a set of meaningful questions to the user by looking at the behaviour of the users which are similar to the target one.

As mentioned so far, there are a lot of data available in the internet in the form of books, articles, movies, music, websites, etc. and therefore selecting particular items that are of our own interest is very difficult. Likewise, as online community activities have increased exponentially, the need for a group recommendation system has also become more and more imperative. So we need systems for recommending items (books, movies, websites etc.) that take into consideration our own as well as a group's interests. These systems are generally divided into two categories namely personal recommender system and group recommender system wherein the former is effective in filtering useful information that fits each user's needs, the latter provides suggestions for group decisions and satisfy user's needs in group desires.

In the case of group recommender systems, like (Masthoff *et al.*, 2002; McCarthy *et al.*, 1998; O'Connor *et al.*, 2001) assume that the input of the system is comprised of item's ratings given by individuals and group recommendation is obtained by aggregating or combining the individual recommendations of the members in the group. Meanwhile, many studies on notifying user through recommender systems (Abbar *et al.*, 2009; Cantador *et al.*, 2008; Adomavicius *et al.*, 2005) used item attributes and combined implicit/explicit user preferences for making recommendations. (Cantador *et al.*, 2008) has merged content-based filtering and collaborative filtering by involving semantic context-aware technologies. Chen (Chen 2005) has proposed a context-ware CF system making use of context similarity techniques to recommend items. A user with the same interest will consider the previous user's interest. Adomavicius in (Adomavicius G. *et al.*, 2005) has presented a general approach (multidimensional model) to handle the contextual information in ranking. However, most of these researches targeted on EMP environment and computed the weights of contexts by simple sum of ranks – SUM (content x weight) but it does not consider the mobility attributes like location. Furthermore, Multi-Criteria Decision Analysis (MCDA) method is recently popular (Manouselis *et al.*, 2007; Adomavicius *et al.*, 2005) for designing and implementing recommender systems that take into account multi-criteria rather than single criterion in systems made use of traditionally. The traditional recommender rating items are based on user rating on items, MCDA rating items may involve user rating on items, contents and ranks. Besides, Abbar (Abbar *et al.*, 2009) in his study intends to implement a service oriented peer-to-peer environment that makes use of discovery function and nearest-neighbours algorithm. Ruffo (Ruffo *et al.*, 2009) demonstrated a pure peer-to-peer recommender the users were self-clustered in the peer network, and introduced the term proactive recommendation in peer-to-peer recommender.

Correspondingly, many attempts tried to draw attention to location-based for the mobile recommender system, such tour guide (Setten *et al.*, 2004), commercial recommendation(Yuan *et al.*, 2003) that serviced by using context information location and time, geographical location represents where mobile device user stays (Lee *et al.*, 2004), time is information related to system or service request (Hofer *et al.*, 2003), mobile phone provides user with more direct recommendation through 'push' service using SMS or other interaction channel (Ho *et al.*, 2003), location for personalized point of interest recommendations in mobile environments (Horozov *et al.*, 2006). Though there has been a lot of work on location sharing applications wherein either people explicitly request another person's current location or where people broadcast their location to friends through social networks (Tang *et al.*, 2010), a combination of user/item/explanation/ location based recommendation is still missing.

In this study, the proposed method takes care of the combination among user/item/ location and the reasoning behind the recommendations. Moreover, the duality and dependency that exists between users rating and items features have been considered whereas most of the hybrid algorithms perform separate clustering of users and items so they cannot detect the item similarity. It provides the actual reason behind its recommendations and justifies them. It is capable of recommending useful information that fits each individual needs, as well as satisfying the group users activities. This is a big advantage when compared to the existing group recommender systems wherein recommendations are made by aggregating or combining the individual recommendations of the members in the group or by aggregating the group's rating of similar items through the item-based collaborative filtering algorithm without considering the duality and the combination among users' preferences and locations data.

Thus, the proposed method has the potentiality to increase consumer satisfaction, enhance consumer/company loyalty, and boost overall sales by giving reasoning and creditability to the products and services that have a higher degree of interest to mobile users.

Chapter 3

This chapter intends to introduce an integrated architecture for MMP and defines such architecture, by focusing on the heterogeneous nature of the components. It is intended to figure out the different components, their relationship, and importance in MMP, which realizes interaction between mobile users and merchants. It begins with proposing an integrated architecture for mobile marketplace for efficient transaction and marketing using mobile devices and related infrastructure. We have highlighted the main components that supposed to be addressed all together in single framework in order to have an adequate mobile market place. Out of this architecture, it searches the notion of recommending the mobile user with the information that meets user/group needs, based on his/her/their profile and location.

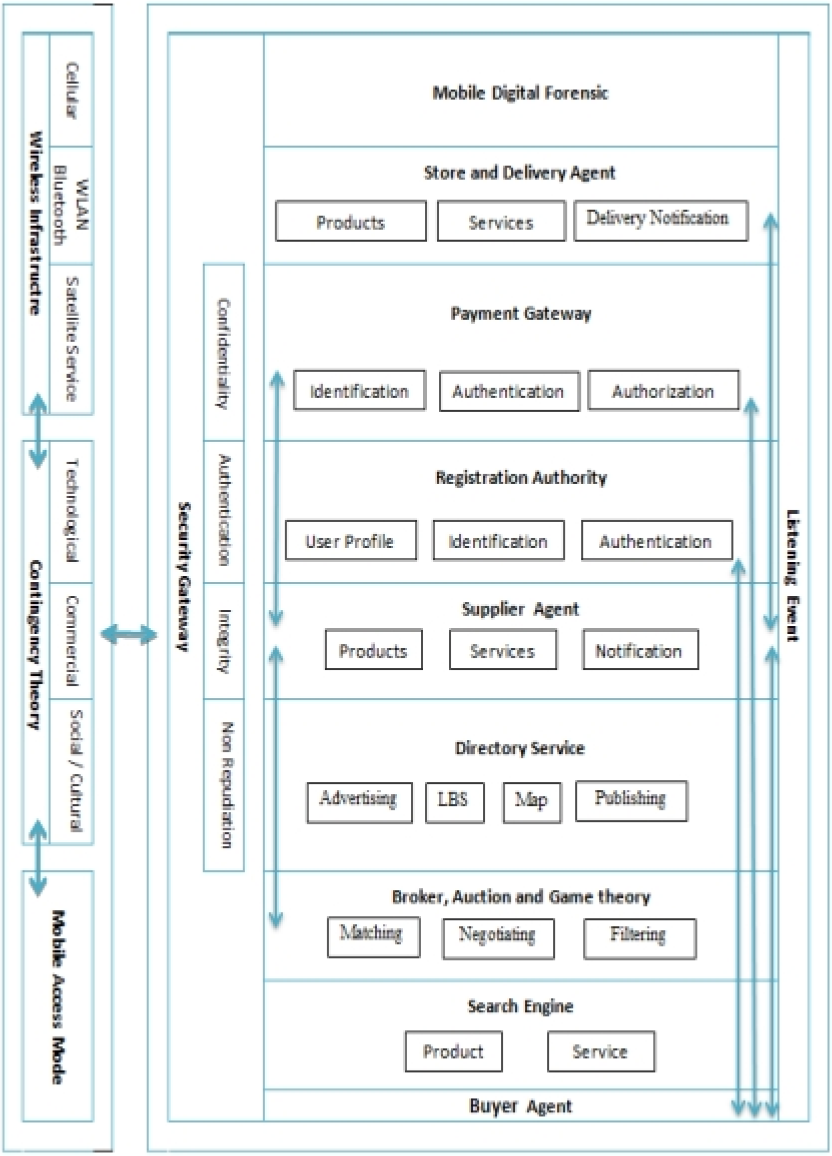
3.1 General Architecture of MMP

The abovementioned architectures in chapter two aimed to provide a great convenience for mobile users as business can be conducted anytime and anywhere. Moreover, such architectures aimed to build an intelligent mobile agent in order to release mobile user from time-consuming task while searching and negotiating with appropriate service provider. Some of these architectures have shown more flexibility and increased the interoperability between mobile agents and provides high scalability design for swiftly moving across the network. However, such architectures involved with some particular problems and there was no architecture so far has covered all the components of the MMP in single framework.

This chapter intends to introduce an integrated architecture for MMP rather than treating various technical aspects in isolation and defines such architecture, by focusing on the heterogeneous nature of the components. It is intended to figure out the different components, their relationship, and importance in MMP, which realizes interaction between mobile users and merchants. It begins with proposing an integrated architecture for mobile marketplace for efficient transaction and marketing using mobile devices and related infrastructure. We have highlighted the main components that supposed to be addressed all together in single framework in order to have an efficient mobile market place. It is our belief that this architecture may paves the way for further research to build more robust architecture for MMP environments. Out of this architecture, our aim is to focus on how to provide mobile user/group with the information that meets such user/group needs, based on the profile and location of the intended user/group.

MMP should bring many benefits to mobile user, service providers, and telecommunication operators. From the mobile user point of view, he/she can access on-demand, at the point of purchase and obtain best prices that are available in the MMP domain. This can happen via mobile application. Although MMP provides a technology to increase merchants' sales, it enhances management efficiency for service providers, as service providers exchange product information with mobile users on time according to their personalized preferences. And that can be done via a web page promotion or a mobile alert to increase their willingness to buy a product. Also there is some portion goes for telecommunication operators; viz. the more the MMP's services are used by mobile users through mobile devices; the more revenue can be achieved by telecommunication operators. In addition, the operators can also achieve revenue via fees charged to service providers for each MMP transaction. Thus, MMP promises business unprecedented market potential, great productivity and high profitability in future.

Fig.(3. 1): The architecture of MMP and the interaction between their components



However, there are still quite a lot of issues that have to be addressed and revolved for different factors, such as, improving the quality of publishing and advertising, increasing security, enhancing the delivering processes along with payment transaction, reducing search costs and locational efficiencies, in order to have an adequate MMP.

As stated so far, the intention was to analyze a general integrated architecture which covers all the aspects of MMP rather than treating various technical aspects in isolation. The invented architecture in Fig.(3.1) above illustrates the main components and the interaction between them. The components of MMP include wireless network, contingency theory, mobile access modes, mobile digital forensic, registration authority, security gateway, directory services, search engine, broker, auction, game theory, payment gateway, delivery agent and listening for event has been explained in the coming sections.

3.1.1 Wireless Network

Generally, the network infrastructure for wireless mobile combines different wireless networks, involving point-to-point wireless bridges, wireless LAN, private and public radio, satellite services, wireless local area networks, multidirectional wireless cellular systems). As well, there are many types of wireless mobile devices (e.g. portable computers, smarts cellular phone, Bluetooth communication device, PDAs, Internet terminals, etc.). These devices have the ability of conducting the desired transaction and preferences of MMP. Nowadays, wireless systems are achieving higher data rates to support Internet and other data-related applications. Through these networks, mobile users and merchants are connected and they are able to manage and accomplish the transaction preferable by them.

The wireless mobile communication devices associated with the potential consumer can receive communications from MMP, either directly or via an intermediate system, and can transmit a reply back to the MMP indicating a proposed offer so that a MMP can revise or improve the offer. However, Mobile wireless communication devices do not normally always communicate with the network infrastructure, i.e. they are unreachable for many reasons according to the consumer desire, viz, when the user is in a meeting, sleeping, or even to reduce power consumption of the mobile or there is no network coverage. In addition, wireless communications are still facing challenges in transfer capacity when it is compared to wired networks. This is caused by the fact that the modulation used and channel allocation schemes designed for voice traffic have rather modest upper bounds. Further, the wireless communications are much more error prone than the wired communications and require much redundancy in the channel coding of the payload. Although the redundancy in the channel coding that makes correcting bit errors in a wide range possible at the receiving end, in wireless retransmission of the data is required more often than in the wired networks.

3.1.2 Contingency Theory

As a matter of fact, MMP as any trade has been influenced by some external factors that have been gathered under the theory of contingency. This theory has been used for classifying mobile payment research and to capture the environmental factors which are characteristic to the mobile payment services markets. Furthermore, it has emphasized the importance of environmental influences, especially technology, on the management of organizations. In addition to technology, other typical contingency factors include cultural, social and economic factors. In the context of mobile payment service markets, because financial services and telecommunication are among the most regulated industries, it is natural to include regulation, jurisdiction and standardization factors, and the use of standards is characteristic to telecommunication (Tomi *et al.*, 2008).

Contingency theory is described as a midrange theory which falls between two extreme views (David *et al.*, 2000; Valarie *et al.*, 1988). According to one extreme, it is possible to find universally true theories, whereas the other one claims that each unit of analysis is unique and has to be analyzed based on situational factors. Further, contingency theory postulates that environmental factors are only important but also that the impacts of environmental factors are systematic, rather than entirely situational. The other helpful feature of contingency theory can be manifested via the environment strategy performance link.

This theory claims that the environment, such as the type of regulation, impacts the structure of the organization, for example, influencing which entities have incentives to become mobile payment service providers. Another example is enhanced technology which makes it possible to provide enhanced services which in turn increase interest toward the services. These contingency factors have significant impacts on the mobile payment services market but they are outside of the influence and control of the market.

Changing Commercial Environment

At the outset, changes in the commercial environment embrace the development of the Internet and mobile networks into commercial channels, as well as increasing automation and self-service orientation of payment services (Hampe *et al.*, 2000). Changes of the commercial environment may operate on the development of the new or the improved mobile payment services (Jayawardhena *et al.*, 2000). Other aspects of this factor include the structure and development of financial and telecommunication infrastructures and markets within the studied environments. The development of mobile payment services might be supported or inhibited by the structures of financial services markets within which various countries may support or inhibit.

Changing Social & Cultural Environment

It is widely argued that a specific part of the overall culture and lifestyle of the society is that of the payment culture. Social and culture environment plays an essential role in affecting people's consumption habits, buying behavior, and thus their needs for new payment services. Changes in these environments (Jayawardhena *et al.*, 2000) can deal with varieties of needs and thus affecting the supply and demand of new payment services.

Changing Legal Standardization & Regulatory Environment

Legislation and standardization of mobile payments according to current researches provide an informative description about the difficulties and the problems surrounding such topics. Yet, no significant solutions can solve the issues of legislation and standardization. Cross-border mobile transactions can be complex due to a complicated web of law and regulations. These contingency items may trigger needs for new or enhanced payment services and drive or hinder the development of mobile payments (Jayawardhena *et al.*, 2000; Rawson 2002).

Changing technological environment

Technological environment consists of wireless and other related technologies which are used to develop and produce mobile payment services (Karnouskos, et al., 2004; Diego S., et al., 2007). Some of these technologies such as mobile network technology or transaction protocols are regarded among the technologies which develop slowly. Some other technologies have very short development cycles, such as mobile handsets and their components. Constant development of technologies facilitates more reliable, user friendly, versatile, and functionally rich mobile payment services.

3.1.3 Mobile Access Mode

The modes of mobile access such as asynchronous, online web, notification, and voice mode apparently do not have to be used in isolation but can be combined within an application design (Song 2006).

Notification Mode

The notification includes other appealing services such as emails, instant messages on Internet, SMS/MMS messages on a GSM/GPRS cellular network. MMP features such as real-time message alerts on a very small portable device enables this mode, but it requires from the mobile network to be always-on. Moreover, a message gateway should be installed in MMP domain to deal with different type of messaging communication, and perform message queue management and notification event management.

Asynchronous Mode

The asynchronous mode enables users to download content to Mobile Devices (MD) and operate the content offline without network requirement, irrespective whether they have occasional network connectivity or are only connected to a PC for synchronization in the office or base location. Moreover, it could greatly enhance the user experience for MMP especially when the wireless network bandwidth is slow or the quality of the wireless signal is poor. This mode is very popular in current generation of PDAs. The MD under consideration on this mode can synchronize with the sync gateway based on IP connectivity to a sync server, or if that gateway is on a PC, using a serial cable, USB, Bluetooth, or infrared connection. The sync gateway can connect the device to a personal productivity data, i.e. Calendar, e-mails, documents, web content, database and application messaging. Regarding Web content, the sync gateway allows the MD to synchronize personalized Web content. The personalized selection is determined using the synchronous mode, usually through a PC. The user selection can be associated with a profile in the Directory service.

Online Web Mode

Mobile users can access MMP applications via a web browser on MDs like the PC users. But different MDs may adopt different display features and communication protocols. Thus, gateway in the MMP architecture should be deployed to support various pervasive devices. A well-known example of this topology is called a WAP-enabled device with a cellular network and a gateway that includes the WAP gateway software. The WAP gateway is responsible for transforming a WAP request into an HTTP request to the web application. The most common configuration of the gateway might be through cellular network provider and connected to the internet. This gateway configuration is important for an ISP to provide a set of public services to subscribers. It is also possible for this gateway to be configured by the mobile network provides via direct connection to that gateway and does not involve the public Internet. This gateway configuration is relevant for a solution to a service intended only for an enterprise group requiring mobile access to MMP services.

Voice Mode

With the limited keypad space and screen size of some MMP device, voice technology promises improved input and output functionality for MMP. The voice mode of interaction with an application requires speech recognition and text-to-speech synthesis (TTS) technology. However, unlike personal computers, the current generation of MDs does not have the processing power to perform these transforms.

3.1.4 Mobile digital forensic

Digital forensics concerns with investigation of cyber-crimes and establishing the identity of intruders and gathering evidence of malicious activity. If this unit has enough evidence (Giannakis *et al.*, 2006) to prove that somebody did try to attack the security transaction of MMP, then it will further investigate for presentation to courts of law. Digital forensic emphasizes that the rules and the protocols are shared and must be understood and followed by everyone relying on it. It can be guaranteed to attain the commitments of participants, otherwise it will receive appropriate penalty. It is necessary for a market institution to be equipped with capabilities that will prevent the occurrence of cyber-crimes from happening, or if they do happen, they will keep or log the evidence, and report the crimes.

3.1.5 Registration Authority

Registration Authority (RA) deals with registration of buyers, suppliers, service providers, of MMP. The participants send their request for a registration which brings along the request, their certificate, and other necessary information to registration authority. RA performs verification of participants' certificates through the Certificate. Certificate is a trusted third party to provide validity of the secrets key which are used for authentication (Narendiran, C., et al., 2008). Those digital certificates are used to proof the identity and authentication of each MMP unit.

3.1.6 Security Gateway

Security gateway becomes the entry and exit points with the process of migrating or transmitting within the MMP components. However, the security is one of the critical issues for successful adoption of payment transaction and it needs to be confidential. Confident transaction in the MMP means that both business and individual mobile users have to be sure that the risk of fraud is minimized or there is no risk at all, providing higher level of security to protect mobile payment transactions (Karnouskos, et al., 2004; Diego S., et al., 2007), taking into account to prevent any trial of fraud payment transaction from stolen devices. Therefore, to make that security system trustworthy, it should involve some security criteria (Norleyza *et al.*, 2002; Norleyza *et al.*, 2008) as follows:

Confidentiality and identification: this means that electronic messages which are sent with unique identification information for verification must not be visible to eavesdroppers and underlying on the mobile network security.

Authentication: where service provider should authenticate the transaction from users via an identification process or cryptographic mechanism. In other words, MMP units must identify each other's identity, reliance on the personal nature of a MMP devices and reliance on authentication by mobile network operators.

Integrity and Non-repudiation: which means MMP units must know when the data they send have been obtained and it must be possible to prove that a transaction has taken place.

Secure Performance, the service provider has the responsibility to ensure that the requested transaction is performed under a secure environment and ensure a safe protocol for payment transfer.

Additionally, Security is more difficult to implement on a mobile environment according to the resource limitation of mobile devices. Therefore, the security mechanisms for electronic transactions engaged with mobile devices must be implemented in an effective manner (Peter L., et al., 2002). Moreover, the mobile agents must be secured and protected against any hostile environment. Some possible security concerns are listed below (Neuenhofen & Thompson, 1998): Malicious mobile agents can try to access services without suitable permissions. A malicious agent may assume the identity of another agent to gain access to services, or to cause mischief or even serious damage to the mobile environment. A malicious agent can sniff the conversations between other agents or monitor the behavior of a mobile agent in order to extract sensitive information from it. A malicious host may steal private information from the agent or modify the agent to compute the wrong result or to misbehave when it jumps to another site. However, Digital signatures and trust management approaches are among many mechanisms to protect a host against malicious agents. Theses mechanisms help identify the agent and evaluate how much it should be trusted.

Currently HTTPS is the most widely used data security protocol in Personal-Java and J2ME/CDC (Java 2 Platform, Micro Edition/ Connected Device Configuration) applications. MIDP 2.0 makes HTTPS support mandatory. HTTPS can be employed to secure communication channels and everything that passes through those channels.

3.1.7 Directory service

The Directory service responsible for publishing and advertising goods and services (Yuan, S., Tsao, Y.: A., 2003; Pantea K., et al., 2012) offered by the existing brokers and provide channels to communicate with other MMP units like Location-Based Service (LBS) unit. Such unit assist to obtain useful information about the exact position of the product in the market, and gives information about location and cities roads. Also user/merchant profile provides useful information about user requirement, merchant offers or product specification. All these components gather information to be supplied for directory service.

Advertising

The technology that enables communication between MMPs via present typical message contains product or service information either huge or small is called advertising. This technology consists of different forms of advertisement. According to the personal needs or integration, it might be advertising one or list of different broker, auction, service provider, product or service (Tom P., et al., 2006; Pantea K., et al., 2012) among different MMP environment. In other words, it helps though providing service to suppliers who could not find any matching buyer registered under the same MMP with a product or service that is being offered. In addition, through advertising MMP can attract more mobile users and dramatically improve sales and business makes more profit.

User Profile/ Merchant

User Profile means a database in which personal data of users or merchants are stored. These data can include a user name, address, preferences, IP address, merchant location, etc. It contains the user's interest and what he/she is searching for. Hence, this data are used by some units of MMP to establish a connection between users and merchants. Knowing the content of user profile enable MMP to ignore or send any advertisement about the available products. It helps prevent receiving undesirable or disturbing advertising. What is more is that it can sort and categorize users according to their profiles (e.g. age, profession, product of interest, selected product, etc.) which may invent new improvement in MMP, i.e. according to selected product, advertisement units can provide suitable advertising for the related products timely or in future. That may enhance the ability of business interaction between merchant and customer from one hand, and obtain information and new features about available and related products (e.g. accessories, terminal, etc.) with selected product on the other hand.

Location-based services

Location-Based Services (LBS) provide a service to target supplier or buyer based on their physical location (Dimitrios *et al.*, 2007, Richard F, et al., 2011; James S., et al., 2010; Shane C., et al., 2010) and presents information about that to the concerned different units in MMP to improve their services according to what is needed. Nowadays, most of smarts phones and mobile devices support the GPS system which is very helpful to gather information about locations. Here, it is possible that subscribers could soon be placed with near pinpoint accuracy. In this regard, such service is still not preferred by some mobile users as it does reveal their personal privacy. However, location information has been the monopoly of the carriers and network operators themselves. In the future, this may not be the case. For example, Bluetooth or WiFi can contribute to location determination.

Maps: it is meant the map database stores which draw information of cities and the exact position of the product, shopping malls. This information is required to produce directions to a given product.

