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Personalized Recommender Systems in e-Commerce and m-Commerce: A Comparative Study

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Abstract

It is apparent that m-commerce and e-commerce have various similarities from operational and services perspectives. However, at the same time, m-commerce has its own a unique technology driven business opportunities with its own unique characteristics, functions, opportunities and challenges. One successful application in e-commerce is personalized recommendations services as results of recommender systems. Personalized recommender systems are emerging in m-commerce. This paper compares and contrasts e-commerce and m-commerce personalized recommender systems in B2C with the objective of finding what additional requirements are needed to adapt the models, methods and techniques developed and advanced in e-commerce for m-commerce. Various similarities and differences are identified and discussed along the dimensions user model, product and service model, recommender engine/algorithms, user interface (I/O and interaction), and confidence and uncertainty model, that make up a personalized recommender system. The two most prominent e-commerce and m-commerce personalized recommender systems of Amazon and MovieLens are discussed. The uncertainty and confidence measures in e-commerce and m-commerce personalized recommender systems are discussed further along with their potential for creating accurate mental model of the recommender system and its processes for the customers. Furthermore, the results from related research using fuzzy set and possibility theory for handling uncertainty in e-commerce showed a great potential for m-commerce. Two of the reasons for this potential are its high recommendation accuracy with a few numbers of recommendations; and its low latency.

1 Introduction

It is apparent that m-commerce and e-commerce have various similarities from operational and services perspectives. Furthermore, m-commerce can adapt and use the various methods and techniques developed and advanced in e-commerce. However, at the same time, m-commerce has its own a unique technology driven business opportunities with its own unique characteristics, functions, opportunities and challenges. One successful application in e-commerce is ***personalized recommendations services*** as results of recommender systems. Personalized recommender systems are emerging in m-commerce. The focus of this paper is to compare personalized recommender systems in B2C e-commerce and m-commerce. And the main goals are to find what additional requirements are there to adapt the models, methods and techniques developed and advanced in e-commerce for m-commerce.

Extending on our recommender system framework for e-commerce to m-commerce, generic system architecture for personalized recommender systems (both for e-commerce and m-commerce) is presented. This framework provides the ground for through comparison between m-commerce recommender systems and e-commerce recommender systems. There are more similarities in components of the system architecture than variations between e-commerce and m-commerce. The most important dimensions or factors that need to be considered for the comparative analysis are user model, product and service model, recommender engine/algorithms, user interface (I/O and interaction), and confidence and uncertainty model. The paper is organized into five sections. Section 2 presents a brief overview on e-commerce and m-commerce followed by discussion and comparison of personalization recommendations in e-commerce and m-commerce in Section 3. In Section 4, the uncertainty and confidence issues in e-commerce and m-commerce recommender systems and our research using fuzzy set and possibility theory to address them are presented. Finally conclusions and further research issues are presented in section 5.

2 e-Commerce and m-Commerce

For the purposes of this study, electronic commerce (e-commerce) refers to the activities of consumers shopping using desktop, workstations, etc. located at a relatively fixed location and connected to the Internet using some kind of wired network. Furthermore, mobile commerce (m-commerce) refers to the activities of consumers shopping using a mobile device such as a cell phone, Personal Digital Assistant or a combination cell phone-PDA device from any where any time connected to the Internet through a wireless network.

Users prefer m-commerce mainly because of mobility, broad reach, ubiquity, convenience, and localization of products and services attributes. However, m-commerce has various limitations. According to Turban et al. (Turban, King, Lee, & Viehland, 2004) some of these limitations are:

i. there is a lack of Standards such as a standard for security protocol, device operating systems and platforms;
ii. customer confidence is still low to cell phone transactions;
iii. bandwidth is still limited and transmissions are more frequently interrupted due to wireless issues such as weather;
iv. going on-line via cell phone significantly decreases battery life because of higher power consumption;
v. and the fees associated with mobile Internet services are higher on average than PC-based Internet services

