Proceedings of the International MultiConference of Engineers and Computer Scientists 2015 Vol II,
IMECS 2015, March 18 - 20, 2015, Hong Kong

Key Factors Affecting User Experience of Mobile Recommendation Systems

Yan Sun, Woon K. Chong, Yo-Sub Han, Seungmin Rho, Ka Lok. Man

***Abstract*— With the growing need for user-friendly design of mobile software, user experience has attracted more attention from researchers and practitioners. In particular, it is vital to improve the user acceptance of mobile recommendation systems that are new technologies that provide convenience for mobile device users. Based on recent studies, this paper provides a conceptual framework including important factors that affect the user experience of mobile recommendation. These factors range from basic factors in terms of classification to other effective factors including personalization, privacy and social norms.**

***Index Terms*—Recommendation systems, Mobile recommendation systems, User experience, User acceptance, E-commerce, Mobile devices**

I. Introduction

In this fast-paced world of information explosion, it is of vital importance for modern citizens to have immediate access to the right information. In this regard, recommendation systems have been widely used in various devices. The widespread use of this technology is owing to its impressive advantages. According to [1], online recommendation systems can reduce search costs and uncertainty for consumers related to the purchase of unfamiliar products. However, the benefits have been explained in different ways, in terms of different orientations and focuses.

For example, a recommendation system was broadly defined by [2] as: "A Web technology that proactively suggests items of interest to users based on their objective behavior or their explicitly stated preferences." Meanwhile, such systems have experienced notable development, including the following steps. The first recommendation systems were based on demographic, content-based and collaborative filtering. At present, systems are applying social information. In the coming years, they will incorporate implicit, local and personal information from the Internet [3]. This technology is quite mature and is commonly used in websites and computer applications, but its application to smart phones is new.

Manuscript received January 08, 2015; revised February 10, 2015.

This work was supported in part by the XJTLU Research Development Fund under Grant No: RDF-13-03-18.

Y. Sun is with the International Business School Suzhou, Xi'an Jiaotong-Liverpool University, Suzhou, China. (e-mail: Yan.Sun11@student.xjtlu.edu.cn).

W.K. Chong is with the International Business School Suzhou, Xi'an Jiaotong-Liverpool University, Suzhou, China. (phone: +86(0)512 8816 1717; fax: +86 (0)512 8816 1730 e-mail: Woonkian.chong@xjtlu.edu.cn).

Yo-Sub Han is with the Department of Computer Science, Yonsei University, Seoul, Republic of Korea (email: emmous@cs.yonsei.ac.kr).

Seungmin Rho is with the Department of Multimedia, Sungkyul University, Anyang, Republic of Korea (email: smrho@sungkyul.ac.kr).

Ka Lok Man is with the Department of Computer Science & Software Engineering, Xi'an Jiaotong-Liverpool University, China. (e-mail: ka.man@xjtlu.edu.cn).

According to the latest statistics, the global mobile phone market grew by 5.2% in 2013 and will see an increase of 18.3% in the next five years [4]. As such, the wide usage of mobile phones is an obvious trend and an important reason behind the application of recommendation systems in mobile phones in recent years. Mobile recommendation systems aim to suggest the right product or information to the right mobile users at anytime and anywhere [5]. Compared with personal computers and televisions, there is less restriction on time and place when using mobile phones, as they are usually portable and lightweight.

Due to the technical property of recommendation systems, previously identified problems have mainly been solved technically, such as through research on algorithms. However, [6] proposed that some results may be counterintuitive if looking at recommenders from the user experience perspective. Therefore, there is a need for research on user experience to bridge the gap between users and designers. Many researchers have started to study system effectiveness and evaluation criteria from the users' perspective [2; 6; 7; 8]. Yet, it is more difficult for mobile recommenders to improve the user experience, because there are serious limitations in terms of the user interface on mobile phones, such as small screen sizes and the lack of keyboard [9]. To overcome these deficiencies, further studies need to be conducted.

The remaining parts of this article are organized as follows. In Section II, existing mobile recommendation systems are summarized and research gaps are identified based on a review of recent studies. Next, Section III presents a conceptual framework to demonstrate the effects of some proposed factors on user experience. Moreover, some feasible ways of validating the framework are discussed in Section IV. Finally, Section V concludes the paper and indicates directions for future research.