3.1.8 Search engine

No doubt that Internet and the wireless supply an actual MMP all over the world are without location and time restriction. Search engine is very helpful unit in MMP. It provides the necessary information to various units of MMP (Ibach *et al.*, 2005;

Tilson *et al.*, 2004) with respect to their request. Usually, MMP make available on the Internet electronic catalogs that support lists of products (such as book, flowers, etc.) or services (e.g. news, ticketing services, financial services, etc.) price information and commercial transactions. Depending on that, search engine will return a list of products or filtered services which meet the requirements specified by the buyer. According to the huge number of agencies i.e., broker, auction, delivery, payment, supplier, buyer, etc. and overloaded information interacted and presented between them, search engine is considered the backbone of MMP.

3.1.9 Broker, Auction and Game theory

This unit contains different components available as separate or combined. Whatever the forms of their availability are, it has to work with integration.

Broker Agent

Broker agent is considered a party that mediates buyers and sellers in an MMP. However, it develops to summarize the results and present it to users via searching through MMP for different characteristics of the products or service. Therefore, it performs different tasks such as matching buyers and sellers (Kannan *et al.*, 2001), filtering the offer information about goods or services' specification and prices (Jailani *et al.*, 2006; Norleyza, *et al.*, 2002; Timon, *et al.*, 2005), register with a certain auction type as the price negotiation mechanism is to match suppliers with buyers. Likewise, it helps buyer agent to search for desired goods or services with specific criteria, then retrieving specific information (e.g. price) to help user determine what to buy, and to decide whom to buy from. The main idea of broker is to obtain multiple searches accomplished by agents working in parallel along with information sources together in one place.

Auction

The term 'auction' means the process with an explicit set of rules of buying and selling goods or services, by offering them up for bid, to determining a resource allocation and prices, taking bids, and then selling the item to the winning bidder (McAfee, R., *et al.*, 1987; Klemperer, P. 1999; Kwang Y., *et al.*, 2003;Dimitrios, M., *et al.*, 2007; Calvin W., *et al.*, 2010; Rajkumar, R., *et al.*, 2011). In economics theory, an auction may refer to any mechanism or set of trading rules for exchange. Auctions have been recognized as an excellent trading mechanism to allocate resources, viz, goods, services, etc. to individuals and firms (Klemperer 1999). In addition, Auctions can be distinguished in a number of participants (Jailani *et al.*, 2006): The first is in supplying (or reverse) auction, where *m-sellers* offer goods that a buyer requests. The second is in demanding auction, *n*-buyers bid for goods being sold; the third is in doubling auction *n buyers* bid to buy goods from *m-sellers*.

To get the items that a buyer wants in an Internet auction, user must search for the items through several auction sites. When the bidding starts, the buyer needs to connect to these auction sites frequently so that user can monitor the bid states and re-bid. A reserve-price auction reduces the number of connections, but this limits the user's bidding strategy. Therefore, there are many types of auctions, the most well-known, can be mentioned briefly as follows:

English auction which is identified as an open ascending price auction. This type of auction is arguably the most common form of auction in use today.

Dutch auction identified as an open descending price auction (Jailani *et al.*, 2006), while the auctioneer begins with a high price and lowered until some participant is willing to accept the auctioneer's price.

Sealed first-price auction known as a first-price sealed-bid auction: In this type, all bidders simultaneously submit sealed bids so that no bidder knows the bid of any other participant. The highest bidder pays the price they submitted.

Vickrey auction well-known as a sealed-bid-second-price auction: This is identical to the sealed first-price auction except that the winning bidder pays the second highest bid rather than their own.

Game Theory:

Game theory can improve the system of negotiation filtering (Manvi and Bhajantri, 2009) and the competition result performance of goods and services in MMP. The scenario of this theory is (Liqiang Z., *et al.*, 2007), firstly, each player estimates the number of competing nodes (i.e. game state). Secondly, based on this state, each player tunes its equilibrium strategy by changing its local contention parameters. Finally, the game is repeated until getting the optimal results.

3.1.10 Payment Gateway

The Payment Gateway (Karnouskos, et al., 2004; Diego S., et al., 2007) means a trust third party responsible for processing the payment transaction from initiation till completion of payment processes along with authorization. Mobile payment has two tasks: (1) inside MMP and (2) outside MMP. The first task could occur when the scenario of MMP reflects the billing and payment for direct transaction-dependent on MMP. This includes mobile value-added services and the purchase of non-digital goods or services via the mobile channel. Typical examples of this are news, financial information, and entertainment. There are two well-known offer models for mobile value-added services; one offer is by the Mobile Network Operator (MNO), and the another offer is direct offer by a Mobile Content Provider (MCP). The MNO produces mobile content or services itself or buys them from a MCP acting as a supplier and thus offering a single face to the customer for network and all other services. Hence, Mobile payment competes directly against other payment systems such as e-payment, credit or debit card, or cash.

There are three essential charging approaches to the payment gateway:

The sponsoring approach performs a particular task. Services are free of charge for mobile users because they are provided at the mobile content provider's expense.

Premium fee charging, here, mobile users pay a data volume fee for transmission and additionally a so-called premium fee for the value of the content or service. The MNO as a payee gets the data volume fee and transfers the premium fee to the MCP after deducting a compensation for its costs. ''Order last goal'', would be a typical example to provide a certain number to receive a multimedia message back, including a video clip of the goal.

Fixed price charging, here, mobile users pay a fixed price for their usage of the service. This revenue as a whole is shared between MNO and MCP according to an agreed upon formula.

Payment Service Provider

Payment service provider provides the payment procedure (Kreyer, N., *et al.*, 2002) to the customer as well as to the portal provider or to transport service provider. The authentication service provider, in turn, provides the verified customer identity to the mobile payment service provider.

3.1.11 Delivery Agent and Store Service

The delivery agent is considered a trusted third party responsible for delivering goods and services. The transport service provider provides data transport to the customer and thereby forwards the product to the customer after getting the details of customer information contact through supplier agent.

The store service (portal), a site bringing together a variety of content and services in one area and attracts a large number of visitors, delivers the product to the transport provider and pays compensation for payment handling to the payment service provider, typically as a transaction fee.

3.1.12 Listening, event log and notification agent

This unit provides the necessary mechanism on the way, topic, time and place to record the activities and information related to transactions carried out by the buyer and supplier agent, based on the agreed privacy policy achieved during the privacy negotiation process. This information is recorded as a log file to be used for mobile forensic investigations (Norleyza *et al.*, 2008).

3.1.13 Buyer Agent

Buyer agent is a mobile bearing its owner's information, certificate, privacy policy, product/service request (Timon *et al.*, 2005). Buyer agent's information includes a unique identification, the broker's registration, a contact address, bank account particulars and bid-related information. To enter the MMP, it has to be authenticated by the security gateway, negotiating privacy policy to hide its identity and protect confidential data, then, forwarded by the directory service to its broker bidding for the requested product/service and returning to its owner when its request has been fulfilled.

3.1.14 Supplier Agent

The procedure of supplier agent is similar to the buyer agent. It returns to its owner when a trading partner has been found. A supplier agent is called a mobile agent who sends requests for its products/services to be advertised and sold. It carries its owner's information, certificate, privacy policy and information on products/services features, reserved price and time limit (Timon *et al.*, 2005).

What a broker agent has to do is respond to buyer agent's requests, acknowledge the Buyer Agent of previously requested information, choose a supplier according to Buyer's specified criteria, and communicate with other brokers. If a product/service requested by a buyer is not available on its supplier's list, the broker will send a message to other brokers querying for the specified product/service.

3.2 Personalized Notification System for Improving the Efficiency of MMP

The huge increase in wireless technology increases the number of mobile device users and provides an opportunity for the rapid development of *Mobile Market Place (MMP)* using these devices. Hence, MMP, defined as the traditional *Electronic Market Place (EMP)* combined with mobile devices, Internet technology and wireless communications, and it is likely to become a major business model in the near future. The internet technologies continue to develop, popularity of mobile terminals to increase, and the quantity of information on the internet is immense and increasing each day. Somehow, MMP has the capability of allowing users to conduct EMP activities on their mobile devices (such as Mobile phone, smart phone, Personal Digital Assistant, laptop, etc.): receiving/gathering sales information, selecting, making a purchase decision, paying for it, obtaining the service or product and delivering the right information to the right place at the right time without location and time constraints. These qualities make MMP prevalent in our daily life, and mobile users are more willing to do business on their mobile devices more readily. In fact, the essence of MMP revolves around the goal of reaching mobile users and suppliers, and satisfies whatever the users' demands by fitting the preferences of the users in combination with time and location whenever they want. In addition, MMP offers a unique business opportunity characterized by some unique attributes that equip it with certain advantages against traditional EMP.

However, the mobile users are still facing some difficulties in searching, browsing and making decisions for buying an item in some MMP environment, which are considered a time-consuming and frustrating task. In this regard, using recommendation system along with notification system in MMP domain will certainly help in: (1) increasing consumer satisfaction, through supplying user with the data of interest when events occur or certain conditions are met via a convenient means (Nader *et al.*, 2008). The means including instant messaging, e-mail, WAP applications, etc. (2) Enhancing consumer/company loyalty, and boost overall sales through targeting a huge number of mobile users based on their interest and location. By the same token, demands for mobile services become stronger and more diversified. However, mobile technology services still need to integrate with computer network services. The integration among information services (e.g. databases), notification services (e.g. E-mail, alarm systems) and telecommunications infrastructure (e.g. GSM, Fax, etc.) is one of the strategic issues to satisfy mobility needs (Messerschmitt 1996).

The NS is a telecommunication method of delivering a message to a set of recipients. For instance, the NS can send an e-mail or gets notified by another gateway when a new topic has been added to the MMP or when a desired good or service is made available. Moreover, this architecture is important for both mobile users and services providers to provide the necessary information when it is needed.

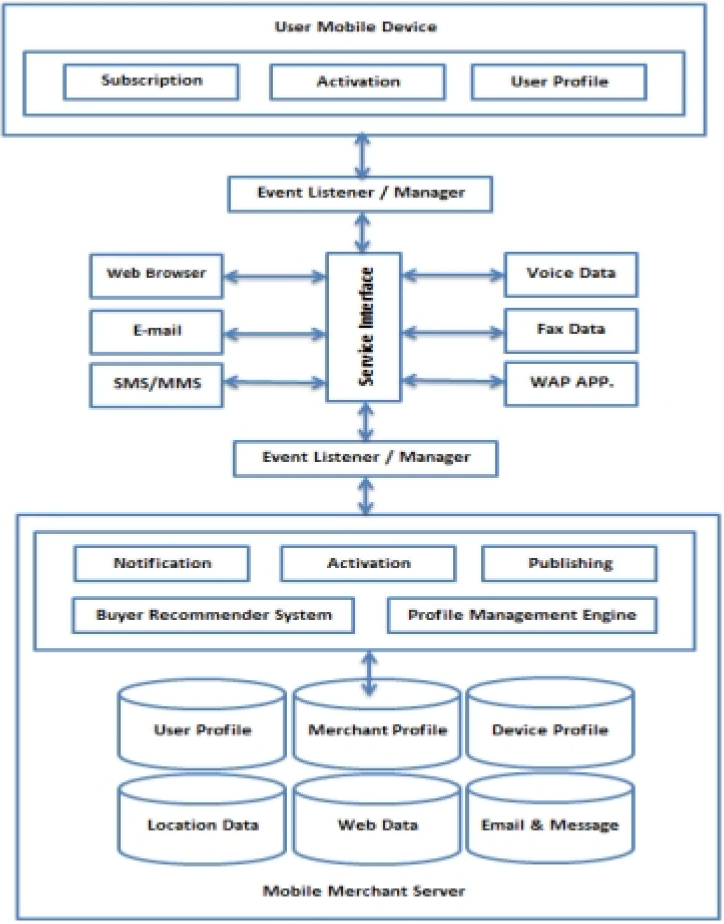
The complexity of the NS is often dependent on the types of messages that must be sent. However, the NS models should have the following attributes:

- ☐ The ability of notifying individuals' users in real-time interaction, or when the events take place.
- ☐ Supporting the scheduling and fail-over scenarios.
- ☐ The NS can be controlled by mobile user to permit or escalate (spam) the unwanted notification.
- ☐ Supporting customer reviews and item features and accept them as a feedback to determine what tasks the system should perform.
- ☐ Considering users' location, and notifying them about their interest according to their profiles and locations.
- ☐ Supporting the scalability, without changing the model design when there is a need to add new notification service by means of a plug-in approach.

3.2.1. Notification System of Mobile Market Place

Fig. (3.2) below depicts the proposed architecture of the Notification System for the Mobile Market Place (NSMMP). In such an environment, end users (i.e., customer or service provider) can access the NS and register for their events of interest and obtain the expected content when matching has occurred. The architecture of NSMMP system consists of two main components: Customer's Mobile Devices and Mobile Merchant Server, in addition to the interfaces among these components.

Fig.(3. 2): The architecture of the notification system of mobile market place (NSMMP)



A. User Mobile Devices:

The User Mobile Device (UMD) consists of subscription unit, user profile and authentication unit.

The subscription:

Mobile Marketplace Subscriber (MMPS) is a mobile user that subscribes to events of interest, and the action of this user can be performed at the client's site or at the broker's site. This unit is responsible for performing the subscription activities and making the user able to subscribe for the information of interest or action supplied by Mobile Merchant Server (MMS) or service provider. The subscriber lets the system know which channel that they like to be informed through, whenever certain events occur according to subscriber location or other conditions.

User profiles:

The user profile is defined as data stores that contain information about user, including user preferences, locations, credit card details, authorization and password information and so on.

Authentication:

Authentication processes should accomplish when the transaction between service provider and mobile user has taken place, and that could be done via an identification process or cryptographic mechanism, though certificates which are trusted, to provide validity of the secrets key which are used for authentication. Those digital certificates used to proof the identity and authentication of each marketplace units.

B. Mobile Merchant Server:

Another main component of NSMMP is the Mobile Merchant Server (MMS). This component has to monitor and handle all users' requests and figure out the changeable requirement of users timely. This component consists of:

Notification Unit:

With the help of this unit, the MMS can notify mobile marketplace subscribers via sending them a text or multimedia message about the available services. Notification is a form of push data delivery mechanism where information is transferred as a result of an event (Weichang *et al.*, 2008; Tilson *et al.*, 2004). However, synchronization notifications, common in mobile networked application are designed to provide real-time access to information sources.

Activation Unit:

If the MMPS is interested in the content of notification, he/she has to reply back to the activation unit to make him/her a member of this content and allow him/her to receive the data of interest from publication unit in timely manner. In other words, this unit handles the users' activation process and informs the publication unit about each subscriber's interest and his/her preferable gateway that he/she likes to be informed through (e.g., SMS, real-time alert notification, e-mail message, etc.).

Publication Unit:

While the requirements of activation processes have been done, and the conditions have been met, as well as the events have occurred, publication unit will immediately publish the events to all mobile users who have subscribed to that particular event through the most appropriate gateway to the mobile user. In addition, this unit will publish to subscribers all the recommendation events that have been generated by Buyer Recommendation Engine (BRE).

Notification Database:

Notification system database can be simply defined as a data store for the heterogonous type of data resources, which are involved by interpreting the conditions of subscribers' notification, that is associated with the item. This unit can retrieve the conditions of information as its availability by their names if the sources of information are a set of files, or generates a logic expression based on table fields in case of the data sources are database. The notification mechanism operates as triggers in database, when the event has occurred, the notification action will be fired, if the trigger condition is satisfied. In addition, the database intended for use in heterogeneous distributed environments allow for objects to be shared between different client applications. The goal of the database is to provide highly available and highly reliable storage for items, while supporting safe sharing of these sources by applications working in different platforms.

Event Listener /Manager:

This unit takes into account filtering and controlling the process of those items selected by the subscribers, which are meaningful to their requirement and met with the merchant's rules and conditions. It is also responsible to take input from the user and converting it into a standard format.

Profile Management Engine:

Profile Management Engine (PME) stands for creating, updating, handling and providing the storage of saving relevant information that consists of user preference profile, mobile device profile, user personal information and location.

Buyer Recommendation Engine:

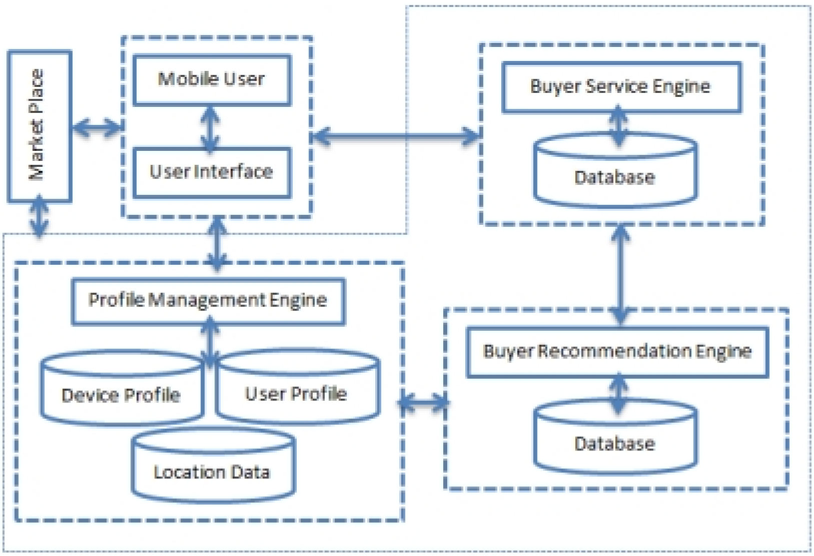
Buyer Recommendation Engine (BRE) stands for servicing a mobile user community, providing each user with a list of items which are the most wanted items by such user based on his/her profile and location. This can be addressed by analyzing profile management engine data and generate the recommendation based on that data. This component is elaborated with more details in next section.

3.2.2. Recommendation System for Mobile Market Place

In fact, this study focuses on the issue of notifying the mobile user/group with the information that meets such user/group needs, based on the profile and location of the intended user/group. The significance of this study lies in investigating the notification and decision support system in a mobile market place environment. To achieve this goal, recommender systems can be applied to the domain of mobile marketplace. More precisely, in this thesis, a recommender system using individuals/group profile and location-based model for efficient recommendation is presented.

The proposed architecture of Recommendation System for Mobile Market Place (RSMMP) consists of several steps as illustrated in Fig.(3.3) below. There are five components: (1) User agent, (2) Buyer services engine, (3) Profile management engine, (4) Buyer recommendation engine and (5) marketplace. Each component may have several mobile agents. The task of recommendation process is accomplished through the collaboration of all agents.

Fig.(3. 3): Recommender module as a part of notification system (RSMMP)



User Agent

This agent consists of a user interface witch is the top component of the architecture of MMP. This interface provides a GUI that is highly required for supporting mobile user's interaction among the different components of MMP system. This interface has also tackled the requirement of providing a convenient way of interacting with the system (the amount of information is specific to the attributes of mobile device), even via some mobile devices that have many constraints such as small screen with helps of device's profile. This interface also provides necessary services to make the accessibility, and security mechanisms more attractively among the heterogeneousness components of MMP.

Buyer Services Engine (BSE)

The main objective of this component is collecting user behavior data (i.e., navigating pages behavior, purchasing behavior, user rating, feedback behavior for recommendation, etc.). This type of data can be observed and recorded during the processes of user interaction with the heterogeneousness components of MMP. User behavior data are dynamic and do changes while the user interacts with the system. The user delegates his/her navigation activities carried out by a mobile device to a mobile merchant agent. It is created at the beginning of an exploration session when a user visits the MMP site and destroyed at the end of the session. This component is necessary to provide accurate input data for different recommendation algorithms.

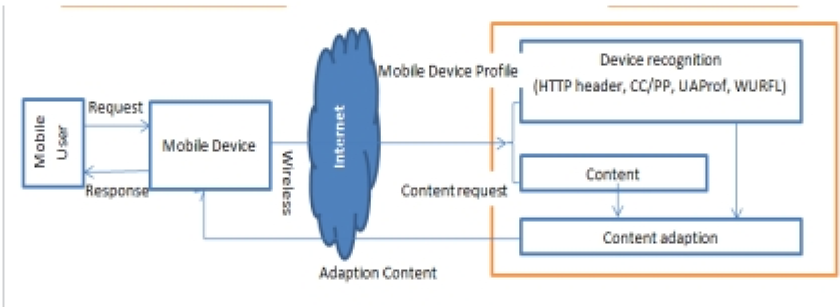
Profile Management Engine (PME)

Profile management engine stands for creating, updating, handling and providing the storage of saving relevant information that consists of user preference profile, mobile device profile, user personal information and location. It is always active. Whenever profile management engine receives a request or query from user agent, it generates the relevant profiles information to buyer recommendation engine.

The user profile describes the interest of the user and provides input data to buyer recommendation engine. The user profile must involve comprehensive user information that includes static user description data (i.e., gender, age, occupation, etc.) which do not change in time.

The mobile device profile describes the characteristic of user's mobile device (i.e., screen size, keyboard layout, etc.). It is the guide of content presented to the device as illustrated in Fig.(3.4) below. Many mobile device ontology standards, such as Composite Capabilities/Preferences Profile (CC/PP), User Agent Profile (UAProf) and FIPA (Device Ontology Specification), have been set to describe the capabilities of different mobile devices (Foundation for Intelligent Physical Agents FIPA 2009 available at *http://www.fipa.org/;* Open Mobile Alliance 2009 available at *http://www. Open mobile alliance.org/).* Mobile device profile uses standardized format built from CC/PP, UAProf or Device Ontology Specification.

Fig.(3. 4): Mobile device profile



The CC/PP specification defines a high-level structured framework for describing capability of mobile device (Composite Capabilities/Preferences Profile, *http://www.w3. org/ Mobile/CCPP/).* CC/PP provides the rules of how to construct a vocabulary that describes capabilities and preferences, but does not specify the actual attribute names and values. The UAProf based on CC/PP, has a base of existing implementations for many devices (User Agent Profile, *http://www.wapforum.com/ what/technical.htm*). The UAProf specification is concerned with capturing classes of device capabilities and preference information that is used only for content formatting purposes.

The mobile device profile described in RDF consists of three parts: hardware platform, software platform and WAP characteristics. The hardware platform describes the hardware information that is associated with user interface format such as screen size, image capability, etc. the software platform describes the available application style, operation system and Java environment. The WAP characteristics describe the supported WAP version and the script library.

Buyer Recommendation Engine (BRE):

A Buyer Recommendation Engine invokes the weights of all recommendation algorithms agent. Each recommendation algorithm agent encapsulates a specific recommendation algorithm. It is just to introduce a new agent to encapsulate the new algorithm when a new recommendation algorithm is required. Each agent makes recommendations according to its recommendation mechanism. Then, the hybrid algorithm combines and sorts the results and chooses the first top-N items as the final recommendation. Thus, BRE transfers the final recommendation list to the user interface agent. Considering the steps mentioned above, BRE can stand for servicing a user community and providing each user with a list of items which are the most wanted items by this user and introducing new items for target users. This can be addressed by analyzing user behavior data. The format of the final recommendation result will be transferred through the mobile interface agent to the mobile user according to mobile device profile. Interface format agent reads the mobile device profile and creates user interfaces dynamically according to the characteristic of different devices to present the item and service information.

Marketplace

A marketplace is the space, actual or metaphorical in which a market operates. i.e., the "real market" in which items and services are provided and consumed. In other words, marketplace is a place that lets the mobile agents of buyer and seller trade with each other and provides kinds of trading services such as: information query, negotiations, and auctions, etc.