Moreover, Ghinea and Angelides (Ghinea & Angelides, 2004) and Nielsen et al. (Nielsen, Molich, Snyder, & Farrell, 2001) have also identified the following limitations of m-commerce compared to e-commerce

i. limited data or query input capability,
ii. limited display capability such as Small screen size limited to 2-2.5 inches and poor screen resolution,
iii. limited processing speed and memory capabilities for activities such as retrieval of large size information including images of products and sample video clips. These tasks require longer time and result in higher fees to the end users,
iv. limited data transmission capability speeds (between 9.6-14.4 kbps which are too slow),
v. and low battery power of devices

It is apparent that m-commerce and e-commerce have various similarities from services perspectives. Furthermore, m-commerce can adapt and use the various methods, and techniques developed and advanced in e-commerce. However, at the same time, m-commerce should be recognized as a unique technology-driven business opportunity with its own unique characteristics, functions, opportunities and challenges. Table 1 presents a conceptual summary of comparison between e-commerce and m-commerce(Sadeh, 2002)

3 Personalized Recommender Systems in E-commerce and M-commerce

3.1 Current Status of Personalized Recommender Systems in e-commerce and m-commerce

Personalized recommender systems in e-commerce are well developed and various systems are operational for various application domains. Among many, two of the most popular and successful systems are Amazon’s personalized recommendations that recommends books, DVDs, etc., and MovieLens (Sarwar, Karypis, Konstan, & Riedl, 2000) which is a movie recommender system. Interested reader can refer (Herlocker, Konstan, Terveen, & Riedl, 2004; Schafer, J, & Riedl, 2001). However, personalized recommender systems in m-commerce are relatively recent applications. With the emergence of mobile technology Amazon provides a service called Amazon Anywhere. According to PC Magazine Review in June 2002, Amazon Anywhere for Palm PDAs and WAP devices got a very good rating for a set of search services for books, music, DVDs, electronics, toys, and software. It also list individual product's list price, Amazon's price, your savings, stock status, basic specs, and a review summary, with links for details on the latter two. Finally, for purchasing an item, user can use all of Amazon's online buying features, including 1-Click shopping.

Table 1: A summary of comparison between e-commerce and m-commerce

Factor		E-Commerce	M-Commerce
Technology	Device	PC	Smartphones, Pagers, PDAs, Cell phones
	Operating System	Windows, Unix, Linux	Symbian (EPOC), PalmOS, Pocket PC, proprietary platforms.
	Common Communication protocols in m-commerce are	Web's Hyper Text Transfer Protocol (HTTP)	Wireless Application Protocol (WAP) and DoCoMo"s (Japan) proprietary protocol
	Programming and presentation Standards	HTML, XML, JavaScript, Java, etc.	HTML, WML, HDML, i-Mode, Java support
	Browser	Microsoft Explorer, Netscape	Phone.com UP Browser, Nokia browser, MS Mobile Explorer and other micro-browsers
	Bearer Networks	TCP/IP & Fixed Wired-line Internet	GSM, GSM/GPRS, TDMA, CDMA, CDPD, paging, Wireless Fidelity (Wi-Fi) networks
Services	Personalized Recommendation	Well Developed	Not Well Developed as e-commerce except a few location-based systems ???; Begins via wired Internet
	Accessibility	At desktop, workstation, etc.	Ubiquitous: Any time and anywhere
	Customer Usage Motivation	if they have good reasons or not	Only if they have good reasons
Usability		relatively good number of studies	very few studies