II. Literature review

A. Recommendation System

Recommendation systems have been widely recognised in the last few decades. [10] reviewed research on such systems between 2001 and 2010, and classified them into two categories, namely collaborative filtering (CF) and content-based filtering (CB). To compare these two techniques, CF includes algorithms and models based on the previous behaviours of the users and their neighbours who share similar preferences to them, while CB focuses on identifying users' preferences and tries to determine a cluster of objects with similar properties. The limitations of these approaches have been shown to include the scalability problem, the cold-start problem and the selection problem [10; 6; 11]. For example, the cold-start problem of insufficient information about new users has become a common problem in almost all recommendation systems [12]. Such problems will affect the quality of recommendation system as they are directly concerned with the users' experience.

However, successful recommendation systems provide many benefits. For users, they can not only save them the time of filtering through a lot of information but can also help them to choose the right products or services. [13] suggested that the adoption of recommendation systems made users more confident about their choices, and [14] proved that recommendation agents had positive effects on consumer decision-making performance.

Retailers usually use these systems to increase sales. [15] argued that recommendation systems are generally provided as a service (software as a service, or SaaS), and retailers will pay a percentage of the incremental revenue to the service provider. However, increasing sales is just the short-run benefit. Using a recommendation agent can enable effective product promotion and customer satisfaction in the long run [16].

B. Mobile recommendation systems

With the wide usage of mobile phones, researchers have started to conduct studies on mobile recommenders. One example is the remarkable overview of the technologies related to mobile recommendation systems provided by [17]. Previously, recommendation systems were successfully applied to e-commerce web sites [18]. However, the emergence of mobile commerce (m-commerce) is driving new developments of recommendation systems. [17] argued that the use of personalization and recommendation systems was encouraged by the rapid development of mobile phone platforms such as the Google Android and the Apple iPhone.

In order to introduce mobile recommendation systems specifically based on previous studies, Figure 1 demonstrates four ways of classifying them:

1) According to the algorithms used, there are six categories [18]. CF and CB are the most commonly used and have been discussed above. The third category is knowledge-based filtering, in which knowledge is built by analysing users' habits or queries. Fourthly, demographic filtering is usually used in marketing and recommends items based on users' demographic information such as age and gender. The next one is matrix factorization, in which a model is built to record the specific parameters for each user and item. Lastly, multiple algorithms can be combined together to improve the overall performance; these are termed hybrid methods.

2) According to the extent of user involvement, three categories can be identified [18; 19]. First, [19] proposed that there were two channels for delivering recommendations through mobile phones, the push channel and the pull channel. Then, [18] modified this classification by adding a category named reactive recommendation. In detail, pull-based recommendations are requested by users and are usually driven by queries. In contrast, there is no obvious user intervention in reactive systems, which simply react to changed context. Lastly, push-based or proactive systems can proactively recommend appropriate content by using particular mobile technologies, such as the short messaging service (SMS) or the multi-media messaging service.

3) According to their objectives, systems can be classified in to four categories, as suggested by [20] who suggested that recommending mobile applications can use a multiple-objective approach. First, the accuracy can be measured by the similarity between the item accessed by the user and the recommended item. Second, diversity indicates the difference between recommended items which may affect the accuracy of the recommendations. Next, the utility is directly related to the profit expectation for the recommendation system. Finally, robustness is set so as to control the whole system, indicating that different objectives may need to be traded off to achieve higher robustness. In other words, some of these objectives cannot work together, such as accuracy and diversity, because an increase in one will normally reduce the other.

4) According to the different mobile services used, there are five categories [21]. Firstly, the location information of the mobile phone, such as the GPS information, can be accessed by a recommender so that it can make suggestions. Secondly, the user-based approach concerns the use of personal profiles stored in phones. The next type is based on the mobile device itself, such as the memory, processor speed and screen size information. Fourthly, the spatio based approach can make use of information such as weather conditions. Finally, the social-based approach has become more widely used recently. It depends on the user's social networks or communication with other similar users.