Various factors and services in mobile marketplace play important roles in enhancing the success of a current marketing field. The recommender systems are considered one of the most important tools that make great significance in the marketing activities of MMP.

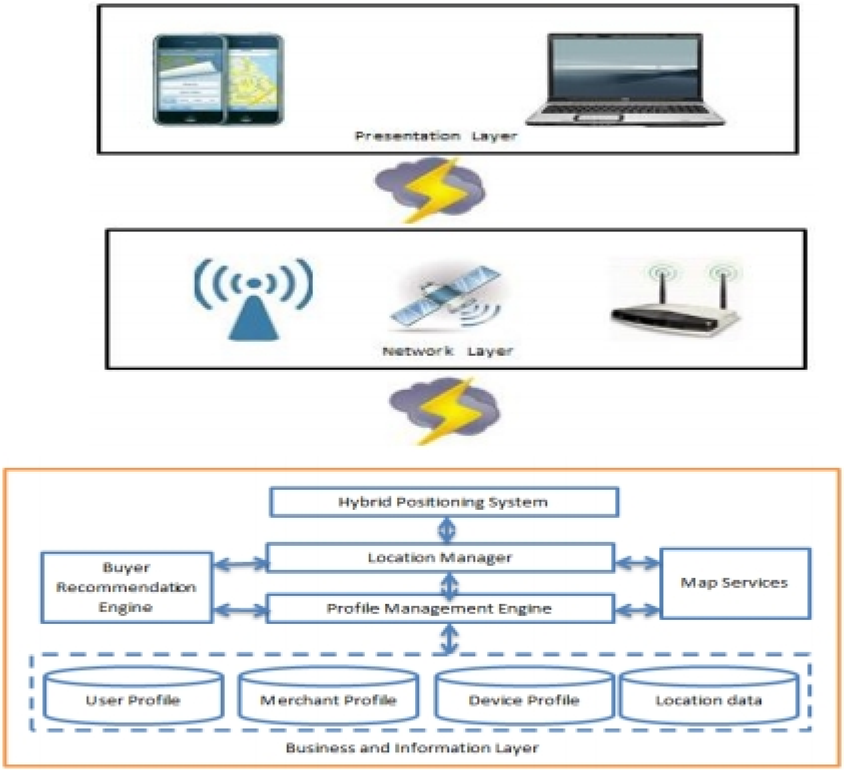
3.3 Positioning System and Location based Service

Location based services (LBS) are defined as the application that utilize the location of the user to adapt the service accordingly. LBS do not provide the services themselves, but rather enable location based services. Nowadays location features are becoming a fundamental part of different mobile devices. Such features played important roles in enhancing the mobile location service, thus supplying the user with an accurate transition towards context-aware services. Meanwhile, LBS have been integrated to the current mobile and have been used in different application such as travel information, shopping, entertainment, event in- formation and different mobile professions. However, the location information of the user can be measured more or less accurately depending on the positioning systems in use and their service infrastructure. The technical and service infrastructure may differ or change in the middle of a usage session (Richard F, *et al.*, 2011; James S., *et al.*, 2010; Shane C., *et al.*, 2010) e.g. the network or the positioning system may change when the user moves from one place to another. Similarly, the service infrastructure, i.e. the available services and applications, may change.

Utilizing location based features can enhance the potential of user satisfaction toward the quality of recommendation that reveals user needs. It makes it possible to find and recommend items for users operating mobile devices based on his/her location. However, a user's preferences and item's features are assumed to be directly related to recommendation quality.

Fig.(3.5) depicts the architecture of the Positioning System of Mobile Market Place (PSMMP).

Fig.(3. 5): The Positioning System of Mobile Market Place (PSMMP)



This system uses different techniques to return a list of location information for both user and item as shown in Fig (3.6) to assists the recommender system of MMP with the necessary information about the current location of items and mobile users

Fig.(3. 6): (a) User location, (b) Item location

L_1	L_2	L_3	L_4
U_1		U_3	U_2
		U_4	
	U_5		U_4
:	:	:	:
:	:	:	:
U_6			U_3

(a)

L_1	L_2	L_3	L_4
I_1	I_1	I_2	I_5
I_2	I_3	I_4	I_2
I_3	I_6	I_6	I_4
:	:	:	:
:	:	:	:
I_6	I_3	I_2	I_5

(b)

PSMMP consists of presentation layer which shows the mobile devices in use, the network layer which represents the communication medium between the mobile devices and MMP domain, and business and information layer which contains two main components: Hybrid Positioning System (HPS) and Location Manager (LM), in addition to the interfaces among these components like Buyer recommendation engine and profile management engine which have been discussed so far:

Hybrid Positioning System: Current mobile devices (e.g., mobile phone, laptop or PDA) are combined with one or more complementary technologies of positioning system. The technology uses the location data from GPS, mobile cellular and nearby Wi-Fi access points to calculate the position of a mobile device. These positioning systems are complementary, because they balance each other's strengths and weaknesses. Accordingly, based on the needs of the applications and the required accuracy, HPS uses several techniques (Richard F, *et al.*, 2011; James S., *et al.*, 2010; Shane C., *et al.*, 2010) to determine which active technology is most reliable at any given moment.

HPS occasionally estimates the error of each of its active technologies and prefer the one with the highest degree of confidence at that particular moment. And sometimes, the usage scenario or the confidence histories of each source are leveraged. Generally, HPS uses this data to decide which technologies are more preferable or how to combine the various inputs into a superior overall calculation. e.g., sometimes, Wi-Fi does not work properly according to the poor covering of Wi-Fi signals, and the Wi-Fi hotspots database must be constantly updated to keep up with Wi-Fi hotspot changes. In this regards, HPS may be allow Wi-Fi to works beside cell phone tower triangulation and GPS to provide reliable and accurate position data under a wide range of conditions, including among tall buildings and indoors, when GPS signals may be weak or intermittent.

Location Manager: the location manager function uses to enable the use of various positioning technologies and convert the positioning information that is obtained by HPS into useful location information and make it available for LBS applications. Thus, this function acts as a gateway or hub for location. In addition, LM provides a mechanism for user to obtain the device's geographical location and a facility for user to be notified when the device enters a specified geographical by using location providers which are available to HPS. Currently, many location providers are available for obtaining location information, but three of them have gained a good reputation and became more popular:

- GPS providers use a Global Positioning System (GPS) that comprises of a network of twenty-four satellites and ground stations. Each satellite transmits a signal containing the time and its location back to the earth synchronised by its internal atomic clock. Using a minimum of three satellite signals a GPS receiver triangulates its position by calculating its distance from each of the satellites using the information contained in each satellite signal. This method of triangulation is referred to as trilateration. GPS based location tracking systems are proficient way for tracking the exact co-ordinates of a mobile user to get the information about his/her current location. This mechanism is widely used in the M-Commerce based advertisement systems where the point of interest information about the hotel, restaurant in specific location will be sent to the mobile user based on the GPS location co-ordinates.
- Network providers use Wi-Fi networks that utilises existing Wi-Fi equipment such as those installed in personal computers, and smart mobile phones. The

technology uses modulated Wi-Fi transmission signals to detect the presence of a device (Wi-Fi card periodically scans its environment to discover wireless networks. i.e. the laptop periodically broadcasts an 802.11 probe request frame and listens for probe responses from nearby access points. The distance between the access point and a receiver computed according the signal strength values (when it is closer to zero), which does not necessarily have to be connected to the network in question, just visible to it, the system is then able to determine the position of the device based on the signals received from the various Access Points (AP).

- Network providers use cell-phone towers that calculate the location of the mobile phone by measuring the mobile phone signal strength and the signal travel time relative to the different towers with in a cell. Table. (3.1) below depicts the advantages and drawbacks for the abovementioned positioning system.

Table (3. 1) Advantages and drawback of the most popular positioning system

Technologies	Common principles used for localization	Advantage	Drawback
GPS	Triangulation method using timing signals from 3 satellites out of a system of 24 satellites. Time of Arrival (TOA)	Works extremely well - accurate and reliable- in open areas (outdoor), sparsely populated areas. No new network infrastructure required. Number of GPS devices steady growing. Can locate within thousands of kilometres.	GPS satellite signals are weak (when compared to cellular phone signals or Wi-Fi), so it does not provide any coverage inside a building or indoor. Only determines the location of object within a few hundred meters Very high Power consumption.
Wi-Fi	Time Difference of arrival (TDoA)	Wi-Fi coverage is thin or non-existent so it performs best in congested population	Its accuracy depends on the density of Wi-Fi signals or the number of routers. The technology performs better in the

	Time of Arrival (TOA) Received Signal Strength Indicator (RSSI)	centers and indoors. It is one of the most important wireless networks under location-based service used for determining positions of an object or person. Can locate within 20 to 30 meters of an object depending on the deployment of Wi-Fi routers.	urban areas that have more Wi-Fi beacons. It is not popular in rural areas where access points are deployed far from each other. Unlike GPS satellites or cell towers, during moving it needs timely update the location database by searching for new Wi-Fi access points in a particular area and only then the application can locate the precise position. high Power consumption
Cell tower	Time Difference of arrival (TDoA) Time of Arrival (TOA) Received Signal Strength Indicator (RSSI) Angle of Arrival (AOA) Proximity Cell ID, others Triangulates the location of the subscriber using timing of signals sent from the mobile unit to at least three different cell sites. Time difference of arrival (TDOA) requires synchronization among base stations and uses differences in arrival time.	HPS can combine cell ID and Wi-Fi to increase the location coverage for a wireless network without adding or modifying any hardware on the devices or the network. No handset modifications Low cost TOA does not require any handset modifications Good Availability Can locate within tens of meters to tens of kilometres low high Power consumption Uses the location of the base station currently handling a call to represent the subscribers location. Accuracy can be increased by sectorization (using directional antennas at the base station).	lower accuracy, especially in large rural cells. loss of privacy for user inferior accuracy for TDOA in analogue and narrow band digital systems. new equipment needed at base stations. TDOA requires modification to handset.

As mentioned before, the accuracy of exact location depends on the location providers. The location will be computed based on the latitude and longitude or the received signal strength to the closer referenced AP or cell-tower. Thereafter, LM will despatch the location information to the recommender system as required. In a similar manner, map service uses Geocoder technique that takes an address and returns a latitude/longitude pair, and then translates a latitude/longitude pair into a list of addresses. However, the returned address it may be not always an exact address. Thus, based on the matched location information that retrieved from PSMMP for both user and item, the recommendation will take place according to user interest.

Chapter 4

Recommender System for MMP

4.1 Introduction

This chapter deals with the design and implementation of the proposed method that can help mobile individuals /group formulate better decision-making by incorporating user/group profile as well as the geographical location. However, this system not only recommends items for individual/group of users with applicable recommendations based on their preferences and closest location, but is also capable of providing an explanation for the actual reasons behind the recommendations for individual and group users alike. To achieve this end, it should subdivide a MMP into distinct subsets of users where any subset may be selected as group or individual target. This can lead to the creation of a distinct justifiable recommendation according to the preferences of a specific users/group. In order to tackle this problem, users profiles have been constructed and processed based on information related to users' ratings and item features. Such process reflects dependencies among items and users, thus disclosing user's rating behaviour. The next step is to assign weight on user's profile in order to show the features that are more interesting and peculiar to each user. Thereafter, grouping users and items into clusters based on the most coherent rating. A subsequent step is using neighbourhood technique- Cosine Similarity- to find the clusters that contain the partial matching with the target user/group. This is, in fact, carried through observing ratings/features patterns of users/items for the target user/group vs. the available clusters. Hence, items are identified based on similarity of their features that are selected together by a sufficient number of users. Then, a list of recommended items is generated. Hence, reviewing the features of user profile against the features of recommendations list is essential to make the justification of recommendation more reasonable and understandable for service providers as well as for mobile users. The results of the recommendation list show how the features of recommended items are coherent and similar to the features of user profile.

In the experimental setup of our recommender system, a bicluster may denote a group of users that prefer some specific features. Collective features can be extracted by using groups rather than individual users. As far as a group recommendation is concerned, we assume that the input data contain item's ratings given by both individuals and groups and instead of calculating similarity between one test user and each bicluster, we calculate similarity between a group of test users and each bicluster " considering the duality of content and rating data ". For instance, if we have a group of users G = u_1, u_2, u_3 and suppose we have ratings of a particular item I_a by users u_1, u_2, u_3, subgroup $\{u_1, u_2\}$ and subgroup $\{u_2, u_3\}$. To predict what rating group G would give on an item, most of the previous researches will make their predictions only based on the ratings from users' u_1, u_2 and u_3, while some of the researches would ask users provide additional information and some others would ask the help of domain experts. In our work, for example, if users u_1 and u_2 rate the item I_a as 1 and 5, respectively, but they as a whole rate the item I_a as 4, then we realize that user u_2 seems play more influential role in this group, which somewhat reflects the personalities of users u_1 and u_2 Hence, our approach is capable of taking into account the dependency of features influence among the preferences of the majority of users so as to come up with reasoning behind the justification that gives credibility to the recommendation.

By exploring the features of items that recommended to the target 'individual user/group' with his/her/their user profile, the coherent match appears. This similarity is much closer among the recommended items that have highest values of influence. In contrast, the values revealing poor influence are evidence of the poor matching between the features of both those items and the tested user/group. Both the high and low values can be taken to interpret the significance of the role of influence among the features and user/group profile. Thus, the list of recommended items which contains the highest influence values is actually meets the interest of the tested user/group by involving the most desirable features that user/group are looking for. Hence, the system was able to grasp the user/group needs and recommend items accordingly.

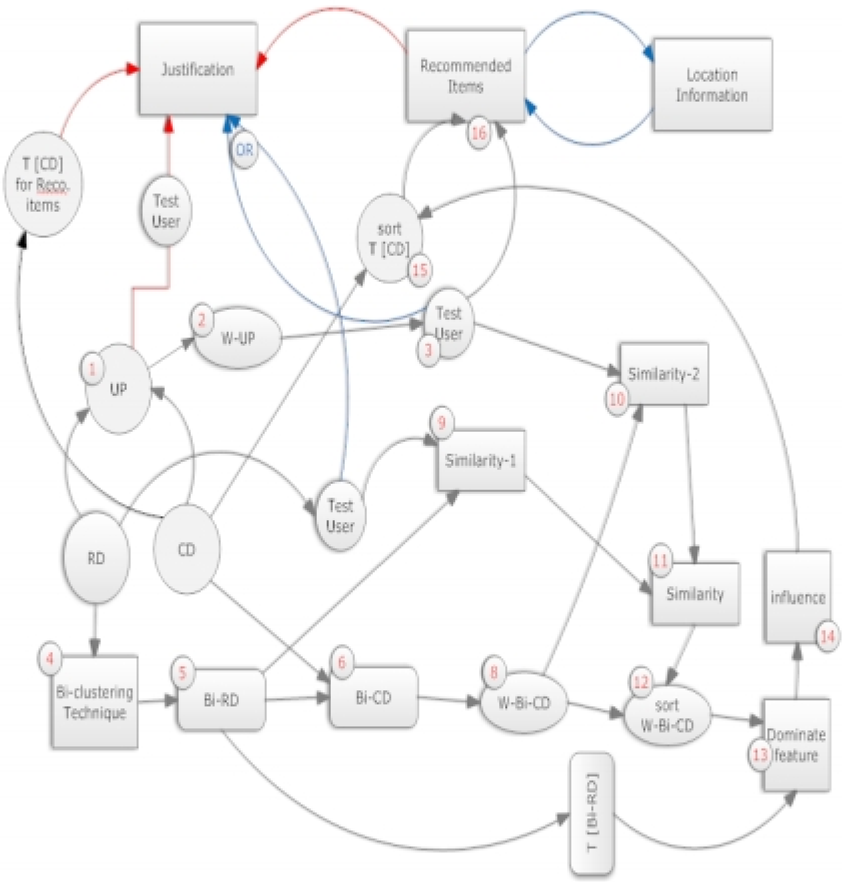
Meanwhile, it should emphasize that the items that got poor influence value with individual user are not supposed to be eliminated during building the recommendation for group. When these values have been eliminated less accuracy of recommendations has been observed. Therefore, those values play important roles to improve the accuracy and the quality of recommendations for the group. In other words, the influence of content data among users' profiles has strong effect on the quality of the group recommendations. The influence values may changes from case to case for the same user due to items/users influence among the different groups. However, that change does not affect the accuracy of recommended items or the justification for the target user. This can also be considered as another aspect of the system ability of filtering useful information that fits each individual needs, as well as satisfying the group users interests. Thereafter, the items that already have been rated by user could be excluded or kept the same 'if needed' to provide a recommendation to the specific user about the new generation of item that user got/rated it before.

Finally, we have constructed the users/items location profile; the system has been subjectively designed not only to generate accurate recommendation in respect to user interest, but also to help users find the closest place that surely contains their item of interest. However, the location of users may continuously be updated due to user movement but the recommendation has to take place according to the last updates.

The graphical representation of the proposed method is illustrated by Fig. 4.1 and will be detailed in the coming sections.

The proposed method has achieved significant results by recommending the user/group with items that match his/her/their interest according the evaluation metrics. The evaluation metrics we adopted here and used to calculate the performance of our recommender systems are recall and precision measures which are among the popular evaluation metrics in information retrieval systems. The quantification of recommendation is subjectivity captured by understanding the influence of user/group rating and item's features among user's profiles vis-à-vis his/her/their location. The framework has been implemented and evaluated using synthetic and benchmark datasets and has shown significant results. The generated recommendations have been categorized as individuals, groups which contain random users and groups which consist of biclusters that have been built during bi-clustering processes. Moreover, this approach takes into account the duality and dependency that exists between users rating and items features whereas most of the hybrid algorithms perform separate clustering of users and items so they cannot detect item similarity. It provides the actual reason behind its recommendations and justifies them. It is capable of recommending useful information that fits each individual needs, as well as satisfying the group users activities. Thus, the proposed method has the potentiality to increase consumer satisfaction, enhance consumer/company loyalty, and boost overall sales by giving justification and creditability to the products that have high degree of interest to mobile users.

Fig.(4. 1): Graphical Representation of the Proposed Method



4.2 The Proposed Method

The following steps describe in details the design and the implementation of the proposed method:

4.2.1 Building user(s) profile

As shown below in Fig. (4.2-c), user profile $P\ (U_i,\ f_n)$ constructed based on the rating and content data to show the users and their interested features. Rating data $R\ (U_i, i_k)$ as shown in Fig. (4.2-a) represents the rating data given by user U for a specific item I. In the rating data matrix the rows represent the users and the columns represent the items. Whereas content data $C\ (I_k,\ f_n)$ as shown in Fig.(4.2-b), represents the features f for an item I. In the content data matrix the rows represent the items and the columns represent the features. The values of rating data of I could easily reflect and disclose the users' behavior and show the degree level of their interest in a particular item. However, such data is still lacking and unable to explain what precisely a user prefers most in a specific item. Therefore, it is necessary to use the content data. Considering values for such features will help to figure out the features that are more important and preferable by each user. For instance, combining the features of rating items for each user individually would yield a clear picture with optimal meaning for user profile $P\ (U_j,\ f_n)$ and would lead to accurate recommendation. Here, we assign the minimum value of threshold for rating data as $T_{i=1}$ to bring out the most coherent dependencies of items features among user profile. In our proposed model, the equation below is used to build a user profile:

$$P[u_i] \leftarrow \sum_{i_k \in S} C[i_k] \quad where\ \ S \leftarrow S \cup \{i_k\}\ and\ R[i_k] > \ T_i \tag{1}$$

Where, S: set of the items which have been rated by user

To give an example, the U_6 *(Samuel)* has rated for items I_1, I_3, and I_5 (*Xperia S, Iphone 4S,* and *Galaxy 2)* as (2, 4, 5) respectively, and the content features of those items are (*Xperia S =101011, Iphone 4S=011011, and Galaxy-2 =101111*). Here, it is possible to observe and understand the user behavior by his/her profile, and thereby getting to know that *Samuel* is more interested on the features f_1, f_3, f_5, f_6(*Price, Quality, Battery-Life and Display*). However, it is clear that the features f_3, f_5, f_6 *(Quality, Battery-Life and Display)* are more interesting to *Samuel* and able to describe him better than features f_1, f_2, f_4 *(Price, Design, Simplicity)* can.

Fig.(4. 2): (a) Rating Data R, (b) Content Data C, (c) User Profile P

	Xperia S	Sony Tablet-S	Iphone-4S	Nokia-N8	Galaxy-2	Asus-EP121
John	3	-	-	5	-	-
Emad	2	-	5	4	-	3
Nazek	4	-	2	2	5	-
Alisa	-	3	-	1	-	5
Elbert	4	1	-	5	3	2
Samuel	2	-	4	-	5	-

(a)

	Price	Design	Quality	Simplicity	Battery-life	Display
Xperia S	1	0	1	0	1	1
Sony Tablet-S	0	1	0	1	0	1
Iphone-4S	0	1	1	0	1	1
Nokia-N8	0	0	1	0	0	0
Galaxy-2	1	0	1	1	1	1
Asus-EP121	1	1	0	1	0	1

(b)

	Price	Design	Quality	Simplicity	Battery-life	Display
John	1	0	2	0	1	1
Emad	2	2	3	1	2	3
Nazek	2	1	4	1	3	3
Alisa	1	2	0	2	0	2
Elbert	3	1	3	2	2	3
Samuel	2	1	3	1	3	3

(c)

4.2.2 Assigning weight

The weighting mechanism on user profile denoted as *WP (U, f)* and has been used to find out the dominant features that better describe and distinguish the particular user from the remaining users. Fig. (4.3) illustrates the weighted user profile by using inverse document frequency (IDF) (Salton, G. *et al.*, 1983; Ho Chung *et al.*, 2008) as follows:

$$WP\ (Uj, fn) = FF\ (Uj, fn) * IUF\ (fn). \qquad (2)$$

$$IUF\ (f) = \log\ (|u| / UF\ (fn))$$

Where,

$|u|$ - the total number of users

IUF - inverse user frequency

UF - users frequency in user profile

FF - feature frequency in user profile

If UF=U then UF=UF-0.1

Fig.(4. 3): Weighted user profile WP

	Price	Design	Quality	Simplicity	Battery-life	Display
John	0.007	0	0.158	0	0.079	0.007
Emad	0.014	0.158	0.238	0.079	0.158	0.022
Nazek	0.014	0.079	0.318	0.079	0.238	0.022
Alisa	0.007	0.158	0	0.158	0	0.015
Elbert	0.021	0.079	0.238	0.158	0.158	0.022
Samuel	0.014	0.079	0.238	0.079	0.238	0.022

4.2.3 Grouping users and items into clusters based on the most coherent rating

An attempt to organize users into sub-groups according to their rating by using traditional clustering is not efficient since the traditional clustering algorithms put each user/item in exactly one cluster.The shortcoming of this approach is that they cannot detect a partial matching of a user's preferences, because two users may share similar preferences only for a subset of items. Simultaneous using bi-clustering/co-clustering for clustering users and items can discover the exhibiting highly correlated ratings on groups of users and items. Biclusters allow the computation of similarity between a test user and a bicluster only on the items or features that are included in the cluster. The biclustering process on the rating data matrix involves the determination of a set of clusters taking into account both rows and columns. Each bicluster is defined on a subset of rows and columns. Moreover, two biclusters may overlap, which means that several rows or columns of the matrix may participate in multiple biclusters. Another important characteristic of biclusters is that each bicluster should be maximal, i.e., it should not be fully contained in another determined bicluster. To ensure that a user may exist in more than one cluster, a degree of overlap between bi-clusters is introduced to cover all the different preferences of a user (Banerjee, A., *et al.*, 2007; Madeira *et al.*, 2004; Dhillon, I., *et al.*, 2003; Cheng, Y., *et al.*, 2000; Mirkin 1996).