At present, using Amazon's Anywhere, web-enabled Cell phone users with wireless Internet service can find and buy products from Amazon.com. They need to set up or registered with same forms to fill like the one for the e-commerce site. PDA users can visit new stores, browse top-selling categories and personalized recommendations, and manage their account. Second, any mobile users who have placed bids on Amazon's auction site and select the service get Auction Alerts and Auction Outbid information delivered to them as soon as there is any change in the status of their bid. (http://www.amazon.com/exec/obidos/subst/misc/anywhere/anywhere.html/, accessed on 2/17/2005). Finally, Amazon.com Voice Shopping allows customers to use their voices to access Amazon.com. For instance, "Callers can now say "Music" at the #121 main menu and be offered three new services: Editor's Choice, Now Playing, and the Warner Music Channel. Editor's Choice provides recommendations and song samples selected by Amazon.com's music editors. Now Playing enables callers to access their favorite radio station's playlist. The Warner Music Channel provides a comprehensive list of albums and song samples from their network of artists." (http://www.amazon.com/exec/obidos/subst/misc/anywhere/anywhere.html/002-8517382-2954445, accessed on 2/17/2005).

Based on these information and as per our knowledge, there is no personalized recommendation service for cell phones users in Amazon for digital access. MovieLens are also not yet fully adapted to mobile access. There are research undertakings including PocketLens (Miller, Knostant, & Riedl, 2004)and MovieLens Unplugged (Miller, Albert, Lam, Knostant, & Riedl, 2003). The former is a study on the adaptation of MovieLens personalized recommender system for palmtop computers in peer-to-peer architecture; and the latter is a study on implementing a wireless movie recommender system for MovieLens users using a cell phone browser, an AvantGo channel, a wireless PDA, and a voice-only phone interface. As the results of a nine month field study of MovieLens Unplugged it was found that mobile recommender systems have the potential to provide value to customers.

3.2 Comparison of m-Commerce and e-Commerce Personalized Recommender Systems

Extending on our recommender system framework for e-commerce (Zenebe & Norcio, 2005) to m-commerce, generic system architecture for personalized recommender systems for e-commerce and m-commerce is presented in Figure 1. This framework provides the ground for thorough comparison between e-commerce and m-commerce recommender systems. Its main components are:

- A User Modeling Subsystem that build the user model (see figure 2) including inferring user's interests and preferences for products and services, current location and context of states, devices used, etc. It can also incorporate ontology on the products under consideration for recommendation.
- A Personalized Recommender Subsystem (ARS) or Recommender Engine that makes recommendation decisions using the user model and inference mechanism;
- A User Interface Subsystem – is a gateway to the user - system interaction; and
- A Data Storage and Retrieval Subsystem – responsible for storage, retrieval and maintenance of user and product data.

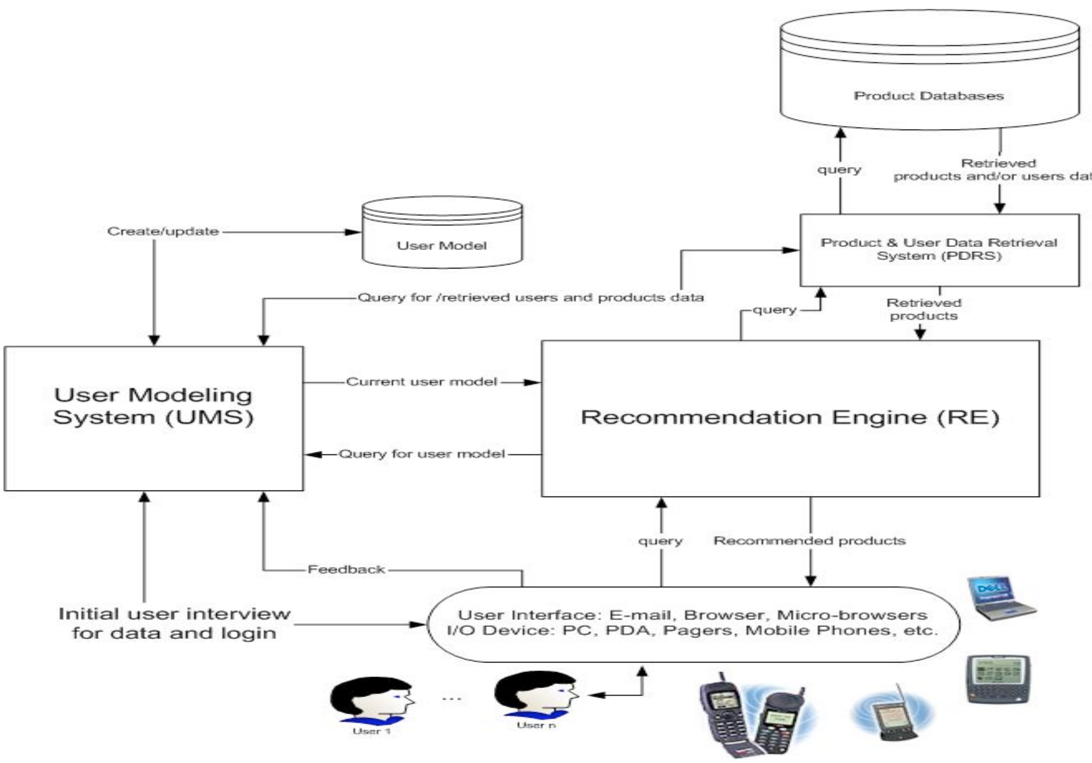

Figure 1: A Generic system architecture for personalized recommender system in e-commerce and m-commerce

There are more similarities in components of the system architecture than variations for e-commerce and m-commerce. The most important dimensions or factors that need to be considered for the comparative analysis are user model, product and service model, recommender engine/algorithms, user interface (I/O and interaction), and confidence and uncertainty model. These dimensions are discussed and their roles in m-commerce and e-commerce are presented along with examples from literature and commercial systems in the following sections.

3.2.1 User Modeling and User Model

Customer or user model (its simplest form called profile) has a vital role in personalization electronic and mobile commerce services that aim at provisions of services including presentation of product information and recommendation of alternative and/or related products and services to individual user or group of users based on their user models. A customer model has the following facets consisting of facts and assumptions about a user: personal facets mainly include demographic and other personal data like job type, educational level and the like; behavioral facets include interests, preferences, attitude and the like; cognitive facets include goals, plans, beliefs, knowledge, ability, disability and the like; and contextual facets include physical location, past interaction, hardware and software available, tasks, and other users in the environment. Figure 2 presents a generic user model.

Based on this user model framework, user model in e-commerce and m-commerce comprises of most of the features. For m-commerce, the contextual facets including operating environment (hardware and software), location, and time are essential for effective and useful recommendation decisions. For instance, understanding the customers' activity schedules are useful to determine what to recommend because services accessed by customers during working hours can differ from those during the evening or on weekends.

To organize and represent user models effectively in m-commerce, methods and techniques from e-commerce can be used with additional requirements that these models need to incorporate the peculiar mobile user and mobile device features and their relationships in the model. These methods include the attribute-value pairs, vectors, frames and rules.