In order to provide recommendations to a specific user, it is obligatory to find only the bi-clusters that have subsets of constant values and represent the users who have similar behavior to that particular user. For this purpose, we use a simple binary inclusion-maximal bi-clustering algorithm Bi-Max. It is an exact biclustering algorithm based on a divide-and-conquer strategy capable of finding all maximal biclusters in a corresponding graph-based matrix representation (Mirkin 1996). For the Bimax algorithm, a bicluster defines a sub-matrix which corresponds to a subset of users that jointly present positively rating behavior across a subset of items and for which all elements are satisfied by threshold condition. For instance, if we consider Fig.(4.2-a) and select the positive rating threshold as $Ti > 3$ then the resulting sub-matrix will be having 1's under columns U_1(*John*)=I_4(*Nokia N8*), U_2(*Emad*)= I_3,I_4(*Iphone 4S, Nokia N8*),U_3(*Nazek*)=I_1, I_5(*Xperia, Galaxy 2*),U_4(*Alisa*)=I_6(*Asus EP121*),U_5 (Elbert)=I_1, I_4(*Xperia, Nokia N8*),and U_6 (*Samuel*)=I_3, I_5(*Iphone 4S, Galaxy 2*). Now, if we apply Bimax algorithm to the sub-matrix, it finds clusters with constant values (i.e., value 1). The main goal of the Bimax algorithm is to find all biclusters that are inclusion maximal, i.e., that are not entirely contained in any other bicluster. The run-time complexity of Bi-Max is *O (mnb)*, where *m* is the number of users, *n* is the number of items, and *b* is the number of the resulting biclusters. Thus, in our example, given a set of *m* users and *n* items (i.e., an $m \times n$ matrix) as represented in rating data $R\ (U,\ i_k)$, the Bi-Max algorithm generates biclusters as a subset of users that have exhibited similar behavior across a subset of items. The biclusters of bi-max are shown in Fig. (4.4).

Fig.(4. 4): Applying Bi-max algorithm on rating data R

	Sony Tablet-S	Iphone-4S	Xperia S	Nokia-N8	Asus-EP121	Galaxy -2
John			3	5		
Emad			2	4	3	
Elbert			4	5	2	
Nazek			4	2	0	
Alisa						
Samuel						

Biclusters:-

b_1 : U_{b1} = {John, Emad Nazek, Elbert}, I_{b1} = {Xperia S, Nokia-N8}
b_2 : U_{b2} = {Nazek, Elbert, Samuel}, I_{b2} = {Xperia S, Galaxy -2}
b_3 : U_{b3} = {Nazek, Elbert}, I_{b3} = {Xperia S, Nokia-N8, Galaxy-2}
b_4 : U_{b4} = {Emad, Nazek Samuel}, I_{b4} = {Xperia S, Iphone-4S}
b_5 : U_{b5} = {Emad, Nazek}, I_{b5} = {Xperia S, Iphone-4S, Nokia-N8}
b_6 : U_{b6} = {Nazek, Samuel}, I_{b6} = {Xperia S, Iphone-4S, Galaxy -2}
b_7 : U_{b7} = {Elbert, Emad}, I_{b7} = {Xperia S,Nokia-N8,Asus-EP121}

Applying binary inclusion-maximal -Bi-max- algorithm on R

Once the biclusters are created, the biclusters of rating data *BR(b,i)* are generated as the frequency of users in a bicluster U_{bi} for every item among I_{bi} to figure out the items those are matching between the users preferences among biclusters and find out the frequency of users those have shared the same items. The BR matrix as shown below in Fig.(4.5-a) generated as follows:

$$BR(i,j) = \begin{cases} |u_{bi}| & if\ i_j \in I_{bi} \\ 0 & otherwise \end{cases} \quad (3)$$

Where, U_{bi} are the subset users of b_i and I_{bi} are the subset items of b_i.

Thereafter, in order to figure out the features those are matching between the users preferences among biclusters based on the users frequency. biclusters of content data $BC(b,f_n)$ are constructed based on the summation of features f in content data $C(I, f_n)$ for particular items included in a specific bicluster of rating data $BR(b,i_k)$ multiplied by the common frequency for the same items existing in bicluster of BR. Fig.(4.5-b) shows the BC which constructed as follows:

$$S \leftarrow S \cup \{i_k\}\ when\ bj[i_k] \neq 0$$

$$v \leftarrow \sum_{i_k \in S} C[i_k]$$

$$bf \leftarrow v * b_j[s[1]] \quad (4)$$

Where, S is set of the items i_k inside the biclusters b_j of BR, v is the summation of content features of S, bf is the distinguish value for each features among biclusters b_j of BC.

Finally, to figure out the variety and differences between the features among the biclusters of BC, inverse document frequency was applied on BR to generate a weighted biclusters $WC(b, f_n)$ as shown in Fig. (4.5-c). The WC generated as follows:

$$WC(b, f) = FF(b, f) * IUF(f) \quad (5)$$

$$IUF(f) = \log(|b|/BF(f))$$

Where,

|b| - the total number of biclusters in BC

IUF - inverse user frequency

BF - users frequency in bicluster of BC

FF - feature frequency in bicluster of BC

If UF=|b| then UF=UF-0.1

Fig.(4. 5): (a) Bicluster of Rating Data BR, (b) Bicluster of Content Data BC, (c) Weighted bicluster of Content Data WC

	Xperia S	Sony Tablet-S	Iphone-4S	Nokia-N8	Galaxy-2	Asus-EP121
b_1	4	0	0	4	0	0
b_2	3	0	0	0	3	0
b_3	2	0	0	2	2	0
b_4	3	0	3	0	0	0
b_5	2	0	2	2	0	0
b_6	2	0	2	0	2	0
b_7	2	0	0	2	0	2

(a)

	Price	Design	Quality	Simplicity	Battery-life	Display
b_1	4	0	8	0	4	4
b_2	6	0	6	3	6	6
b_3	4	0	6	2	4	4
b_4	3	3	6	0	6	6
b_5	2	2	6	0	4	4
b_6	4	2	6	2	6	6
b_7	4	2	4	2	2	4

(b)

	Price	Design	Quality	Simplicity	Battery-life	Display
b_1	0.025	0	0.050	0	0.025	0.025
b_2	0.037	0	0.037	0.729	0.037	0.037
b_3	0.025	0	0.037	0.486	0.025	0.025
b_4	0.019	0.729	0.037	0	0.037	0.037
b_5	0.012	0.486	0.037	0	0.025	0.025
b_6	0.025	0.486	0.037	0.486	0.037	0.037
b_7	0.025	0.486	0.025	0.486	0.012	0.025

(c)

4.2.4 Finding Similarity

The neighborhood is defined in terms of similarity between users, either by taking a given number of most similar users (k nearest neighbors) or all users within a given similarity threshold. Therefore, the predictions for an individual can be made by averaging the opinions of the other users in that cluster, the prediction for groups could similarly be the average across the clusters, weighted by degree of participation, that represent each user in several cluster. However, the nearest neighbor algorithms (Breese *et al.*, 1998) have obtained better results compared to what the clustering techniques do. Clustering techniques can also be used as a preliminary step for reducing the candidate set in a nearest neighbor algorithm or for distributing nearest-neighbor computation across several recommender engines.

Therefore, in order to identify similar users and justify the recommendation, we measure the similarity between the biclusters b_i which contains strong partial similarity with target user u, considering only the similarity between the set of items/features that are included in b_i and the set of items/features rated by u. Thereafter, the similarity between each test user/group and the generated biclusters is calculated, thus creating the test users' neighborhood, which consists of the most k nearest biclusters. Then, each test user/group is provided with a Top-N recommendation list based on the most frequent items in the neighborhood. Thus, cosine similarity has been used to measure and find similarity in two different ways:

i. To find the k nearest neighbors, we calculate the similarity between the test user/group and each bicluster based on their "ratings data" and then select the k bicluster with the highest similarity.

The similarity (Sim_1) for individual user (*John*) as shown in Fig.(4.6-c) is computed according to his rating behavior on items and the related biclusters as follows:

$$Sim_1 \leftarrow Cosin\ Similarity\ (R[U_i],\ BR) \tag{6}$$

$$sim_1(u,b) = \frac{\sum R(U,\ i).BR\ (b,i)}{\sqrt{\sum R(U,\ i)^2}\,.\sqrt{\sum BR\ (b,\ i\ )^2}}$$

Fig.(4. 6): (a) Test user from Rating Data R, (b) biclusters of rating data BR (c) Similarity between R and BR for individual user.

Individual User	Xperia S	Sony Tablet-S	Iphone-4S	Nokia-N8	Galaxy -2	Asus-EP121
John	3	0	0	5	0	0

(a)

	Xperia S	Sony Tablet-S	Iphone-4S	Nokia-N8	Galaxy -2	Asus-EP121
b_1	4	0	0	4	0	0
b_2	3	0	0	0	3	0
b_3	2	0	0	2	2	0
b_4	3	0	3	0	0	0
b_5	2	0	2	2	0	0
b_6	2	0	2	0	2	0
b_7	2	0	0	2	0	2

(b)

	Sim1 John
b_1	0.970
b_2	0.364
b_3	0.792
b_4	0.364
b_5	0.792
b_6	0.297
b_7	0.792

(c)

The similarity ($sim1_{John,\ Alisa}$) for random group users and $sim1_{Ub1}$ for the regular group that has been created during biclustering processes, as shown in Fig.(4.7-c and 4.8-c) is computed according to their rating behavior on items and the related biclusters as follows:

$$\mathbf{RG} \leftarrow \sum_{u_k \in U_{bl}} \mathbf{R}[\mathbf{U_k}]$$

$$\boldsymbol{Sim_1 \leftarrow Cosin\ Similarity\ (RG,\ BR)} \tag{7}$$

$$sim_1(u,b) = \frac{\sum R(U,\ i).BR\ (b,i)}{\sqrt{\sum R(U,\ i)^2}\,.\sqrt{\sum BR\ (b,\ i\ )^2}}$$

Fig.(4. 7): (a) Test user from Rating Data R, (b) biclusters of rating data BR (c) Similarity between R and BR for random group.

Random Group John and Alisa	Xperia S	Sony Tablet-S	Iphone-4S	Nokia-N8	Galaxy -2	Asus-EP121
John & Nazek	3	3	0	6	0	5

(a)

	Xperia S	Sony Tablet-S	Iphone-4S	Nokia-N8	Galaxy -2	Asus-EP121
b_1	4	0	0	4	0	0
b_2	3	0	0	0	3	0
b_3	2	0	0	2	2	0
b_4	3	0	3	0	0	0
b_5	2	0	2	2	0	0
b_6	2	0	2	0	2	0
b_7	2	0	0	2	0	2

(b)

	Sim1 U=john and Alisa
b_1	0.716
b_2	0.239
b_3	0.585
b_4	0.239
b_5	0.585
b_6	0.195
b_7	0.909

(c)

Fig.(4. 8): (a) Test user from Rating Data R, (b) biclusters of rating data BR (c) Similarity between R and BR for biclustered group.

Biclustered Group $b_1 : U_{b_1}$ = {John, Emad, Nazek, Elbert}	Xperia S	Sony Tablet-S	Iphone-4S	Nokia-N8	Galaxy -2	Asus-EP121
b_1	13	1	7	16	8	5

(a)

	Xperia S	Sony Tablet-S	Iphone-4S	Nokia-N8	Galaxy -2	Asus-EP121
b_1	4	0	0	4	0	0
b_2	3	0	0	0	3	0
b_3	2	0	0	2	2	0
b_4	3	0	3	0	0	0
b_5	2	0	2	2	0	0
b_6	2	0	2	0	2	0
b_7	2	0	0	2	0	2

(b)

Sim1	U-b1
b_1	0.863
b_2	0.625
b_3	0.910
b_4	0.596
b_5	0.875
b_6	0.681
b_7	0.827

(c)

ii. To find the k nearest neighbors, we calculate the similarity between the test user/group and each bicluster based on "item features" and then select the k bicluster with the highest similarity.

The similarity (*Sim₂*) of individual user (*John*) as shown in Fig.(4.9-c) is computed according to weighted user profile and weighted bicluster of content data as follows:

$$Sim_2 \leftarrow Cosin\ Similarity\ (WP[U_i],\ WC) \tag{B}$$

$$sim_2(u,b) = \frac{\sum WP(U,\ f).WC\ (b,\ f\ )}{\sqrt{\sum WP(U,\ f)^2} \cdot \sqrt{\sum WC\ (b,\ f\ )^2}}$$

Fig.(4. 9): (a) Test user from Weighted User Profile WP, (b) weighted bicluster of Content Data WC (c) Similarity between WP and WC for individual user.

Individual User	Price	Design	Quality	Simplicity	Battery-life	Display
John	0.007	0	0.158	0	0.079	0.007

(a)

	Price	Design	Quality	Simplicity	Battery-life	Display
b_1	0.025	0	0.050	0	0.025	0.025
b_2	0.037	0	0.037	0.729	0.037	0.037
b_3	0.025	0	0.037	0.486	0.025	0.025
b_4	0.019	0.729	0.037	0	0.037	0.037
b_5	0.012	0.486	0.037	0	0.025	0.025
b_6	0.025	0.486	0.037	0.486	0.037	0.037
b_7	0.025	0.486	0.025	0.486	0.012	0.025

(b)

Sim2	John
b_1	0.874
b_2	0.072
b_3	0.094
b_4	0.071
b_5	0.093
b_6	0.075
b_7	0.043

(c)

The similarity ($sim2_{John,\ Alisa}$) for random group users and $sim2_{Ub1}$ for the regular group that has been created during biclustering processes, as shown in Fig.(4.10 and 4.11) is computed according to weighted user profile and weighted bicluster of content data as follows:

$$WPG \leftarrow \sum_{u_k \in U_{bi}} WP[U_k]$$

$$Sim_2 \leftarrow Cosin\ Similarity\ (WPG,\ WC) \qquad (9)$$

$$sim_2(u,b) = \frac{\sum WP(U,\ f).WC\ (b,\ f\ )}{\sqrt{\sum WP(U,\ f)^2}\,.\sqrt{\sum WC\ (b,\ f\ )^2}}$$

Fig.(4. 10): (a) Test user from Weighted User Profile WP, (b) weighted bicluster of Content Data WC (c) Similarity between WP and WC for random group.

Random Group John and Alisa	Price	Design	Quality	Simplicity	Battery-life	Display
John & Nazek	0.014	0.158	0.158	0.158	0.079	0.022

(a)

	Price	Design	Quality	Simplicity	Battery-life	Display
b_1	0.025	0	0.050	0	0.025	0.025
b_2	0.037	0	0.037	0.729	0.037	0.037
b_3	0.025	0	0.037	0.486	0.025	0.025
b_4	0.019	0.729	0.037	0	0.037	0.037
b_5	0.012	0.486	0.037	0	0.025	0.025
b_6	0.025	0.486	0.037	0.486	0.037	0.037
b_7	0.025	0.486	0.025	0.486	0.012	0.025

(b)

	Sim2
b_1	0.570
b_2	0.598
b_3	0.611
b_4	0.597
b_5	0.610
b_6	0.828
b_7	0.809

(c)

Fig.(4. 11): (a) Test user from Weighted User Profile WP, (b) weighted bicluster of Content Data WC (c) Similarity between WP and WC for biclustered group.

Biclustered Group $b_1 : U_{b1}$ = {John, Emad, Nazek, Elbert}	Price	Design	Quality	Simplicity	Battery-life	Display
b_1	0.056	0.316	0.952	0.316	0.633	0.073

(a)

	Price	Design	Quality	Simplicity	Battery-life	Display
b_1	0.025	0	0.050	0	0.025	0.025
b_2	0.037	0	0.037	0.729	0.037	0.037
b_3	0.025	0	0.037	0.486	0.025	0.025
b_4	0.019	0.729	0.037	0	0.037	0.037
b_5	0.012	0.486	0.037	0	0.025	0.025
b_6	0.025	0.486	0.037	0.486	0.037	0.037
b_7	0.025	0.486	0.025	0.486	0.012	0.025

(b)

	Sim2
b_1	0.819
b_2	0.326
b_3	0.345
b_4	0.325
b_5	0.344
b_6	0.435
b_7	0.403

(c)

To insure the duality existence among the rating and content data the similarity between a target user/group and the biclusters of both rating and content computed as follows:

$$Sim \leftarrow (1-\alpha).Sim_1 + \alpha.\ Sim_2 \tag{10}$$

Parameter '*a*' takes values between [0 and 1]. Thus, it has been noticed that the more "*a*" increases, the more justifiable recommendation the system is required to give, concentrating on the dominant features because user-features can give more precise recommendations than what user-items can do. Here, the best result is obtained when "*a*" was equal to'0.8' as shown in Fig.(4.12, 4.13 and 4.14) for individual, random group and biclustered group respectively.

Fig.(4. 12): (a) Similarity between R and BR (b) Similarity between WP and WC (c) similarity between target individual user and the similarity of biclusters of both rating and content.

John	Sim1
b_1	0.970
b_2	0.364
b_3	0.792
b_4	0.364
b_5	0.792
b_6	0.297
b_7	0.792

(a)

	Sim2
b_1	0.874
b_2	0.072
b_3	0.094
b_4	0.071
b_5	0.093
b_6	0.075
b_7	0.043

(b)

$Sim_{U\text{-}John}$	
b_1	0.893
b_2	0.130
b_3	0.234
b_4	0.130
b_5	0.233
b_6	0.119
b_7	0.193

(c)

Fig.(4. 13): (a) Similarity between R and BR (b) Similarity between WP and WC (c) similarity between target random group and the similarity of biclusters of both rating and content.

$Sim1_{U\text{-}John\ \&\ Alisa}$	
b_1	0.716
b_2	0.239
b_3	0.585
b_4	0.239
b_5	0.585
b_6	0.195
b_7	0.909

(a)

$Sim2_{U\text{-}John\ \&\ Alisa}$	
b_1	0.570
b_2	0.598
b_3	0.611
b_4	0.597
b_5	0.610
b_6	0.828
b_7	0.809

(b)

$Sim_{U\text{-}John\ \&\ Alisa}$	
b_1	0.599
b_2	0.526
b_3	0.606
b_4	0.525
b_5	0.605
b_6	0.701
b_7	0.829

(c)

Fig.(4. 14): (a) Similarity between R and BR (b) Similarity between WP and WC (c) similarity between target biclustered group and the similarity of biclusters of both rating and content.

$Sim1_{U-b1}$	
b_1	0.863
b_2	0.625
b_3	0.910
b_4	0.596
b_5	0.875
b_6	0.681
b_7	0.827

(a)

$Sim2_{U-b1}$	
b_1	0.819
b_2	0.326
b_3	0.345
b_4	0.325
b_5	0.344
b_6	0.435
b_7	0.403

(b)

Sim_{U-b1}	
b_1	0.828
b_2	0.386
b_3	0.458
b_4	0.379
b_5	0.450
b_6	0.484
b_7	0.488

(c)

4.2.5 Extracting the dominant features and calculating the influences

The biclusters of BR and the biclusters of WC have been sorted based on the correspondent Sim values in descending order in order to extract the most dominant features among the nearest biclusters of test user/group. Hence, the dominate features for the items that are selected by user/group with the same biclusters that contain the features and weight computed as follows:

$$DF(i,f) = \acute{B}R^{T}(b,I) \times \acute{W}C(b,f) \quad (11)$$

Figs. (4.15, 4.16 and 4.17) illustrate the dominate features for the individual, random group and biclustered group respectively.

Fig.(4. 15): (a) Bicluster of Rating Data BRT, (b) Weighted bicluster of Content Data(WC,) (c) The Dominate features DF for the individual user.

John	b_1	b_3	b_5	b_7
Xperia S	4	2	2	2
Sony Tablet-S	0	0	0	0
Iphone-4S	0	0	2	0
Nokia-N8	4	2	2	2
Galaxy -2	0	2	0	0
Asus-EP121	0	0	0	2

(a)

John	Price	Design	Quality	Simplicity	Battery-life	Display
b_1	0.025	0	0.050	0	0.025	0.025
b_3	0.025	0	0.037	0.486	0.025	0.025
b_5	0.012	0.486	0.037	0	0.025	0.025
b_7	0.025	0.425	0.025	0.846	0.012	0.025

(b)

John	Price	Design	Quality	Simplicity	Battery-life	Display
Xperia S	0.224	1.822	0.398	2.664	0.224	0.25
Sony Tablet-S	0	0	0	0	0	0
Iphone-4S	0.024	0.972	0.074	0	0.05	0.05
Nokia-N8	0.224	1.822	0.398	2.664	0.224	0.25
Galaxy -2	0.05	0	0.074	0.972	0.05	0.05
Asus-EP121	0.05	0.85	0.05	1.692	0.024	0.05

(c)

Fig.(4. 16): (a) Bicluster of Rating Data BRT, (b) Weighted bicluster of Content Data(WC,) (c) The Dominate features DF for the random group.

U=John & Alisa	b_7	b_6	b_3	b_5
Xperia S	2	2	2	2
Sony Tablet-S	0	0	0	0
Iphone-4S	0	2	0	2
Nokia-N8	2	0	2	2
Galaxy -2	0	2	2	0
Asus-EP121	2	0	0	0

(a)

U=John & Alisa	Price	Design	Quality	Simplicity	Battery-life	Display
b_7	0.025	0.486	0.025	0.846	0.012	0.025
b_6	0.025	0.486	0.037	0.846	0.037	0.037
b_3	0.025	0	0.037	0.486	0.025	0.025
b_5	0.012	0.486	0.037	0	0.025	0.025

(b)

U=John & Alisa	Price	Design	Quality	Simplicity	Battery-life	Display
Xperia S	0.174	2.916	0.272	4.356	0.198	0.224
Sony Tablet-S	0	0	0	0	0	0
Iphone-4S	0.074	1.944	0.148	1.692	0.124	0.124
Nokia-N8	0.124	1.944	0.198	2.664	0.124	0.15
Galaxy -2	0.1	0.972	0.148	2.664	0.124	0.124
Asus-EP121	0.05	0.972	0.05	1.692	0.024	0.05

(c)

Fig.(4. 17): (a) Bicluster of Rating Data BRT, (b) Weighted bicluster of Content Data(WC,)' (c) The Dominate features DF for the biclustered group.

U_{b1}	b_1	b_7	b_8	b_3
Xperia S	4	2	2	3
Sony Tablet-S	0	0	0	0
Iphone-4S	0	0	2	3
Nokia-N8	4	2	0	0
Galaxy -2	0	0	2	0
Asus-EP121	0	2	0	0

(a)

U_{b1}	Price	Design	Quality	Simplicity	Battery-life	Display
b_1	0.025	0	0.045	0	0.025	0.025
b_7	0.025	0.486	0.024	0.486	0.012	0.025
b_8	0.025	0.486	0.037	0.486	0.037	0.037
b_3	0.025	0	0.037	0.486	0.025	0.025

(b)

U_{b1}	Price	Design	Quality	Simplicity	Battery-life	Display
I_1	0.275	1.944	0.413	3.402	0.273	0.299
I_2	0	0	0	0	0	0
I_3	0.125	0.972	0.185	2.43	0.149	0.149
I_4	0.15	0.972	0.228	0.972	0.124	0.15
I_5	0.05	0.972	0.074	0.972	0.074	0.074
I_6	0.05	0.972	0.048	0.972	0.024	0.05

(c)

Thus, the extracted features used to find out the most influenced items in order to create the top-N recommendation list. The influence of items calculated as follows:

$$INF[i] \leftarrow \sum_{j=1}^{n} DF[i,j] \tag{12}$$

Figs. (4.18, 4.19 and 4.20) illustrate the influence values among items for the individual, random group and biclustered group respectively.