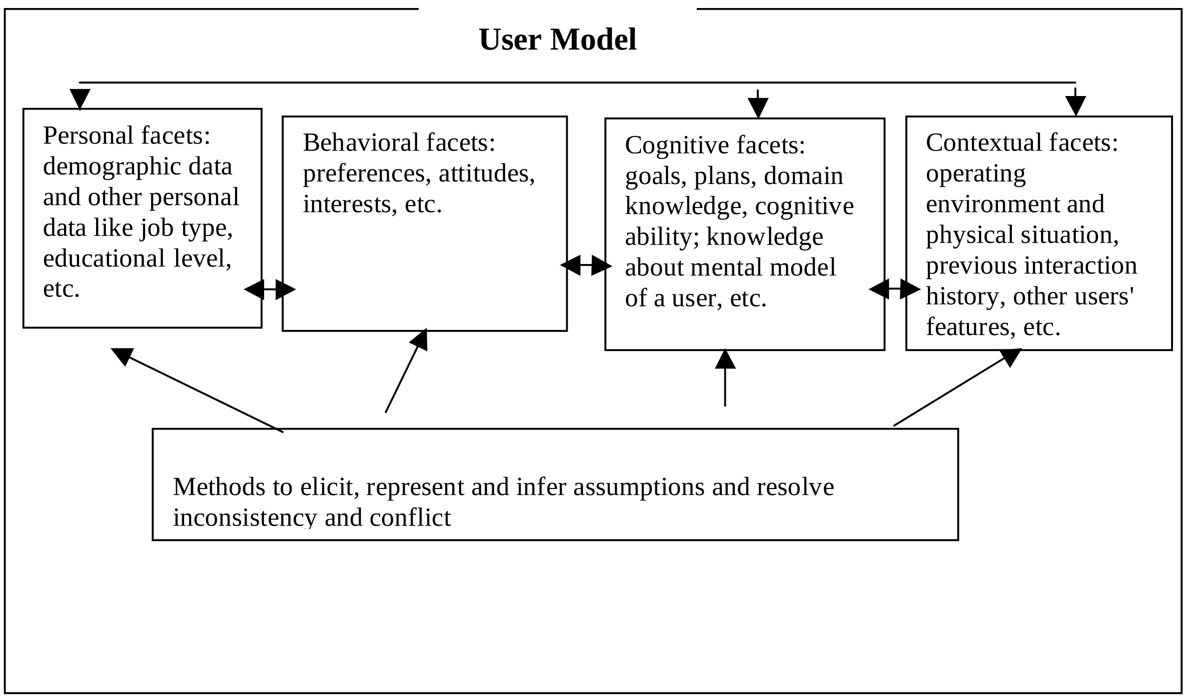

Figure 2: A framework for a generic user model

3.2.2 User Interface for I/O and Interaction

In e-commerce, the inputs include (i) individual user's implicit navigation such as items currently viewed; (ii) explicit navigation such as indicating preference from list of categories of products; (iii) explicit ratings of items, purchase history and keywords and other item attributes used during a search; and (iv) community inputs' reflect overall group of users' opinions to item attribute assignments like film genre and book categories, external item popularity like national best-seller lists, community purchase history, and community text comments and rating (Schafer et al., 2001).

Due to limitations of m-commerce described in section 2, it becomes more challenging for m-commerce on how to elicit these input data from customers. In e-commerce customers fill forms during signing to a service and the system implicitly gathers information about their behavior through their actions- items they buy, rate, etc. Initially, customers have to sign in wired web version of the service. Some systems provide user interface that can be used by customers to rate a movie using their mobile devices. MovieLens Unplugged (Miller et al., 2003) is an example that attempts to provide a link on the mobile device. It later found customers are rarely using the "Rate Movies" link. Moreover, location information needs to be gathered using devices like GPS.

In e-commerce, the outputs include: suggestions, providing personalized product information, presenting a summarized community opinion on products, providing community critiques, predictions (e.g. of the rating they would give to an item like the customer Grade/Our Grade in MovieFinder), and individual rating and review (obtained or inferred from the community ratings). These outputs need to be personalized to individual customers (Schafer et al., 2001). Compared to e-commerce, m-commerce has faced challenges in determining what to present and how to present the output on the customers mobile devices due to limitations of wireless technologies discussed in Section 2 . These include:

- Customers need as much information as possible about a product or services before they make any decision. For instance, customers of MovieLens Unplugged indicated that they need to get movie synopsis or reviews on movies. Furthermore, displaying recommendation confidence scores and uncertainty measure along with the explanations of how those recommendations are generated for a particular user. These in turn improve the mental model of customers and create trust in the recommender systems' suggestions and recommendations. In e-commerce adding a confidence metric has the potential to improve usability of the system, this is supported by results of the study reported in (McNee, Lam, Guetzlaff, Konstan, & Riedl, 2003). Is it feasible to display all these outputs in mobile devices' display in effective ways?
- The optimal number of items to be displayed is limited usually in range 1 to 5, e.g. 4 in MovieLens Unplugged compared to 10 to 20 items in e-commerce.
- Which modality to use for I/O and during interaction? Voice is still the "killer application" as most customers use wireless phones for voice phone calls. Hence, wireless data features are much less popular than wireless voice.

3.2.3 Recommendation Methods

The recommendation methods refer to the approaches and steps used in identifying and generating information and assumptions about users/customers useful for making recommendations by recommender systems. Also, the three types of recommendations methods employed by most e-commerce systems are action-to-item based, item-to-item similarity based and user-to-user similarity based (Fink & Kobsa, 2000; Schafer et al., 2001). Furthermore, linear and serial combinations of the results of content-based and collaborative filtering recommendations are the two categories of hybrid approaches (Li & Kim, 2003).

In action-to-item recommendation (also called attribute-based or content-based recommendation), an item is recommended to a user mainly based on his/her personal past actions like purchases, queries, ratings to the item. Standard machine learning techniques such as clustering, Bayesian networks and induction learning are applied in forming attribute-based models. Examples of application systems that employ action-to-items based methods are Amazon Eyes and eBay Personal Shopper (Schafer et al., 2001). In user-to-user collaborative recommendation, an item is recommended to a user based on other similar users' actions like interests, preferences and ratings to the item. An alternative to user-to-user based is item-to-item based collaborative filtering. In item-to-item recommendation, an item is recommended to a user based on the association or similarity of the item to others items for which the user has expressed interest. These two models employ learning techniques that are popular called user-based and item-based collaborative filtering, respectively. Examples of application systems that employ user-user collaborative filtering are Amazon Your Recommendations and My CDNOW(Schafer et al., 2001). Examples of application systems that employ item-item collaborative filtering are Amazon Customers who Bought and Reel.com Movie Matches (Schafer et al., 2001) and Item-Based Top-N movie recommender . Research results using recent machine learning algorithms and approaches are reported in literature (Sarwar et al., 2000; Sarwar, Karypis, Konstan, & Riedl, 2001; Stern, 2001).

In general, e-commerce recommendation system algorithms are computationally expensive, are not scalable and require much higher main memory to be used online during adaptation and recommendation. These limitations are more costly for mobile accesses. For recommender systems in m-commerce, the different inference and recommendation algorithms of e-commerce can be adapted using the input and output requirements of mobile users and mobile devices. Most of computationally expensive operations like computing similarity matrices and other recommendation decisions (.e.g. finding top-N good movies) are performed offline using a dedicated server. These approaches are used in PocketLens and MovieLens Unplugged (Miller et al., 2003; Miller et al., 2004). Moreover, the algorithms need to support localization for location-specific recommendations such as those to locate the nearest movie theater along with list of movies in show.

4 Confidence and Uncertainty Displays

There are various meanings associated to uncertainty. In this paper it refers to degree of doubt associated in making recommendations for users which may be caused from the incompleteness, imprecision, vagueness, randomness and/or ambiguity that exist in the user attributes, product attributes and the methods used during acquisition stage of user modeling, and the representation framework used and the reasoning strategies used to make further inference. Uncertainty in a recommender system generally originates from product and user attributes, values and their representation in model, and propagates in inference/reasoning and maintenance stages throughout the system.

Uncertainty in e-commerce is not studied well due to its inherent abstract and complex nature. It also requires significant effort but the effort could potentially result in providing useful information that can help systems and customers make effective decision making. Some of the information includes: level of confidence in user and product model estimates, level of confidence or robustness about the results of inference or reasoning, and level of confidence in the final personalized recommendations.