Fig.(4. 18): (a) Bicluster of Rating Data BRT, (b) Weighted bicluster of Content Data(WC,)' (c) The Dominate features DF for the individual user.

John	Price	Design	Quality	Simplicity	Battery-life	Display
Xperia S	0.224	1.822	0.398	2.664	0.224	0.25
Sony Tablet-S	0	0	0	0	0	0
Iphone-4S	0.024	0.972	0.074	0	0.05	0.05
Nokia-N8	0.224	1.822	0.398	2.664	0.224	0.25
Galaxy -2	0.05	0	0.074	0.972	0.05	0.05
Asus-EP121	0.05	0.85	0.05	1.692	0.024	0.05

(a)

John	Influence
Xperia S	5.582
Sony Tablet-S	0
Iphone-4S	1.17
Nokia-N8	5.582
Galaxy -2	1.196
Asus-EP121	2.716

(b)

Fig.(4. 19): (a) Bicluster of Rating Data BRT, (b) Weighted bicluster of Content Data(WC,)' (c) The Dominate features DF for the random group user.

John & Alisa	Price	Design	Quality	Simplicity	Battery-life	Display
Xperia S	0.174	2.916	0.272	4.356	0.198	0.224
Sony Tablet-S	0	0	0	0	0	0
Iphone-4S	0.074	1.944	0.148	1.692	0.124	0.124
Nokia-N8	0.124	1.944	0.198	2.664	0.124	0.15
Galaxy -2	0.1	0.972	0.148	2.664	0.124	0.124
Asus-EP121	0.05	0.972	0.05	1.692	0.024	0.05

(a)

John & Alisa	Influence
Xperia S	8.14
Sony Tablet-S	0
Iphone-4S	4.106
Nokia-N8	5.204
Galaxy -2	4.132
Asus-EP121	2.838

(b)

Fig.(4. 20): (a) Bicluster of Rating Data BRT, (b) Weighted bicluster of Content Data(WC,)' (c) The Dominate features DF for the biclustered group.

U_{b1}	Price	Design	Quality	Simplicity	Battery-life	Display
Xperia S	0.275	1.944	0.413	3.402	0.273	0.299
Sony Tablet-S	0	0	0	0	0	0
Iphone-4S	0.125	0.972	0.185	2.43	0.149	0.149
Nokia-N8	0.15	0.972	0.228	0.972	0.124	0.15
Galaxy -2	0.05	0.972	0.074	0.972	0.074	0.074
Asus-EP121	0.05	0.972	0.048	0.972	0.024	0.05

(a)

U_{b1}	Influence
Xperia S	6.606
Sony Tablet-S	0
Iphone-4S	4.01
Nokia-N8	2.596
Galaxy -2	2.216
Asus-EP121	2.116

(b)

For individual user, we have eliminated those items whose influence have tiny values, or already has been rated by the test user, and keeps the number of items with highest aggregated values that contain the most dominate features. In contrast, for group of users, we kept the tiny influence values and the rated item by some of a group user because such values have shown significant enhancement improving performance of the recommendation among the selected group.

Chapter 5

Experimental Results and Analysis

5.1 Results and Discussion

5.1.1 Generating the of recommendation list

Based on the procedures that have been detailed in chapter 4, the items with highest values of influence have been used to provide the top ranked recommended items for the target user/group with help of weighted user profile. Figs.(5.1, 5.2, 5.3 and 5.4) illustrate the top ranked recommended items for individual (*John*) , random group (*John, Alisa*) and biclustered group (*Ub1*) respectively and the list generated as follows.

$$RI(u,i) = WP(U,f\ ) * \acute{C}^{T}(I,f) \quad \forall i \in DF \tag{13}$$

Fig.(5. 1) : (a) Test user from weighted user profile WP & User profile P, (b) Content data CT, (c) Recommended items RI for individual user when the items rated before have been excluded.

	Price	Design	Quality	Simplicity	Battery-life	Display
	0.007	0	0.158	0	0.079	0.007
John-UP	1	0	2	0	1	1

(a)

	Asus-EP121	Galaxy -2	Iphone-4S	Sony Tablet-S
Price	1	1	0	0
Design	1	0	1	1
Quality	0	1	1	0
Simplicity	1	1	0	1
Battery-life	0	1	1	0
Display	1	1	1	1

(b)

	Asus-EP121	Galaxy -2	Iphone-4S	Sony Tablet-S
	0.014	0.251	0.244	0.007
John-RI	③	①	②	④

(c)

N.B. The numbers in tables of recommended items show the order of the recommendation list, and the symbol '±' exposes user interest in the rated items.

Fig.(5. 2): (a) Test user from weighted user profile WP & User profile P, (b) Content data CT, (c) Recommended items RI for individual user when the items rated before have been included.

	Price	Design	Quality	Simplicity	Battery-life	Display
	0.007	0	0.158	0	0.079	0.007
John-UP	1	0	2	0	1	1

(a)

	Xperia S	Nokia-N8	Asus-EP121	Galaxy -2
Price	1	0	1	1
Design	0	0	1	0
Quality	1	1	0	1
Simplicity	0	0	1	1
Battery-life	1	0	0	1
Display	1	0	1	0

(b)

	Xperia S	Nokia-N8	Asus-EP121	Galaxy -2
	0.251	0.158	0.014	0.244
John-RI	±±	±	②	①

(c)

Fig.(5. 3): (a) Test user from weighted user profile WP & User profile P, (b) Content data CT, (c) Recommended items RI for random group.

John & Alisa	Price	Design	Quality	Simplicity	Battery-life	Display
	0.014	0.158	0.158	0.158	0.079	0.022
John-UP	1	0	2	0	1	1
Alisa-UP	1	2	0	2	0	2

(a)

John & Alisa	Xperia S	Nokia-N8	Galaxy -2	Iphone-4S
Price	1	0	1	0
Design	0	0	0	1
Quality	1	1	1	1
Simplicity	0	0	1	0
Battery-life	1	0	1	1
Display	1	0	1	1

(b)

John & Alisa	Xperia S	Nokia-N8	Galaxy -2	Iphone-4S
	0.273	0.158	0.431	0.417
John-RI	±±	±	①	②
Alisa-RI	③	±	①	②

(c)

Fig.(5. 4): (a) Test user from weighted user profile WP & User profile P, (b) Content data CT, (c) Recommended items RI for biclustered group.

U_{b1}	Price	Design	Quality	Simplicity	Battery-life	Display
	0.056	0.316	0.952	0.316	0.633	0.073
John-UP	1	0	2	0	1	1
Emad-UP	2	2	3	1	2	3
Nazek-UP	2	1	4	1	3	3
Elbert-UP	3	1	3	2	2	3

(a)

U_{b1}	Xperia S	Iphone-4S	Nokia-N8	Galaxy -2
Price	1	0	0	1
Design	0	1	0	0
Quality	1	1	1	1
Simplicity	0	0	0	1
Battery-life	1	1	0	1
Display	1	1	0	1

(b)

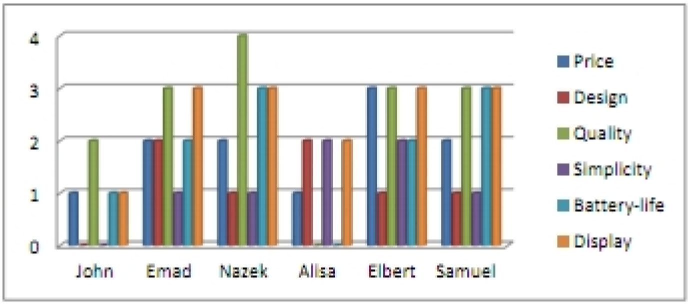
U_{b1}	Xperia S	Iphone-4S	Nokia-N8	Galaxy -2
	1.714	1.974	0.952	2.03
John-RI	±±	②	±	①
Emad-RI	±±±	±±	±	①
Nazek-RI	±±±	±±	±	±±±±
Elbert-RI	±±	①	±	±±±

(c)

5.1.2 Experimental Results and Observations

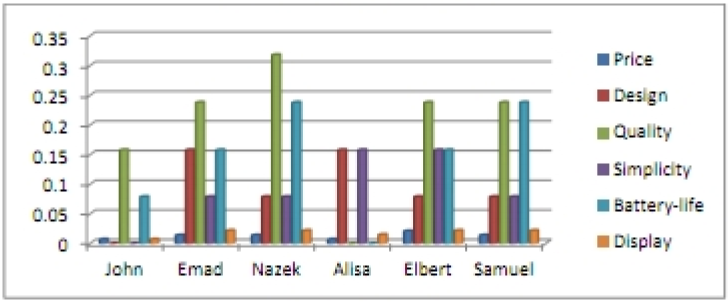
This section discusses the results of the abovementioned experiments that have been carried out and investigated in chapter 4 and 5.

Fig.(5. 5): User Profile



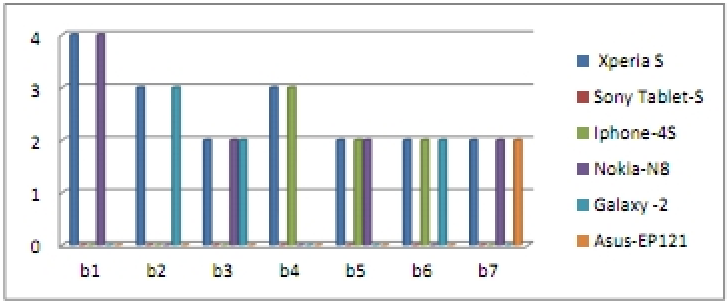
In section 4.2.1, User profile used to capture the interaction between users and their favorite features as illustrated in Fig.(5.5), in order to reveal the real reasons of their rating behaviour. i.e., here, it is possible to observe and understand the user behavior by his/her profile, and thereby getting to know that user *{Nazek}* is more interested on the features *{f_3, f_5, f_6}(Quality, Battery-Life and Display)*. However, it is clear that the features *{f_3, f_5, f_6}* are more interesting to user *{Nazek}* and able to describe her better compared to features *{f_1, f_2, f_4} (Price, Design, Simplicity)* can.

Fig.(5. 6): Weighted User Profile



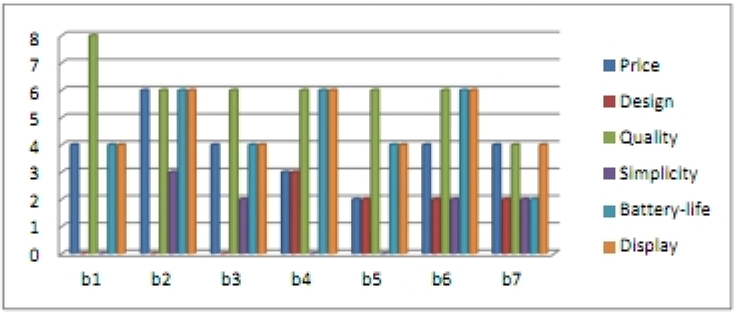
However, the user profile is still unable to explain what precisely a user prefers most in a specific features. Therefore, the weight assignment is done on user profile in order to better describe and distinguish the features' preferences among user profile as illustrated in Fig.(5.6). i.e., after assigning weight for user {Nazek} profile the most distinguished feature appeared were {f_3, f_5}. It has been observed that {f_6} obtained a less value and does not appear among the distinguished feature of weighted profile, while it was equivalent to {f_5} in user profile.

Fig.(5. 7): Bi-clusters of Rating Data (BR)



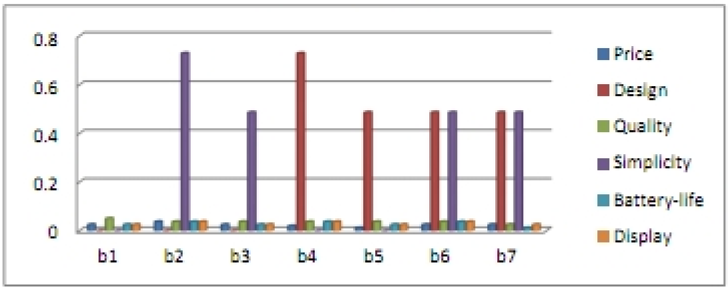
As stated before in section (4.2.3), to detect the partial matching among user's preferences, it is required from users to be grouped into bi-clusters wherein each bicluster corresponds to group of users with highly correlated ratings on groups of items. This allows the computation of similarity between a test user and a bicluster based on the items or features that are included in the cluster. In order to provide recommendations to a specific user, it is required to find the bi-clusters that have subsets of rating values and represent the items that have similar rating behavior to that particular user. This help to figure out the partial matching of the users' preferences among biclusters and find out their frequency as illustrated in Fig.(5.7). i.e., b_1={U_{b1}={John, Emad, Nazek, Elbert}, I_{b1} = {Xperia S, Nokia-N8}}. That means the bicluster b_1 contains the users {John, Emad, Nazek, Elbert} who shared the similar rating behavior for items set {Xperia S, Nokia-N8}.

Fig.(5. 8): Bi-clusters of Content Data (BC)



Previously biclusters of rating data were able to show the interested items by group of users among each bicluster but it didn't show why these items are interested to such users. i.e., the bicluster b_1 shows that the users {John, Emad, Nazek, Elbert} interested in {Xperia S, Nokia-N8} but it didn't show what features such users like more in these items. To figure out the reason behind, it is necessary to know the subsets of the features content for each bi-cluster. Here, Biclusters of content data as illustrated in Fig.(5.8) is able to expose the most distinguished features among each bicluster. i.e., b_1={U_{b1}={John, Emad, Nazek, Elbert}, I_{b1}={Xperia S, Nokia-N8}, I_{bf}={Price, Quality, Battery-life, Display}}. Thus, it is obvious that users {John, Emad, Nazek, Elbert} of b_1 are interested in items {Xperia S, Nokia-N8} that contained the features {Price, Quality, Battery-life, Display}.

Fig.(5. 9): Assigning weight to BC

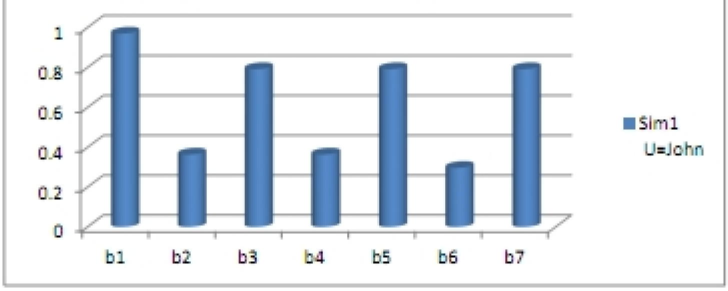


Thereafter, weighting mechanism has been used to figure out the variety and differences between the distinguished features among biclusters of the content data. Here, the results of assigning weight on biclusters content as illustrated in Fig.(5.9) show that the order of distinguished features of b_1 remained the same after assigning the weight among the biclusters but differed with the biclusters $\{b_2, b_3, b_4, b_5, b_6, b_7\}$. That's because of the effect of all the biclusters all together on the distinguished features for each independent bicluster of BC. i.e., the distinguished features order of BC was $\{f_3, f_1, f_5, f_6\}$ and after assigning weight remained the same but the situation has changed with bicluster $\{b_2\}$ while the distinguished features order of BC was $\{f_1, f_3, f_5, f_6, f_4\}$ and changed to $\{f_4, f_1, f_3, f_5, f_6\}$.This disclose the most distinguished features among each bicluster based of the effect of interaction between all biclusters.

As mentioned above in section (4.2.4), there are two ways to find out the biclusters that have strong partial similarity with the preferences of the target user or group as follows:

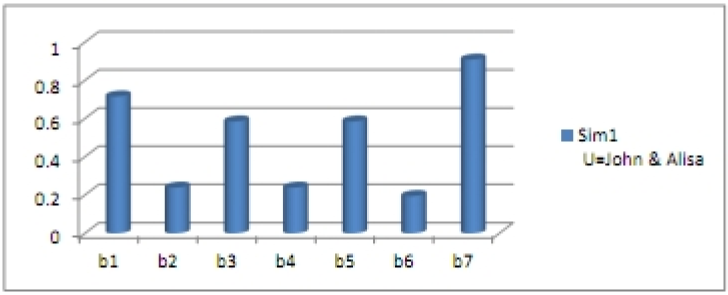
1- Based on Rating Data: To find the nearest neighbors of biclusters, we calculate the cosine similarity between the test user/group and each weighted bicluster based on their "ratings data" on items and then select the weighted biclusters with the highest similarity.

Fig.(5. 10): Similarity between rating data of U=John and BR



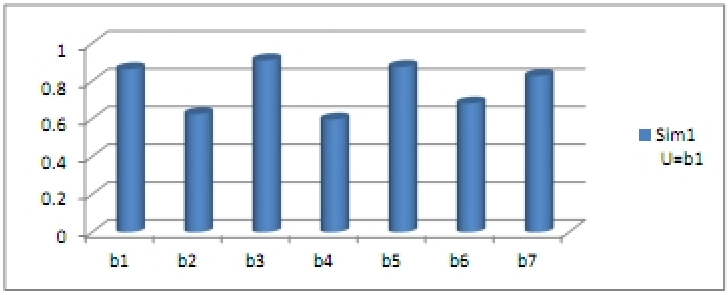
The highest similarity for the individual user {John} was found in the biclusters {b_1, b_3, b_5, b_7} as illustrated in Fig.(5.10).

Fig.(5. 11): Similarity between rating data of U= John & Alisa and BR



The highest similarity for the random group {John & Alisa} was found in the biclusters { b_7, b_1, b_3, b_5} as illustrated in Fig.(5.11).

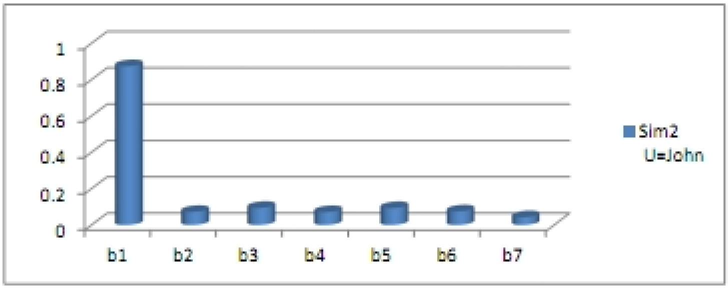
Fig.(5. 12): Similarity between rating data of U=b1 and BR



The highest similarity for the set of user in the bicluster group of b_1 {John, Emad, Nazek, Elbert} was found in the biclusters {b_3, b_5, b_1, b_7} as illustrated in Fig.(5.12).

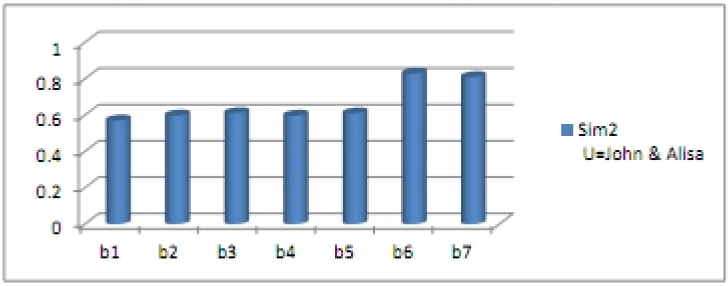
2- Based on Content Data: To find the nearest neighbors of biclusters, we calculate the cosine similarity between the test user/group and each weighted bicluster based on "content data" and then select the weighted biclusters with the highest similarity.

Fig.(5. 13): Similarity between WP of U=John and WC



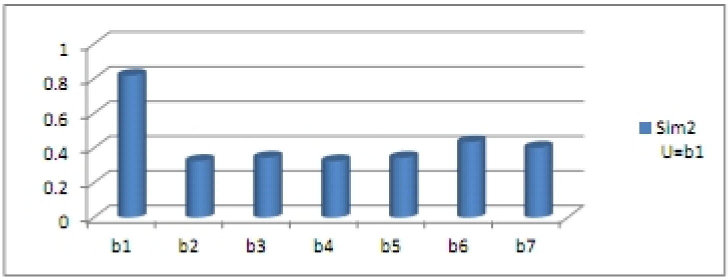
The highest similarity for the individual user {John} was found in the weighted biclusters {b_1, b_3, b_5, b_6} as illustrated in Fig.(5.13).

Fig.(5. 14): Similarity between WP of U=John & Alisa and WC



The highest similarity for the random group {John & Alisa} was found in the weighted biclusters {b_6, b_7, b_5, b_3} as illustrated in Fig.(5.14).

Fig.(5. 15): Similarity between WP of U=b1 and WC

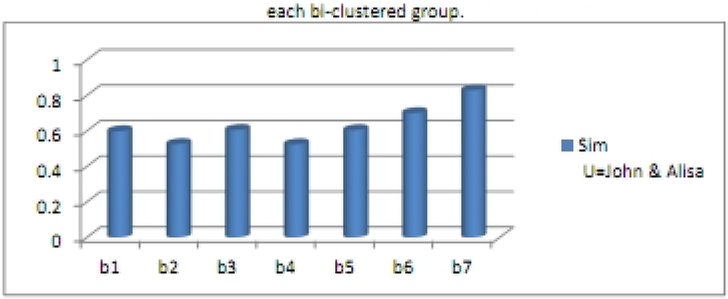


The highest similarity for the set of user in the bicluster group of b_1 {John, Emad, Nazek, Elbert} was found in the weighted biclusters {b_1, b_6, b_7, b_3} as illustrated in Fig.(5.15). To obtain more reasoning for the required recommendation, it is necessary to find out the similarity between a target user/group and the most similar biclusters of rating and weighted biclusters of content. For doing such, we need a parameter that takes values between {0,1}. With increasing the value of that parameter, the portion of the similarity of weighted biclusters of content is increased and the portion of the similarity of biclusters of rating is decreased. Thus, the system is required to provide more justification for its recommendations.

Fig.(5. 16): Partial matching between the preferences of tested biclustered users U=b1 and each bi-clustered group.

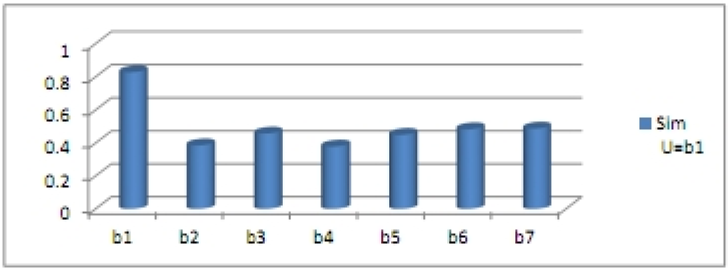
The highest similarity for the individual user {John} was found in the biclusters {b_1, b_3, b_5, b_7} as illustrated in Fig.(5.16).

Fig.(5. 17): Partial matching between the preferences of tested random users U=John & Alisa and each bi-clustered group.