There are various uncertainty formalisms among which crisp set theory and probability theory are the oldest and most widely used. However, since many real marketing problems are fuzzy by nature and not random, the conventional probability formalism have not been satisfactory (Hsu, Chu, & Chan, 2000). Hence, fuzzy theory is recently considered and studied; and the benefits of using fuzzy theory and related mathematics (Hsu, Wu, & Tien, 1998) are : (i) in fuzzy set theory membership function is deliberately designed to treat the vagueness and imprecision in the context of the application. Therefore in using fuzzy set theory, assessing the semantically defined users and product features are more reliable and accurate than using the conventional set theory and statistical methods; (ii) membership functions can be continuous functions which are more accurate in measuring the assessment of users and products features than the traditional discrete methods, e.g., rank from 1 to 7; and (iii) the fuzzy mathematical method is easier to perform than the traditional method, once the membership functions of assessment facets are defined.

For handling uncertainty in e-commerce, the potentials of soft computing paradigms that incorporates fuzzy theory, neuro-computing and evolutionary algorithms coupled with approaches from data mining are recently studied (Basak & Kumar, 2001; Yager, 2000). Basak and Kumar (Basak & Kumar, 2001) and Yager (Yager, 2000) identified forecasting, bidding and auctions, negotiation, targeting, product recommender systems and profiling as problem areas that can benefit from soft computing paradigm and data mining. Particularly, in recommender systems where systems match customer's interest and the products' attributes, uncertainty due to imprecision and vagueness originates from: (i) the difficulty in expressing and representing interest and other related customer properties using crisp values; (ii) the product attributes can also call for fuzzy representation; and (iii) the true relationship among the products as well as users' preference to products cannot be expressed in crisp set and calls for fuzzy relation and possiblistic interpretation. Therefore, in our research Fuzzy and Possibility theories are considered to represent and handle uncertainty that exists in product attributes (e.g. movie genre), user attributes (e.g. ratings) and their relationship in recommender systems. Particularly, for a movie recommender system, relationships between a movie and its genres and level of customer interest in movies are represented using fuzzy set membership functions.

Using fuzzy set and possibility theory for developing of Top-N movie recommender system in e-commerce, we found that the system to be faster, achieve higher precision with 3 to 5 recommendations and require a few (5 to 10) initial ratings from a user (Zenebe & Norcio, 2005). These results show the potentials of the approach for m-commerce mainly due to (i) its high effectiveness with a few numbers of recommendations; (ii) its latency, which are nearly 1/10 seconds to infer a customer's interest for a movie (model time) and nearly 1/5 seconds to recommend a movie (recommendation time), is low compared to the average latency of 5 to 10 seconds found in web usability study of Boutch and his collaborators (2002) as cited in (Miller et al., 2004). Furthermore, the confidence and uncertainty measures computed in the approach along with explanation on how the system arrives to the list of recommendations (additional to the recommendations) are useful in building trust regarding the recommender system reliability. These help in creating an accurate mental model of the recommender system and its process by the customers. This in turn could enhance the usability of the recommender system like the results reported in (McNee et al., 2003)

5 Conclusions and Future Research

In this study, a comparison between m-commerce and e-commerce recommender systems was presented using generic system framework for e-commerce and m-commerce personalized recommender systems. The most important dimensions or factors that are considered for the comparative analysis are user model, product and service model, recommender engine/algorithms, user interface (I/O and interaction), and confidence and uncertainty models. It is shown that there are more similarities in components of the system architecture than variations between e-commerce and m-commerce. Moreover, additional requirements that are required to adapt the models, methods and techniques developed and advanced in e-commerce for m-commerce are identified and discussed.

The uncertainty and confidence measures in e-commerce and m-commerce personalized recommender systems are discussed along with their potential for creating an accurate mental model of the recommender system and its processes for the customers. This in turn could enhance the usability of the recommender system. Furthermore, the results of our research using fuzzy set and possibility theory for handling uncertainty in e-commerce showed a great potential for m-commerce. Some of the reasons for this potential are its high effectiveness with a few numbers of recommendations; and its low latency. We are planning to extend this work to m-commerce by considering the characteristics and challenges of m-commerce. From HCI perspective, we are planning to assess how the recommender system collect input and present output through the interface capabilities of the different mobile devices.

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