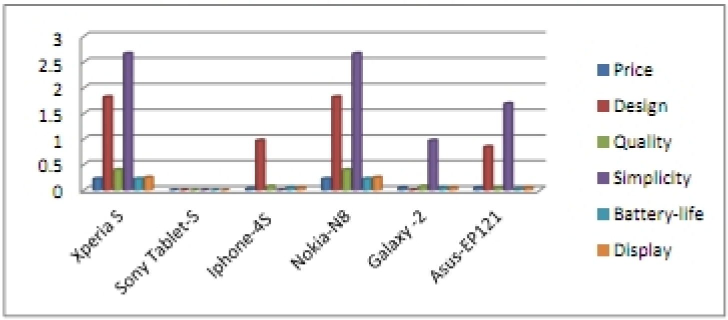
The highest similarity for the random group {John & Alisa} was found in the biclusters {b_7, b_6, b_3, b_5} as illustrated in Fig.(5.17).

Fig.(5. 18): Partial matching between the preferences of tested biclustered users U=b1 and each bi-clustered group.



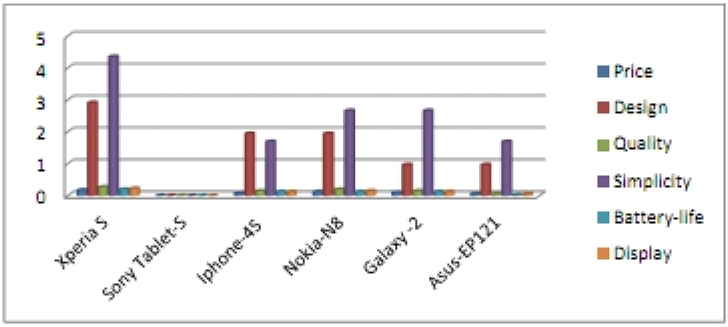
The highest similarity for the set of user in the bicluster group of b_1 {John, Emad, Nazek, Elbert} was found in the biclusters { b_1, b_7, b_6, b_3} as illustrated in Fig.(5.18). Based on the similarity between a target user/group and the most similar biclusters of rating and weighted biclusters of content, the distinguished features inside the nearest biclusters for test user will appear. Thus, items that contain those distinguished features are favored and used to extract their dominant features in order to produce the prefer recommendations. As stated before in section (4.2.5) , extracting the dominant features among the items required knowing the most similar biclusters of rating and weighted biclusters of content for the target user/group.

Fig.(5. 19): Extracting the dominant features for U=John.



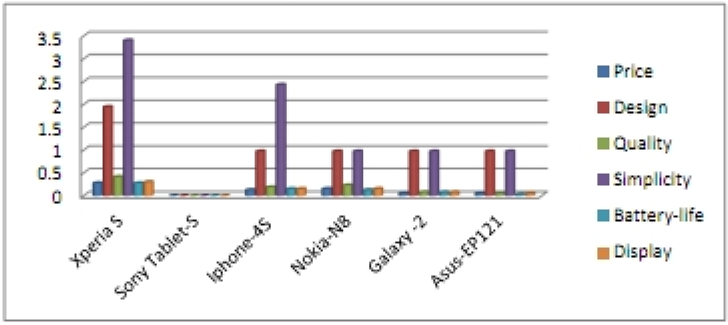
The most similar biclusters of rating and weighted biclusters of content for the target individual user {John} are { b_1, b_3, b_5, b_7} and the dominant features among the items for the particular user are illustrated above in Fig.(5.19).

Fig.(5. 20): Extracting the dominant features for U=John & Alisa.



The most similar biclusters of rating and weighted biclusters of content for the target random group {John & Alisa} are { b_7, b_6, b_3, b_5}. and the dominant features among the items for the particular group are illustrated above in Fig.(5.20).

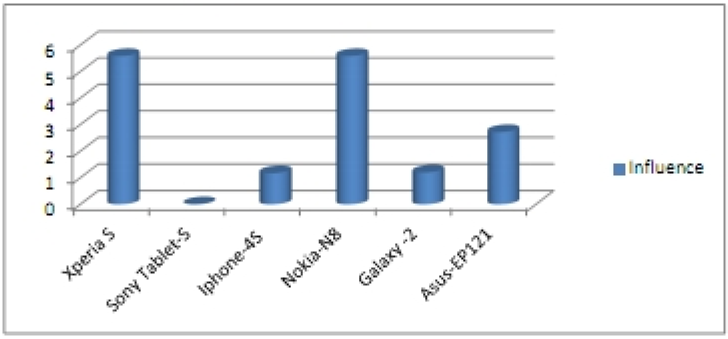
Fig.(5. 21): Extracting the dominant features for U=b1.



The most similar biclusters of rating and weighted biclusters of content for the target biclustered group {John, Emad, Nazek, Elbert} are { b_1, b_7, b_6, b_3}. and the dominant features among the items for the particular group are illustrated above in Fig.(5.21) .

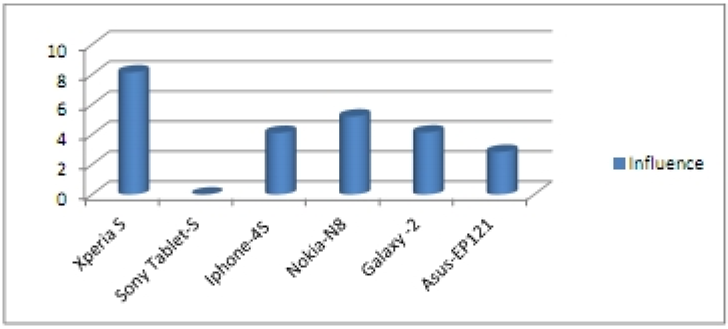
Hence, after knowing the dominant features among the items, it easy to figure out which items are the most influential in the recommended list.

Fig.(5. 22): The most Influenced items with U=John.



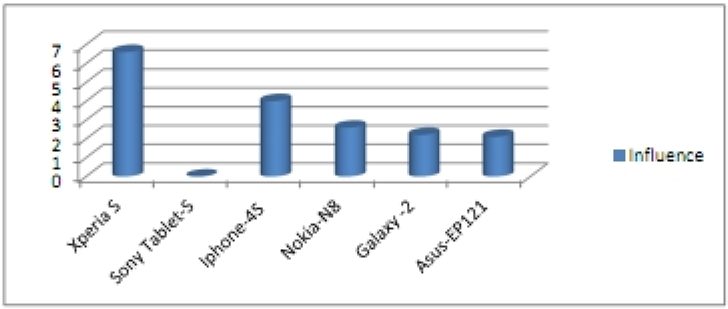
The most influential items in the recommended list for individual user {John} are listed in this sequence {Xperia S, Nokia-N8, Asus-Ep121, Galaxy 2, Iphone-4S, Sony Tablet-S} as illustrated in Fig.(5.22).

Fig.(5. 23): The most Influenced items with U= John & Alisa.



The most influential items in the recommended list for random group {John & Alisa} are {Xperia S, Nokia-N8, , Galaxy 2, Iphone-4S, Asus-Ep121 Sony Tablet-S} as illustrated in Fig.(5.23)..

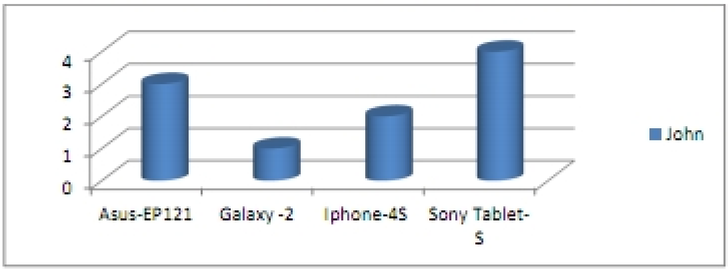
Fig.(5. 24): The most Influenced items with U=b1.



The most influential items in the recommended list for biclustered group {John, Emad, Nazek, Elbert} are {Xperia S, Iphone-4S, Nokia-N8, Galaxy 2, Asus-Ep121 Sony Tablet-S} as illustrated in Fig.(5.24).

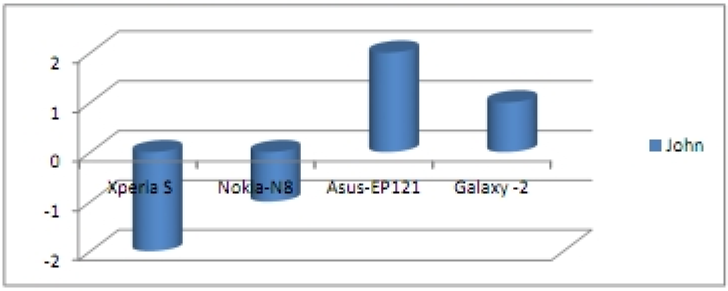
As mentioned above in section (5.1.1), and based on the aggregation of the influence of dominant features for each item, the first forth most influential items was recommend as list of recommendation for the test user/group.

Fig.(5. 25): Recommended items for individual user when the rated items are excluded.



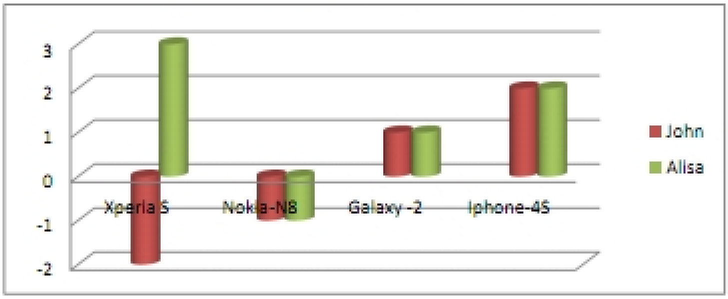
By excluding the items that have been rated by the same tested individual user {John} the recommendation list was given as {Sony Tablet-S, Asus-Ep121, Iphone-4S, Galaxy-2} as illustrated in Fig.(5.25).

Fig.(5. 26): Recommended Items for individual user when the rated item are included.



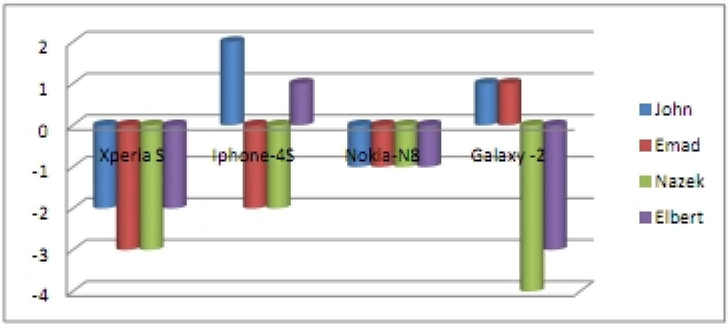
By including the items that have been rated by the same tested individual user {John} the recommendation list was given as {Asus-Ep121, Galaxy-2}. Another recommended list {Xperia S, Nokia N8} was given as a second option for such user if he still interested in such items as illustrated in Fig.(5.26).

Fig.(5. 27): Recommended Items for random group users.



By including the items that have been rated by the same tested random group user {John & Alisa} the recommendation list was given as {Xperia S, Iphone-4S, Galaxy-2} for {John} and { Iphone-4S Galaxy-2} for {Alisa}. Another recommended list {Xperia S, Nokia N8} for {John} and {Nokia N8} was given as a second option for such users if they still interested in such items as illustrated in Fig.(5.27).

Fig.(5. 28): Recommended Items for biclustered group U=b1.



By including the items that have been rated by the same tested biclustered group user {John, Emad, Nazek, Elbert} the recommendation list was given as {Iphone-4S Galaxy-2} for {John}, {Galaxy-2} for {Emad}, and {Iphone-4S} for {Elbert}. Another recommended list {Xperia S, Nokia N8} for {John}, and {Xperia S, Iphone -4S, Nokia N8} for {Emad}, {Galaxy-2, Xperia S, Iphone -4S, Nokia N8} for {Nazek}, and {Galaxy-2, Xperia S, Nokia N8} for {Elbert} was given as a second option for such users if they still interested in such items as illustrated in Fig.(5.28).

5.1.3 The reasoning of recommendations

Reviewing the features of user profile against the features of recommended system is essential to make the reasoning of recommendation more reasonable and understandable by service providers as well as by the users. Here, it is obvious from the results of the recommendation list how the features of recommended items are coherent and similar to the features of user profile. The proposed method has been implemented to work with different test cases that may have different sizes as will be discussed below:

I. Individual user:

Here, the generated list of recommendations for *individual user (John)* contains a set of items in this sequence {*Galaxy 2, Iphone-4S, Asus EP121, and Sony Tablet-S*} as illustrated in Fig.(5.29). If we take a look at the user profile that has been created in the beginning, we will see that *John* is more concerned about giving more attention to the sequence features of *Quality, Price, Battery-life and Display.* By checking the content features of the recommended items, we can infer that the proposed method was able to grasp the user needs and recommend according to user's interest. i.e., *Galaxy-2* was the first ranked recommended item which contains the most desirable features (*Quality, Price, Battery-life and Display*) that highly accepted by *John*. The method was also intelligent enough to suggest *Iphone-4S* as the second option which holds the features *(Quality, Battery-life and Display without Price)* that is considered as the more preferable feature by the same user. Then *Asus-EP121* was recommended as a third item. By discovering the content features of *Asus-EP121*, it is observed that the *quality* which is the most favourite feature by *John* is not included in such item but the features of *Price* and *Display* are included which are preferable by him. *Sony-*

Tablet-s was contains only the feature *Display*, that is why was recommended as the forth option.

Fig.(5. 29): (a) Rating data R of tested user, (b) User profile and content data, (c) Recommended items RI for individual user when the items rated before are excluded.

	Xperia S	Sony Tablet-S	Iphone-4S	Nokia-N8	Galaxy -2	Asus-EP121
John	3	-	-	5	-	-

(a)

	Asus-EP121	Galaxy -2	Iphone-4S	Sony Tablet-S	John-UP
Price	1	1	0	0	1
Design	1	0	1	1	0
Quality	0	1	1	0	2
Simplicity	1	1	0	1	0
Battery-life	0	1	1	0	1
Display	1	1	1	1	1

(b)

	Asus-EP121	Galaxy -2	Iphone-4S	Sony Tablet-S
	0.014	0.251	0.244	0.007
John-RI	3	1	2	4

(c)

Fig.(5.30) shows also the well performance of the system when the items that have been rated before by target user are included. The system recommended items {*Galaxy-2, Asus-EP121*} according to the user interest and items {*Xperia-s, Nokia-N8*}as additional list revealing and expressing though it that those items have been rated before from the same user but it may be still desirable by him or the items may have new features, that is way it recommended again. By matching the user profile of the target user and the content features of the recommended list a coherent match appear.

Fig.(5. 30): (a) Rating data R of tested user, (b) User profile and content data, (c) Recommended items RI for individual user when the rated items are included.

	Xperia S	Sony Tablet-S	Iphone-4S	Nokia-N8	Galaxy -2	Asus-EP121
John	3	-	-	5	-	-

(a)

	Xperia S	Nokia-N8	Asus-EP121	Galaxy -2	John-UP
Price	1	0	1	1	1
Design	0	0	1	0	0
Quality	1	1	0	1	2
Simplicity	0	0	1	1	0
Battery-life	1	0	0	1	1
Display	1	0	1	0	1

(b)

	Xperia S	Nokia-N8	Asus-EP121	Galaxy -2
	0.251	0.158	0.014	0.244
John-RI	±±	±	②	①

(c)

II. Random group (users selected randomly):

We have examined the efficiency of this method from serving under different circumstances and enabled it to work with group that may contains random users in case that was required by service providers according to their interest. For that purpose, we have selected random users as *John* and *Alisa* as an example. The results show the keen ability of the system of doing such with great success. Before giving an explanation for group recommendation, we should emphasize that the items that got poor influence value with individual user are not supposed to be eliminated during building the recommendation for groups. When these values have been eliminated, less accuracy of recommendations has been observed. Therefore, those values may play significant roles to improve the accuracy and the quality of recommendations for the group.

In other words, the influence on items' features and users' profiles has strong effect on the group recommendations according the partial matching of the items influence among the group-users profiles. Unlike the recommendation of individual user which is affected more by the items influence among his/her own profiles rather than the profiles of others. For instance, the influence value of *Sony-Tablet-S* was very small during the recommendation of individual user. Therefore, in this case, such item can be neglected as it does not have any effect on recommendation accuracy of individual user. In contrast, the same cannot be eliminated in group recommendation case, as it may have a different value that could enhance the recommendation accuracy. This reflects the needs of involving those items that have tiny influence values and have been rated by some users of the group during building the recommendation's processes.

For the random group, the proposed method has recommended items {*Galaxy-2, Iphone-4S*} and {*Galaxy-2, Iphone-4S, Xperia-S*} for the *John* and *Alisa* respectively as shown in Fig.(5.31). Items {*Galaxy-2, Iphone-4S*} have been recommended for *John*, for the reasons that have been mentioned above in the individual case. The same items have been recommended for *Alisa* because *Galaxy-2* is holding the *Simplicity, Display* and *Price* features which are more preferable by her. *Iphone-4S* was recommended as a second option for Alisa as it is holding the *Design* and *Display* feature. However, *Xperia-S* has also recommended for her as a third option because it is holding only the *Display* feature which is more preferable by her and the *price* feature which is not that important by her. {*Xperia-S, Nokia-N8*} and {*Galaxy-2, Iphone-4S, Xperia-S*} recommended for the *John* and *Alisa* respectively as additional list because those items have been rated before by the same users. Here, it is observed that how the influence of features among the group users could effect and improve the recommendation of group accuracy. Thereafter, we can eliminate the rated items by the same user from his/her list or leave them in case it may hold the new version of the same items that have been rated.

Fig.(5. 31): (a) Rating data R of tested user, (b) User profile and content data, (c) Recommended Items RI for random group.

	Xperia S	Sony Tablet-S	Iphone-4S	Nokia-N8	Galaxy -2	Asus-EP121
John	3	-	-	5	-	-
Alisa	-	3	-	1	-	5

(a)

John & Alisa	Xperia S	Nokia-N8	Galaxy -2	Iphone-4S	John-UP	Alisa-UP
Price	1	0	1	0	1	1
Design	0	0	0	1	0	2
Quality	1	1	1	1	2	0
Simplicity	0	0	1	0	0	2
Battery-life	1	0	1	1	1	0
Display	1	0	1	1	1	2

(b)

John & Alisa	Xperia S	Nokia-N8	Galaxy -2	Iphone-4S
	0.273	0.158	0.431	0.417
John-RI	±±	±	①	②
Alisa-RI	③	±	①	②

(c)

III. Biclustered group:

Suppose that we have taken the bicluster (*b_1: U_{b1} = {John, Emad, Nazek, Elbert}*), which has been generated during biclustering processes to check out the accuracy of recommendation, the system shows a good result for such cases as well. It is obvious that the influence values are changeable from case to case for the same user due to items influence among the group.

However, that change does not affect the sequence of recommended items or the justification while the top-n ranked list contains the same items. For this biclustered group (U_{b1}), the recommended items have been listed as {*Galaxy-2, Iphone-4S*}, {*Iphone-4S*},{ *Iphone-4S*} for *John, Emad*, and *Elbert* respectively. By figuring out the list of recommendation list for each user, we observed that those entire items have been recommended based on user interest. As mentioned above, the items that have been rated by user could be excluded or kept the same to introduce a recommendation to the specific user about the new generation of item he/she got before. This can also be considered as another aspect of the system ability of filtering useful information that fits each individual needs, as well as satisfying the group users desires.

Fig.(5. 32): (a) Rating data R of tested user, (b) User profile and content data, (c) Recommended Items RI for random group.

	Xperia S	Sony Tablet-S	Iphone-4S	Nokia-N8	Galaxy -2	Asus-EP121
John	3	-	-	5	-	-
Emad	2	-	5	4	-	3
Nazek	4	-	2	2	5	-
Elbert	4	1	-	5	3	2

(a)

U_{b1}	Xperia S	Iphone-4S	Nokia-N8	Galaxy -2	John-UP	Emad-UP	Nazek-UP	Elbert-UP
Price	1	0	0	1	1	2	2	3
Design	0	1	0	0	0	2	1	1
Quality	1	1	1	1	2	3	4	3
Simplicity	0	0	0	1	0	1	1	2
Battery-life	1	1	0	1	1	2	3	2
Display	1	1	0	1	1	3	3	3

(b)

U_{b1}	Xperia S	Iphone-4S	Nokia-N8	Galaxy -2
	1.714	1.974	0.952	2.03
John-RI	±±	②	±	①
Emad-RI	±±±	±±	±	①
Nazek-RI	±±±	±±	±	±±±±
Elbert-RI	±±	①	±	±±±

(c)

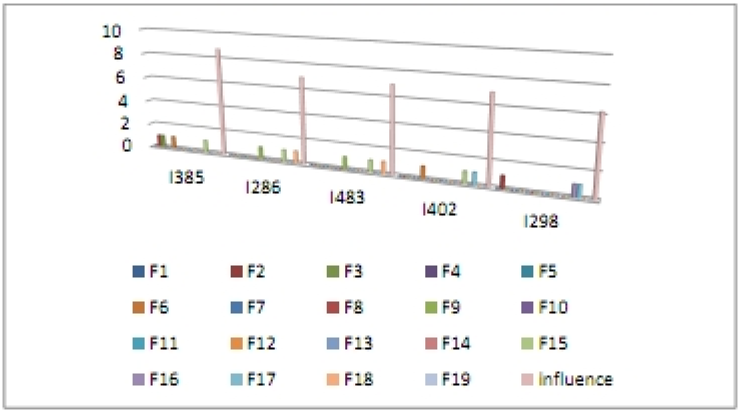
Fig.(5.32) has shown the significant results for the biclustered group recommendations. The results also show the coherent matching between the features of recommended items and users profiles and it makes an obvious answer to why those items have been recommended.

Iv. *Real Data:*

In order to have a proof of concept to demonstrate that the proposed method works, we have performed experiments with a real data set called (MovieLens) which are commonly used as the bench mark data set for movie recommender systems. These data sets have been collected by the GroupLens Research Project at the University of Minnesota. This data set consists of: 100,000 ratings from 943 users on 1682 movies. The range of rating is between 1 (bad) and 5 (excellent). Each user has rated at least 20 movies. Movies are classified according to their 19 genres and these genres are the features of the movies in our data set. The 19 genres are: Unknown, Action, Adventure, Animation, Children's, Comedy, Crime, Documentary, Drama, Fantasy, Film-Noir, Horror, Musical, Mystery, Romance, Sci-Fi, Thriller, War, Western. '1' under a particular genre indicates that movie is of that genre and '0' indicates it is not; movies can include several genres at the same time.

For this data, same procedures that discussed in sections (4.2 & 5.1) have been applied in order to generate the recommendation for individuals and group of users. Thus, after knowing the dominant features among the items, it easy to figure out which items are the most influential in the recommended list. For instance, we have selected $\{U_1\}$ as a random user among the 943 users of the data-set as individual target and the most influential items in the recommended list for this user$\{U_1\}$ are listed as $\{I_{385}, I_{286}, I_{483}, I_{402}\}$ as illustrated in Fig.(5.33).

Fig.(5. 33): Dominant features and their influence on U1- MovieLens Data.



The items that having the highest values of influence have been used to provide the top ranked recommended list for the target user $\{U_1\}$ with help of weighted user profile as illustrated in Fig.(5.34).

Fig.(5. 34): (a) Test user from weighted user profile WP (b) Content data CT, (c) Recommended Items RI for individual user (d) User Profile P.

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19
WP-U1	0.69	2.56	1.19	1.99	1.99	3.25	0.91	1.11	4.25	0.44	0.05	0.5	1.24	0.18	1.74	1.69	2.01	1.01	1.33

(a)

	385	286	483	402
F1	0	0	0	0
F2	1	0	0	0
F3	1	0	0	0
F4	0	0	0	0
F5	0	0	0	0
F6	1	0	0	1
F7	0	0	0	0
F8	0	0	0	0
F9	0	1	1	0
F10	0	0	0	0
F11	0	0	0	0
F12	0	0	0	0
F13	0	0	0	0
F14	0	0	0	0
F15	1	1	1	1
F16	0	0	0	0
F17	0	0	0	1
F18	0	1	1	0
F19	0	0	0	0

(b)

Items	385	286	483	402
U1	8.74	3.46	2.06	5.26
	①	③	④	②

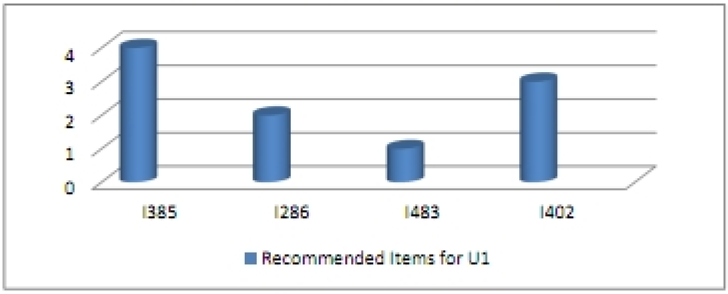
(c)

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19
UP	1	56	26	9	9	71	20	5	93	2	1	11	8	4	38	37	44	22	6

(d)

As mentioned so far in section (5.1.1), and based on the aggregation of the influence of dominant features for each item, the first forth most influential items was recommend as list of recommendation for the test user/group. Thus, the recommendation list of $\{U_1\}$ was given as $\{I_{483}, I_{286}, I_{402}, I_{385}\}$ as illustrated in Fig.(5.35).

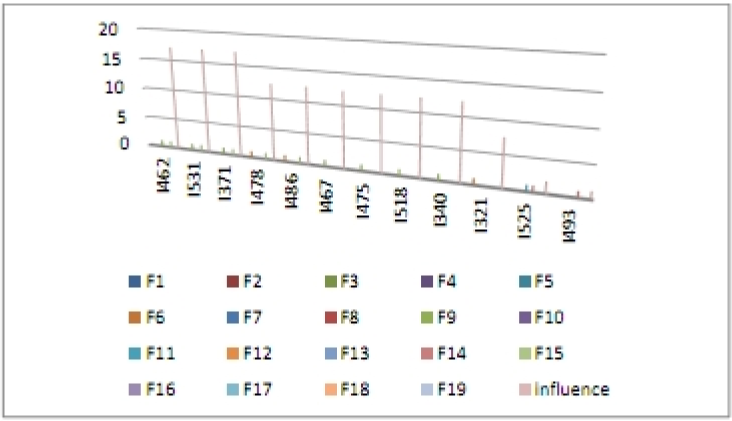
Fig.(5. 35): Recommended Items for U1- MovieLens Data.



The reasoning behind the recommendation can be interpreted as saying that item (I_{385})={*Stand by Me(1986)*} has been recommended as a first option because it contains features {(f_3) *Adventure*, (f_6) *Comedy*, (f_9) *Drama*} which are more preferable by the target user$\{U_1\}$according to his/her profile. Item (I_{402})={*True Lies(1994)*} has been recommended as a second option because it contains features {(f_2) *Action*, (f_6) *Comedy*, (f_3) *Adventure*, (f_{15}) *Romance*} which are more desirable by the target user{U_1} according to his/her profile.

Accordingly, the most influential items in the recommended list for group users{$U_{1,2,7}$} are listed as {I_{385}, I_{286}, I_{483}, I_{402}} as illustrated in Fig.(5.36).

Fig.(5. 36): Recommended Items for the group user {U1, U2, U7} -MovieLens Data.



The items that having the highest values of influence have been used to provide the top ranked recommended list for the target group users {$U_{1,2,7}$} with help of weighted user profile as illustrated in Fig.(5.37).

Fig.(5. 37): (a) Test user from weighted user profile WP (b) Content data CT, (c) Recommended Items RI for biclustered group (d) User Profile P.

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19
U_1	0.6990	2.5624	1.1897	1.9966	1.9966	3.2488	0.9152	1.1092	4.2554	0.4437	0.0458	0.5033	1.2392	0.1830	1.7588	1.6930	2.0133	1.0067	1.3311
U_2	0.0000	0.4118	0.1373	0.2218	0.6655	0.6864	0.3661	0.0000	1.5100	0.2218	0.0915	0.0915	0.1549	0.1830	0.7521	0.1830	0.5033	0.0915	0.0000
U_7	0.0000	3.9809	2.4709	2.8840	7.7647	3.7064	1.4185	1.1092	6.5433	1.3311	0.5033	1.5100	4.0275	0.8236	2.3794	2.0133	3.2488	1.8303	3.5496
$U_{1,2,7}$	0.6990	6.9551	3.7979	5.1025	10.4269	7.6415	2.6997	2.2185	12.3088	1.9966	0.6406	2.1048	5.4216	1.1897	4.8503	3.8894	5.7654	2.9285	4.8807

(a)

	462	531	371	478
F1	0	0	0	0
F2	0	0	0	0
F3	0	0	0	0
F4	0	0	0	0
F5	0	0	0	0
F6	0	0	0	1
F7	0	0	0	0
F8	0	0	0	0
F9	1	1	1	0
F10	0	0	0	0
F11	0	0	0	0
F12	0	0	0	0
F13	0	0	0	0
F14	0	0	0	0
F15	1	1	1	1
F16	0	0	0	0
F17	0	0	0	0
F18	0	0	0	0
F19	0	0	0	0

(b)

Items	462	531	371	478
$U_{1,2,7}$	17.1591	5.886	6.406	15.2373
	①	④	③	②

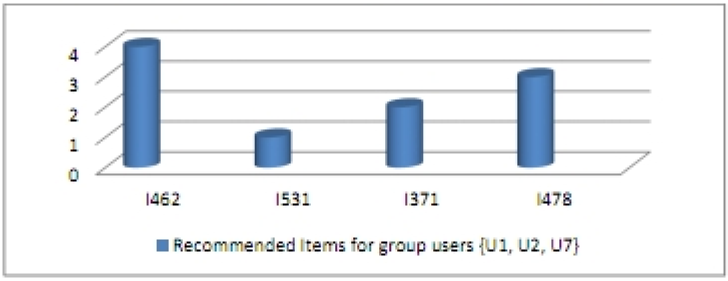
(c)

	f1	f2	f3	f4	f5	f6	f7	f8	f9	f10	f11	f12	f13	f14	f15	f16	f17	f18	f19
U1	1	56	26	9	9	71	20	5	93	2	1	11	8	4	38	37	44	22	6
U2	0	9	3	1	3	15	8	0	33	1	2	2	1	4	16	4	11	2	0
U7	0	87	54	13	35	81	31	5	143	6	11	33	26	18	52	44	71	40	16
$U_{1,2,7}$	1	152	83	23	47	167	59	10	269	9	14	46	35	26	106	85	126	64	22

(d)

Based on the aggregation of the influence of dominant features for each item, the first forth most influential items was recommend as list of recommendation $\{I_{462}, I_{531}, I_{371}, I_{478}\}$ for the test group users $\{U_{1,2,7}\}$ as illustrated in Fig.(5.38).

Fig.(5. 38): Recommended Items for group users (U1,2,7) - MovieLens Data.



The reasoning behind the recommendation can be interpreted as saying that item (I_{462}) has been recommended as a first option because it contains features {(f_9) *Drama*, (f_{15}) *Romance}* which are more preferable by the target users {$U_{1,2,7}$} according to his/her profile. Item (I_{478}) has been recommended as a second option because it contains features {(f_6) *Comedy*, (f_{15}) *Romance}* which are more desirable by the target users {$U_{1,2,7}$} according to his/her profile. Hence, the desirable features that exist among the recommendation for the individual user, are also exist among the recommendation for group users that contain the same individual user. i.e., (f_9) *Drama*, was one of the desired features that exists in the first recommended item for the *individual user {U_1}* and was also one of the desired features that exists in the first recommended item for the *group users{$U_{1,2,7}$}* that contained the same *individual user{U_1}*. Meanwhile, (f_6) *Comedy* was one of the desired features that exists in the second recommended item for the *individual user {U_1}* and was also one of the desired features that exists in the second recommended item for the *group users{$U_{1,2,7}$}*that contained the same *individual user{U_1}*. This reflect the method capability of recommending useful information that fits each individual needs, as well as satisfying the group users interest.

5.1.4 Generating the recommendation lists based on the location of items and users

Finally, we have constructed the User Location profile *UL (U l_m)*. An example of a user location profile is given in Fig.(5.39-a), where *rows* are symbolize the mobile users and *columns* are represent users' locations. In Fig.(5.39-b) *rows* symbolize the items available at MMP and *columns* represent items' locations. No exact locations are presented with dash. 'A' represents the availability of the items and users in that particular location. 'R' symbolizes the recommended location for the items of interest for the specific user. 'RC' represents the closest location of the item of interest.

Fig.(5. 39): (a) User location (u,l), (b) Item location (i,l).

	L_1	L_2	L_3	L_4
John	A	A	-	-
Emad	A	-	A	-
Nazek	-	A	-	A
Alisa	-	-	A	A
Elbert	A	A	-	-
Samuel	-	-	A	-

(a)

	L_1	L_2	L_3	L_4
Xperia S	A	-	-	A
Sony Tablet-S	-	A	-	A
Iphone-4S	A	-	A	-
Nokia-N8	-	A	A	-
Galaxy -2	A	-	-	A
Asus-EP121	-	A	-	A

(b)

Hence, the system has been subjectively designed not only to generate the intelligent recommendation in respect to user interest, but also to help users find the exact or closest place that surely contains their item of interest. The recommended location has been generated as follows:

$$Rl(U,l) = Il\ (i,l) \cap Ul\ (u,l) \tag{14}$$

In our examples, the recommendation location computed as the intersection between user location and the location for every item that was recommended to the target user. However, the location of user may changeably and continuously be updated regarding user movement, but the recommendation will fire and take place according to the last updates. Thus, the recommendation locations for the individual user, random group and biclustered group have been listed as shown in Figs.(5.40, 5.41, 5.41) below.

i. Recommended location for individual user (John)

Fig.(5. 40): (a) User locations, (b) Items locations, (c) Recommended Items, (d) Recommended locations based on the availability of user and items.

	L_1	L_2	L_3	L_4
John	A	A	-	-
Emad	A	-	A	-
Nazek	-	A	-	A
Alisa	-	-	A	A
Elbert	A	A	-	-
Samuel	-	-	A	-

(a)

	L_1	L_2	L_3	L_4
Xperia S	A	-	-	A
Sony Tablet-S	-	A	-	A
Iphone-4S	A	-	A	-
Nokia-N8	-	A	A	-
Galaxy -2	A	-	-	A
Asus-EP121	-	A	-	A

(b)

	Asus-EP121	Galaxy -2	Iphone-4S	Sony Tablet-S
	0.014	0.251	0.244	0.007
John-RI	③	①	②	④

(c)

U_1	L_1	L_2	L_3	L_4
	A	A	-	-
Asus-EP121	-	R	-	A
Galaxy -2	R	-	-	A
Iphone-4S	R	-	A	-
Sony Tablet-S	-	R	-	A

(d)

ii. Recommended location for random group (John & Alisa)

Fig.(5. 41): (a) User locations, (b) Items locations, (c) Recommended Items, (d) Recommended locations based on the availability of user and items.

	L_1	L_2	L_3	L_4
John	A	A	-	-
Emad	A	-	A	-
Nazek	-	A	-	A
Alisa	-	-	A	A
Elbert	A	A	-	-
Samuel	-	-	A	-

(a)

	L_1	L_2	L_3	L_4
Xperia S	A	-	-	A
Sony Tablet-S	-	A	-	A
Iphone-4S	A	-	A	-
Nokia-N8	-	A	A	-
Galaxy -2	A	-	-	A
Asus-EP121	-	A	-	A

(b)

John & Alisa	Xperia S	Nokia-N8	Galaxy -2	Iphone-4S
	0.273	0.158	0.431	0.417
John-RI	±±	±	①	②
Alisa-RI	③	±	①	②

(c)

John	L_1	L_2	L_3	L_4
	A	A	-	-
Xperia S	R	-	-	A
Nokia-N8	-	R	A	-
Galaxy -2	R	-	-	A
Iphone-4S	[illegible]	[illegible]	[illegible]	[illegible]

Alisa	L_1	L_2	L_3	L_4
	-	-	A	A
Xperia S	A	-	-	R
Nokia-N8	-	A	R	-
Galaxy -2	A	-	-	R
Iphone-4S	A	-	R	-

(d)

iii. Recommended Location for the biclustered group (John, Emad, Nazek & Elbert)

Fig.(5. 42): (a) User locations, (b) Items locations, (c) Recommended Items, (d) Recommended locations based on the availability of user and Items.

	L_1	L_2	L_3	L_4
John	A	A	-	-
Emad	A	-	A	-
Nazek	-	A	-	A
Alisa	-	-	A	A
Elbert	A	A	-	-
Samuel	-	-	A	-

(a)

	L_1	L_2	L_3	L_4
Xperia S	A	-	-	A
Sony Tablet-S	-	A	-	A
Iphone-4S	A	-	A	-
Nokia-N8	-	A	A	-
Galaxy-2	A	-	-	A
Asus-EP121	-	A	-	A

(b)

U_{b1}	Xperia S	Iphone-4S	Nokia-N8	Galaxy -2
	1.714	1.974	0.952	2.03
John-RI	±±	②	±	①
Emad-RI	±±±	±±	±	①
Nazek-RI	±±±	±±	±	±±±±
Elbert-RI	±±	①	±	±±±

(c)

John	L_1	L_2	L_3	L_4
	A	A	-	-
Xperia S	R	-	-	A
Iphone-4S	R	-	A	-
Nokia-N8	-	R	A	-
Galaxy -2	R	-	-	A

Emad	L_1	L_2	L_3	L_4
	A	-	A	-
Xperia S	R	-	-	A
Iphone-4S	R	-	R	-
Nokia-N8	-	A	R	-
Galaxy -2	R	-	-	A

Nazek	L_1	L_2	L_3	L_4
	-	A	-	A
Xperia S	A	-	-	R
Iphone-4S	A	RC	A	-
Nokia-N8	-	R	A	-
Galaxy -2	A	-	-	R

Elbert	L_1	L_2	L_3	L_4
	A	A	-	-
Xperia S	R	-	-	A
Iphone-4S	R	-	A	-
Nokia-N8	-	R	A	-
Galaxy -2	R	-	-	A

(d)

5.1.5 Evaluation Metrics

The data has been divided into two disjoint sets, viz. the training set and the test set. The algorithms employed by the system work only on the training set and generate a ranked list of recommended items. The main goal is to scan through the test set, representing the portion of the initial data set which was not used by the recommender system, and matched items in the test set with items included in the generated list of recommendation. Items that appear in both sets will become members of a special set, called the hit set. The existing studies of recommendation systems use several measures to evaluate the quality of recommendation produced (Jonathan *et al.*, 2004). The evaluation metrics we adopted and used to examine the performance of the proposed method are recall and precision measures which are among the popular evaluation metrics in information retrieval systems. We can now define recall and precision for the recommended list in the following steps:

1. Recall describes the idea of all items which are relevant to the query that are successfully retrieved. Here, it can be defined as the ratio of relevant retrieved items over the relevant items.

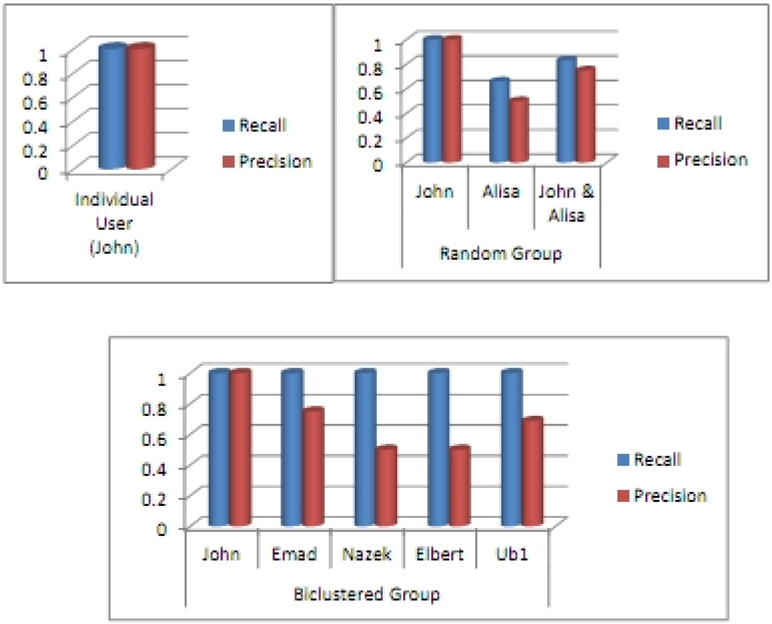
$$Recall = \frac{|\{relevant\ items\} \cap \{retrieved\ items\}|}{|\{relevant\ Items\}|} \tag{15}$$

2. Precision describes the idea of only those items which are relevant to the user's information need. Therefore, we have used the precision for measuring the correctness of recommendation as the ratio of the relevant retrieved items to the number of retrieved recommended items.

$$Precision = \frac{|\{relevant\ items\} \cap \{retrieved\ items\}|}{|\{retrieved\ items\}|} \tag{16}$$

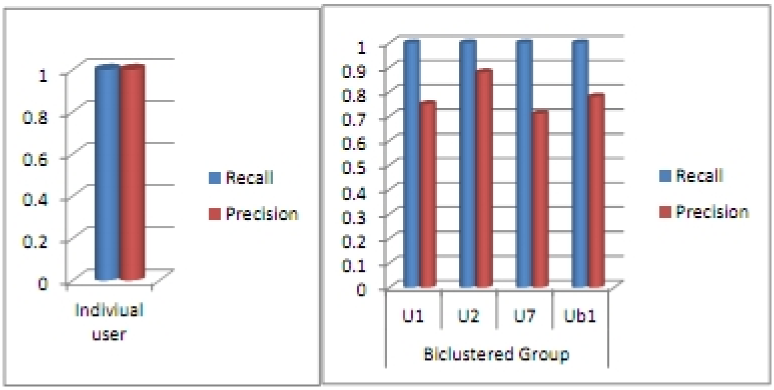
Figs (5.43) illustrates the values of recall and precision of the recommendation in our running examples

Fig.(5. 43): Precision and recall for the recommendation items.



The result for the MovieLens data set of different values of 'a' which was used in Equation (10) is shown in Fig. (5.44).

Fig.(5. 44): Precision and Recall for MovieLens.



This is so to say, precision represents the probability of recommendations that chosen for each user. The difference among the different groups is rather small, and the proposed method consistently results in better recommendations for all group sizes that have been taken in our examples. However, the proposed method obtains good precision because the similarity measure is based on the nearest bicluster and thus, being able to detect partial matching of users preferences and can provide accurate recommendations.

5.2 The Procedures and Algorithms

This section summarizes the work done so far and discussed in chapters 4 and 5. Hence, the required proposed procedures and algorithms have listed below in order to address the issue of notifying the mobile user/group with the information of interest. These procedures meant to build an effective recommender system that can help mobile individuals /group formulate better decision-making by considering the combination and dependencies among user/group preferences along with geographic location. This recommender system can tackle the following issues as needed:

- ☐ Generate an accurate recommendation list along with justification for individual user of MMP domain based on items/features and user profile.
- ☐ Generate a recommendation list for individual user based on user preferences and the closest location of items and user.
- ☐ Generate an accurate recommendation list along with justification for group users of MMP domain based on items/features and user profile.
- ☐ Generate a recommendation list for group users based on their preferences and the closest location of items and users.

Algorithm 5.1 *Recommendation Based User Preference For Individual User*(RBIUPFI)

input:
R:int[ ][ ] // R is the Rating_Data_Matrix
C:int[ ][ ] // C is the Content_Data_Matrix

Intermediate variables :
P:int[ ][ ] //P is the User_Profile_Matrix
b:int[ ][ ] //b_i is the biclusters of Bi-Max
C:int[ ][ ] //U_{bi} is the subset users of b_i
C:int[ ][ ] //I_{bi} is the subset items of b_i
BR:int[ ][ ] //BR is the Bicluster_ Rating_Data_Matrix
BC:int[ ][ ] //BC is the Bicluster_ Content_Data_Matrix
WP:real[ ][ ] //WP is the Weighted_User_Profile_Matrix
WC:real[ ][ ] //WC is the Weighted_Bicluster_Content_Data_Matrix
DF:real[ ][ ] //DF is the Dominant_Feature_Matrix
INF:real[ ][ ] //INF is the influence of the DF

Output:
RI:real[ ][ ] //RI is the Recommendation items List

begin

P_ Constructing (n, m, t, R, C, P)
Assigning_Weight _to_ P (n, m, P, WP)
Create_BR (n, m, R, b, BR)
Create_BC (cn, m, C, BR, BC)
Assigning _weight_ to_ BC (cn, m,BC, WC)
Finding_ similarity(i, R, BR, WP, WC, Sim)
Extracting_ DF(BR, WC, DF)
Generating_RI(i, R, C,RI)
end

Algorithm 5.2 *Recommendation Based User Preference* and *Location* For Individual user (RBUPLFI)

Input:
R:int[ ][ ] // R is the Rating_Data_Matrix
C:int[ ][ ] // C is the Content_Data_Matrix

Intermediate variables :
P:int[ ][ ] //P is the User_Profile_Matrix
b:int[ ][ ] //b_l is the biclusters of Bi-Max
C:int[ ][ ] //U_{bl} is the subset users of b_l
C:int[ ][ ] //I_{bl} is the subset items of b_l
BR:int[ ][ ] //BR is the Bicluster_ Rating_Data_Matrix
BC:int[ ][ ] //BC is the Bicluster_ Content_Data_Matrix
WP:real[ ][ ] //WP is the Weighted_User_Profile_Matrix
WC:real[ ][ ] //WC is the Weighted_Bicluster_Content_Data_Matrix
DF:real[ ][ ] //DF is the Dominant_Feature_Matrix
INF:real[ ][ ] //INF is the influence of the DF
RI:real[ ][ ] //RI is the Recommendation items List
RL:char[ ] // RL is the recommendation location
UL:char[ ] // is the users_ locations_matrix

Output:
IL:char[ ] // items_ locations_ matrix

begin
P_ Constructing (n, m, t, R, C, P)
Assigning_Weight _to_ P (n, m, P, WP)
Create_BR (n, m, R, b, BR)
Create_BC (cn, m, C, BR, BC)
Assigning _weight_ to_ BC (cn, m,BC, WC)
Finding_ similarity(i, R, BR, WP, WC, Sim)
Extracting_ DF(BR, WC, DF)
Generating_RI(i, R, C,RI)
Generating _RL(i, UL, IL, RL)
end

Algorithm 5.3 *Recommendation Based Users Preferences for Group Users* (RBIUP)
Algorithm RBGUP

// recommendation based group users preferences

Input:
R:int[ ][ ] // R is the Rating_Data_Matrix

C:int[ ][ ] // C is the Content_Data_Matrix

Intermediate variables :
P:int[ ][ ] //P is the User_Profile_Matrix
b:int[ ][ ] //b_l is the biclusters of Bi-Max
C:int[ ][ ] //U_{bl} is the subset users of b_l
C:int[ ][ ] //I_{bl} is the subset items of b_l
BR:int[ ][ ] //BR is the Bicluster_ Rating_Data_Matrix
BC:int[ ][ ] //BC is the Bicluster_ Content_Data_Matrix
WP:real[ ][ ] //WP is the Weighted_User_Profile_Matrix
WC:real[ ][ ] //WC is the Weighted_Bicluster_Content_Data_Matrix
DF:real[ ][ ] //DF is the Dominant_Feature_Matrix
INF:real[ ][ ] //INF is the influence of the DF

Output:
RI:real[ ][ ] //RI is the Recommendation items List

begin
P_ Constructing (n, m, t, R, C, P)
Assigning_Weight _to_ P (n, m, P, WP)
Create_BR (n, m, R, b, BR)
Create_BC (cn, m, C, BR, BC)
Assigning _weight_ to_ BC (cn, m,BC, WC)
Finding_ similarity_group(i, R, BR, WP, WC, Sim)
Extracting_ DF(BR, WC, DF)
Generating_RI_group(i, R, C, RI)
end

Algorithm 5.4 *Recommendation Based User Preference* and *Location* For Group user (RBUPLFG)

Input:
R:int[ ][ ] // R is the Rating_Data_Matrix
C:int[ ][ ] // C is the Content_Data_Matrix

Intermediate variables :
P:int[ ][ ] //P is the User_Profile_Matrix
b:int[ ][ ] //b_l is the biclusters of Bi-Max
C:int[ ][ ] //U_{bl} is the subset users of b_l
C:int[ ][ ] //I_{bl} is the subset items of b_l
BR:int[ ][ ] //BR is the Bicluster_ Rating_Data_Matrix
BC:int[ ][ ] //BC is the Bicluster_ Content_Data_Matrix
WP:real[ ][ ] //WP is the Weighted_User_Profile_Matrix
WC:real[ ][ ] //WC is the Weighted_Bicluster_Content_Data_Matrix
DF:real[ ][ ] //DF is the Dominant_Feature_Matrix
INF:real[ ][ ] //INF is the influence of the DF
RI:real[ ][ ] //RI is the Recommendation items List
RL:char[ ] // RL is the recommendation location
UL:char[ ] // is the users_ locations_matrix

Output:
IL:char[ ] // items_ locations_ matrix

begin
P_ Constructing (n, m, t, R, C, P)
Assigning_Weight _to_ P (n, m, P, WP)
Create_BR (n, m, R, b, BR)

```
        Create_BC (cn, m, C, BR, BC)
        Assigning _weight_ to_ BC (cn, m,BC, WC)
        Finding_ similarity_group(i, R, BR, WP, WC, Sim )
        Extracting_ DF(BR, WC, DF)
        Generating_RI_group(i, R, C, RI)
        Generating _RL_group(i, UL, IL,RL)
  end
```

Procedure 1: P_ Constructing *(Input n:integer, m:integer,t:integer R:integer[ ][ ], C:integer[ ][ ]; Output P:integer[ ][ ])*

```
    // n: int //is the number of items
    // m: int // is the number of users
    // t :int // is the threshold values of R
    /* to construct the User_Profile_Matrix P from the Input Rating_Data_ Matrix R and
    Content_Data_Matrix C */
begin
    s:set of items
    i: integer
    k:integer
   for i : 1 → m
     begin
       // S: set of the items which have been rated by user
      S ← ∅
       U ← R[u_i]
           for k : 1 → n
             begin
                 if U[i_k] > t then
               S ← S ∪ {i_k}
             end
           P[u_i] ← Σ_{i_k ∈ S} C[i_k]
     end
end
```

Procedure 2: Assigning_Weight _to_ P *(Input n:integer, m:integer, P: integer[ ][ ]; Output WP: Real [ ][ ])*

```
   /* to compute the Weighted_User_Profile_Matrix WP for the User_ Profile_ Matrix P* /
begin
   // n is the number of users
   // m is the number of features
   sum:real
   v:real
   j:integer
   k:integer
   for j: 1 → m
     begin
       sum ← 0
       for k : 1 → n
          begin
            if P[u_k, f_j] ≠ 0 then
            sum ← sum + 1;
          end
        if sum = n then
        sum ← sum − 0.1
```

```
        v ← log(n/sum)
        for k : 1 → n
          begin
            P[u_k, f_j] ← v * [u_k, f_j]
          end
      end
end
```

Procedure 3: Create_BR *(Input n:integer, m:integer,R:integer[ ][ ], b: integer[ ][ ]; Output BR: integer[ ][ ])*

```
begin
/* Converting the Rating_Data_Matrix R into biclusters b by using Bi-Max biclusters algorithm*/
/* Converting the Output biclusters of Bi-Max b into Bicluster_ Rating_ Data_ Matrix BR */
// Bi-Max is the binary inclusion maximal bi-Clustering algorithm
  U_bi : integer // is the subset users of b_i
  I_bi:integer //is the subset items of b_i
  i:integer
  j:integer
  // n is the number of items
  // m is the number of biclusters
  //Apply the Bi-Max on R.
  b   ←Bi-Max (R)
  //Convert the Output of Bi-Max into BR as follow:
  for i: 1 → m
  begin
    for j : 1 → n
      begin
        if i_j ∈ I_bi then
        BR(i, j) = |u_bi|
           else
              BR(i, j) = 0
```

$$// BR(i,j) = \begin{cases} |u_{bi}| & if\ i_j \in I_{bi} \\ 0 & otherwise \end{cases}$$

```
        end if
      end
    end
end
```

Procedure 4: Create_BC *(Input cn:integer, m:integer, C:integer[ ][ ], BR:integer [ ][ ]; Output BC:integer[ ][ ])*

```
Begin
  /* creating Bicluster_ Content_Data_Matrix BC from Content_Data_Matrix
  C and Bicluster_ Rating_Data_Matrix BR*/
  // S: set of the items inside bj of BR
  // m is the number of items
  // cn is the number of clusters
  j: integer
  k:integer
  v:int[]
  bf:int[]
  for j : 1 → cn
    begin
      S ← ∅
        for k : 1 → m
```

```
            begin
              if bj[i_k] ≠ 0
              S ← S ∪ {i_k}
            end
            v ← Σ_{i_k ∈ S} C[i_k]
          bf ← v * b_j[s[1]]
      end
end
```

Procedure 5: Assigning_weight_ to_ BC *(Input cn:integer, m:integer, BC: integer[ ][ ]; Output WC:integer[ ][ ])*

```
begin
 /* assigning weight to Bicluster_ Content_Data_Matrix  BC to produce the
 Weighted_Bicluster_Content_Data_Matrix  WC */
 // m is the number of Features
 // cn is the number of clusters
 s:set of items
 j: integer
 k:integer
 for j: 1 → m
    begin
       sum ← 0
       for k : 1 → cn
         begin
            if BC[b_k, f_j] ≠ 0 then
              sum ← sum + 1;
         end
       if sum = n then
       sum ← sum − 0.1
       v = log(n/sum)
       for k : 1 → cn
          begin
             BC[b_k, f_j] ← v * [b_k, f_j]
          end
    end
end
```

Procedure 6: Finding_ similarity(*Input i: integer, R:integer[ ][ ], BR:integer[ ][ ], WP:real[ ][ ], WC:real[ ][ ]; Output Sim:real[ ]*)

```
begin
 /* finding the similarity Sim1  between the selected  user i of Rating_Data_
 Matrix R and  Bicluster_ Rating_Data_Matrix BR */.
 /*finding the similarity Sim2  between the selected  user i of Weighted_User_
 Profile_Matrix WP and Weighted_Bicluster_Content_Data_Matrix WC */
 /* finding the similarity Sim between the biclusters that have strong partial
 similarity with the selected user i*/
 // b_l is the biclusters of Bi-Max clustering algorithm
 // U_bl is the subset users of b_l
 // I_bl is the subset items of b_l
 i: integer
 Sim_1: real
 Sim_2: real
 Sim: real
```

α: real
// Finding the similarity between the target user/group of R and BR as follow:
$Sim_1 \leftarrow Cosin\ Similarity\ (R[i], BR)$
// Finding the similarity between the target user of WP and WC as follow:
$Sim_2 \leftarrow Cosin\ Similarity\ (WP[i],\ WC)$.
*/*Finding the biclusters that have strong partial similarity with the target user/group as follow:*/*
$Sim \leftarrow (1-\alpha).Sim_1 + \alpha.Sim_2$ *where α value between* [0 and 1]
end

Procedure 6 : Finding_ similarity_group(*Input i: integer[], R:int[ ][ ], BR: integer[ ][ ], WP:real[ ][ ], WC:real[ ][ ]; Output Sim:real[ ]*)

begin
/ finding the similarity Sim1 between the selected group of user i of Rating_Data_Matrix R and Bicluster_ Rating_Data_Matrix BR */.*
*/*finding the similarity Sim2 between the selected group of user i of Weighted_ User_Profile_Matrix WP and Weighted_Bicluster_Content_Data_Matrix WC */*
/ finding the similarity Sim between the biclusters that have strong partial similarity with the selected group of user i */*
// b_i *is the biclusters of Bi-Max clustering algorithm*
// U_{bi} *is the subset users of* b_i
// I_{bi} *is the subset items of* b_i
i: integer
k: integer
RG: integer[]
WPG:real[]
Sim_1*: real*
Sim_2*: real*
Sim: real
α: real
//Finding the similarity between the target group of R and BR as follow:

$$RG \leftarrow \sum_{u_k \in U_{bi}} R[U_k]$$

$Sim_1 \leftarrow Cosin\ Similarity\ (RG, BR)$

//Finding the similarity between the target group of WP and WC as follow:/*

$$WPG \leftarrow \sum_{u_k \in U_{bi}} WP[U_k]$$

$Sim_2 \leftarrow Cosin\ Similarity\ (WPG,\ WC)$.

*/*Finding the biclusters that have strong partial similarity with the target user/group as follow:*/*
$Sim \leftarrow (1-\alpha).Sim_1 + \alpha.Sim_2$ *where α value between* [0 and 1]
end

Procedure 7: Extracting_ DF(*Input BR:integer[ ][ ], WC:real[ ][ ]; Output DF: real[ ][ ]*)

begin
/ finding the Dominant_Feature DF between Bicluster_ Rating_Data_Matrix BR and Weighted_Content_Data_Matrix WC*/*
$\hat{BR}$*: integer[ ][ ] // is the transpose matrix of the BR Matrix*
$\hat{WC}$*: real[ ][ ] // is the sorted matrix of the WC Matrix*

$\acute{B}R^T$: integer[ ][ ] // is the transpose matrix of the $\acute{B}R$: Matrix

Sort the rows of BR based on correspondent Sim values in descending order.
Let $\acute{B}R \leftarrow BR\ [1-4, \#]$
// $[1-4, \#]$: fix the rows from 1 to 4 with same values of all columns #

Sort the WC based on correspondent Sim values in descending order.
Let $\acute{W}C \leftarrow WC\ [1-4, \#]$
// $[1-4, \#]$: fix the rows from 1 to 4 with same values of all columns #

Compute $DF \leftarrow \acute{B}R^T \times \acute{W}C$

end

Procedure 8: Calculating_INF(Input DF:real[ ][ ]; Output INF:real[ ][ ])

begin

// computing the INF influence of the DF based on Dominant_Feature_Matrix DF.
n:integer // is the number of features
m:integer // is the number of items
i:integer
k:integer
$for\ i : 1 \rightarrow m\ do$
begin

$$INF[i] \leftarrow \sum_{j=1}^{n} DF[i,j]$$

end
end

Procedure 9: Generating_RI(Input i:int, R:int[ ][ ], C:int[ ][ ]; Output RI:real[ ])

begin

/* generating the recommended items list RI based on Rating_Data_Matrix R and Content_Data_Matrix C for the selected user i */
//Ui: the user being selected

$\acute{C}$: int[ ][ ] // is the sorted matrix of the C Matrix
WP:real[ ][ ] // is the Weighted_User_Profile_Matrix
$\acute{C}^T$: int[ ][ ] // is the transpose matrix of the $\acute{C}$ Matrix
$RI'[I_k]$: int[ ] // items rated by the selected user and recommended again for him
$RI''[I_k]$: int[ ] // items don't rated by the selected user and recommended for him
S_1:set of items from RI matrix that are recommended to the target user
S_2:set of items from R matrix that user has rated for it before
S:intersection for items of S_1 and S_2
k:integer
i:integer
begin
Sort the rows of C based on correspondent INF values in descending order.
Let $\acute{C} \leftarrow C\ [1-4, \#]$
// $[1-4, \#]$: fix the rows from 1 to 4 with same values of all columns #
$RI[u_i] \leftarrow WP[u_i] * \acute{C}^T$
Sort $RI[u_i]$ in desending order
$S_1[u_i] \leftarrow RI\{i_k\}$
$S_2[u_i] \leftarrow R_i\{i_k\}$
$S \leftarrow S_1 \cap S_2$
$for\ k : 1 \rightarrow 4\ do$

```
        begin
          If u_i ∈ S then
            RI'[u_i][I_k] ← {S}
            RI[u_i][I_k] ← RI'[u_i][I_k]
          else
            RI''[u_i][I_k] ← { S_1 − S }
            RI[u_i][I_k] ← RI''[u_i][I_k]
        end if
      end
end
```

Procedure 9: Generating_RI_group(*Input i:int[ ], R:int[ ][ ], C:int[ ][ ]; Output RI:real[ ]*)

```
begin

    /* generating the recommended items list RI based on Rating_Data_Matrix R and
    Content_Data_Matrix C for the selected user group i */
    Ć: int[ ][ ] //is the transpose matrix of the C Matrix
    WP: real[ ][ ] // is the Weighted_User_Profile_Matrix
    Ć^T : int[ ][ ] // is the transpose matrix of the Ć Matrix
    RI'[I_k] : int[ ] // items rated by the selected user and recommended again for him
    RI''[I_k]: int[ ] // items don't rated by the selected user and recommended for him
      WPG:real[]
    bi:integer
    m:integer // number of users
    S_1:set of items from RI matrix that are recommended to the target user
    S_2:set of items from R matrix that user has rated for it before
    S:intersection items of S_1 and S_2
    k:integer
    i:integer
    Sort the rows of C based on correspondent INF values in descending order.
    Let Ć ← C [1 − 4, #]
    // [1 − 4, #]: fix the rows from 1 to 4 with same values of all columns #

    WPG ← Σ_{u_k ∈ U_bi} WP[U_k]
    RI ← WPG • Ć^T
    for bi : 1 → m do
    begin
      Sort RI[U_bi] in descending order
      S_1[U_bi] ← RI{I_k}
      S_2[U_bi] ← R_{U_bi}{i_k}
      S ← S_1 ∩ S_2
     for k : 1 → 4 do
        begin
          If U_bi ∈ S then
            RI'[U_bi][I_k] ← {S}
            RI[U_bi][I_k] ← RI'[U_bi][I_k]
            else
              RI''[U_bi][I_k] ← { S_1 − S }
              RI[U_bi][I_k] ← RI''[U_bi][I_k]
        end
     end
end
```

Procedure 10: Generating _RL(*Input i:int, UL:char[ ][ ], IL:char[ ][ ]; Output RL:char[ ]*)

begin

```
/* generating the recommendation location RL for the selected user i based on the users_
locations_matrix UL and items_ locations_ matrix IL */
WP: real[ ][ ] // is the Weighted_User_Profile_Matrix
Ĉ^T : int[ ][ ] // is the transpose matrix of the Ĉ Matrix
  n:integer // is the locations of the item.
  m:integer // is the locations of the user
L:integer// is the number of locations
k:integer
i:integer
j:integer
RI[u_i] ← WP * Ĉ^T
foreach i_k in S_i do
begin
  for j: 1 → L
     if IL[i_k ][l_j] = UL[u_i][l_j] then
     IL'[j, i] ← RI
    // RI is the recommended place to the user which the recommended item
      elseif IL[i_k ][l_j] = UL[u_i][l_{j+1}] then
        IL'[j, i] ← RC  // RC is the closest place to the user
  end
end
```

```
Procedure 10: Generating _RL_group(Input i:int[ ], UL:char[ ][ ], IL:char[ ][ ]; Output RL:char[ ] )
begin
  /* generating the recommendation location RL for the selected user i based on the users_
  locations_matrix UL and items_ locations_ matrix IL;
  WP: real[ ][ ] // is the Weighted_User_Profile_Matrix
  Ĉ^T : int[ ][ ] // is the transpose matrix of the Ĉ Matrix
  IL':char[ ] // the location matrix for the selected users
   WPG:real[]
  bi:integer
  n:integer // is the locations of the item.
  m:integer // is the locations of the user
  L:integer// is the number of locations
  k:integer
  i:integer
  j:integer
  WPG ← Σ_{u_k ∈ U_bi} WP[U_k]
  RI[U_bi ] ← WPG * Ĉ^T

  for bi: 1 → m
  begin
   foreach i_k in S_i do
    begin
     for j: 1 → L
        if IL[i_k ][l_j] = UL[u_i][l_j] then
        IL'[j, i] ← RI
     // RI is the recommended place to the user which the recommended item
          elseif IL[i_k ][l_j] = UL[u_i][l_{j+1}] then
           IL'[j, i] ← RC  // RC is the closest place to the user
    end
  end
end
```

Chapter 6

Conclusions and Future works

This study relies on introducing an integrated architecture for MMP and highlights the main components that supposed to be addressed all together in single framework in order to have an efficient mobile market place. Thereafter, the study searches the notion of improving the decision support system and enhancing the quality and accuracy of the recommended notification in mobile market place environment. In fact, such recommendations are important for both mobile users and services providers to obtain necessary information that helps them make a decision about purchasing items/ availing services. These recommendations also help for faster and easier response to the mobile users' demands and at the same time, mobile users can obtain relevant information for purchasing goods and services anytime, anywhere, according to their interests. Thus, this study aims at recommending the useful information that fits each individual needs, as well as satisfying the group users interest. It is also important that the recommendations that made to mobile user must be justified, in the sense that an explanation is to be provided as to why that particular item/service is of interest to the individual user/group. However, this recommended information not only helps in getting the items having high degree of interest, but also considers the combination of user preferences, item features, recommendation reasoning and geographic location for both individual user/group and items.

In other words, this study presents a recommender system that can serve for both individuals and groups of MMP users based on the influence of item's features, user locations, and user ratings. For this purpose, interesting and relevant items are retrieved and recommended to the target user/group. In our experiments, we have distinguished between two types of information sources: The first one is *rating data*, which represents the past selections and transactions of all users. The second information source is the *content data* which describe the features that items contain.

The user/group preferences and item-features information provided as a series of numeric values. These values provide information about the characteristics of the items and give coherent clue about user/group interest. The information combination among user preferences, item features, reasoning of recommendation and geographic location for both user/group and items is considered during the recommendation processes. Such information used to make strong recommendation and provide reasonable reasoning. Finally, we have constructed the users/items location profile. Hence, the system has been subjectively designed not only to generate accurate recommendation in respect to user interest, but also to help users find the closest place that contains their item of interest.

The quantification of recommendation is subjectively captured by understanding the influence of user/group rating and items' features among users profile vis-à-vis his/her/their location. The framework has been implemented and evaluated using synthetic and benchmark datasets and has shown significant results. The generated recommendations have been categorized as individuals, groups containing random users and groups which consist of biclusters that is built during bi-clustering processes.

By exploring the features of items that recommended to the target 'individual user/group' with his/her/their user profile, the coherent match appears. This similarity is much closer among the recommended items that have highest values of influence.

In contrast, the values revealing poor influence are evidence of the poor matching between the features of both those items and the tested user/group. Thus, the list of recommended items which contains the highest influence values is actually meets the interest of the tested user/group by involving the most desirable features that user/group are looking for. In accordance, it actually meets the requirements of the interest of the tested user, whose attention is drawn most to the same features. Both the high and low values can be taken to interpret the significance of the role of influence among the features and user/group profile. Hence, the system was able to grasp the user/group needs and recommend items accordingly. Moreover, the items that got poor influence value with individual user are not supposed to be eliminated during building the recommendation for group. When these values have been eliminated less accuracy of recommendations has been observed. Therefore, those values play important roles to improve the accuracy and the quality of recommendations for the group. In other words, the influence of content data among users' profiles has strong effect on the quality of the group recommendations. The influence values may changes from case to case for the same user due to items/users influence among the different groups.

However, that change does not affect the accuracy of recommended items or the reasoning for the target user/group. This can also be considered as another aspect of the system ability of filtering useful information that fits each individual needs, as well as satisfying the group users desires. Thereafter, the items that already have been rated by user could be excluded or kept the same 'if needed' to provide a recommendation to the specific user about the new generation of item that user got/rated it before. As a result, the proposed method obtained a significant role in providing efficient and effective means for recommendation to enhance the quality of notification in MMP environment.

Moreover, this approach takes into account the duality and dependency that exists between users rating and items features whereas most of the hybrid algorithms perform separate clustering of users and items so they cannot detect item similarity. It provides the actual reason behind its recommendations and justifies them. It is capable of recommending useful information that fits each individual needs, as well as satisfying the group users desires. Thus, the proposed method has the potentiality to increase consumer satisfaction, enhance consumer/company loyalty, and boost overall sales by giving justification and creditability to the products that have high degree of interest to mobile users.

The proposed method has achieved significant results by recommending the user/group with items that match his/her/their interest according to the evaluation metrics. The evaluation metrics we adopted here and used to calculate the performance of our recommender systems are recall and precision measures which are among the popular evaluation metrics in information retrieval systems. Thus, the proposed method has the potentiality to increase consumer satisfaction, enhance consumer/company loyalty, and boost overall sales by giving reasoning and creditability to the products that have high degree of interest to mobile users.

Moreover, this system has been designed with the goal of providing accurate, low-cost item recommendations, where searching for a particular item costs is prohibitively expensive and takes a lot of time especially in mobile market place domain. It generates not only reasonable recommendation but also applicable recommendations for the mobile users of mobile marketplace based on their location.

As a result, such recommendations can play important role in revenue increase, cost reduction and enhancing the ability of MMP finance. More effectively the framework has the potential to increase consumer satisfaction, enhance consumer/ company loyalty, and boost overall sales by targeting huge number of mobile users based on their interests and locations.

In fact, there are several ways in which our method could be extended. One aspect which we have not looked into is how *requirements* (Aditya *et al.*, 2011) affect recommendations. For instance, in a University environment, for a student to graduate, the student needs to satisfy a bunch of requirements like take two courses from {a, b, c, d}, but b and c together don't count. Also we have not looked into the problem of *prerequisites* (Aditya *et al.*, 2010) wherein when we make recommendations we need to make sure that we recommend a package of items such that the prerequisites are present in the package itself like the course database needs to be taken before data mining. There is also some recent work on how sequence mining (Aditya *et al.*, 2010) can be used to form an aggregated recommendation and environment which propose to explore in future.

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