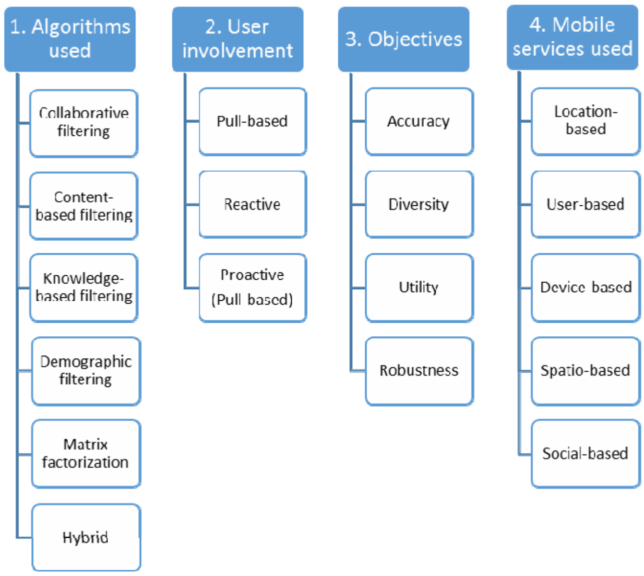

Fig 1. Framework for classifying mobile recommendation systems [18; 19; 20; 21].

With all these systems that have been developed, researchers have also found some inevitable limitations in the design of mobile recommenders. One problem comes from the mobile device itself. Smartphones and tablets take extra parameters into consideration, including location, time and screen limitations [17]. Location and time may be an advantage, but screen limitations have been a serious problem in the mobile recommendation system industry. [22] argued that there was currently a lack of standardization across all platforms, which could help mobile recommender systems to communicate with users and provide the best recommendations.

C. User experience

As one way to improve mobile recommendation systems, some researchers have observed user experiences in recent years. [18] suggested that the experiences of users are critical

ISBN: 978-988-19253-9-8
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

for measuring the success and usefulness of mobile recommendation systems. This same idea has been supported by other researchers. [22] argued that the major concern when designing any effective recommender system was to determine how users would react to and accept the new technology, rather than how quick or accurate the recommendation results would be. In terms of applications, a user-preference-oriented collaborative recommendation algorithm was proposed, in which user preferences were added and proved to be helpful for improving the performance of the recommendation system [23]. Therefore, user experiences need to be considered and can be used to solve the existing problems.

In summary, two main research motivations have been identified in the mobile recommendation systems industry based on the available literature:

1) Mobile recommenders form a relatively new research field that has not been systematically studied. Further investigation needs to focus on the application of recommendation systems in mobile phones.

2) There is a gap between the users and service providers of mobile recommendation systems. The solutions to the existing problems need to be based on the mobile phone users' experience.

According to the relevant motivations identified above, this project aims to make up for the lack of research in the mobile recommendation systems industry and bridge the gap between users and service providers. By evaluating the potential factors that may influence the quality of the user experience, this study will further the understanding of the new challenges and opportunities faced by mobile recommenders, from the users' perspective.

III. Hypotheses

A. Pull, reactive and push methods

First of all, the user experience may differ depending on the kind of recommendation system used. As mentioned above, mobile recommendation systems can be classified as pull-based, reactive, or push-based [18; 19]. These three categories differ greatly in the extent of user involvement, which is directly related to the quality of the user experience because the greater user involvement in pull-based systems is commonly considered to be less intrusive [24].

By contrast, it may be harder to improve user acceptance of reactive and push-based systems due to the lower user involvement. Specifically, [18] suggested that intelligent techniques are required by reactive and proactive systems in order for them to recommend the right items and improve users' acceptance. To illustrate these intelligent techniques, [19] proposed a context-sensitive recommendation system for sending optimal recommendation messages in push-based systems. Compared to pull-based and reactive systems, push-based systems are more likely to be subject to multiple factors such as perceived utility, social norms and innovativeness, according to studies conducted in different cultures [25; 26; 27; 28; 29]. Therefore, it is a commonly held view that different recommendation approaches can lead to some basic differences in user experiences, and the following three hypotheses are proposed:

H1: Quality of user experience is positively related to the use of a pull-based mobile recommendation system.

H2: Quality of user experience is negatively related to the use of a reactive mobile recommendation system.

H3: Quality of user experience is negatively related to the use of a push-based mobile recommendation system.

B. Personalization factor

With the basic factors identified, some specific factors need to be analysed in detail. Personalization, also related to customization, refers to the perception of how well the recommendation is customized based on the user's profile [30]. Although personalization cannot improve the effectiveness of recommendation systems, it can increase the ease of use or enjoyment of the user [31]. Thus, another hypothesis can be drafted:

H4: Personalization in mobile recommendation systems has a positive effect on the quality of the user experience.

C. Privacy factor

Privacy is regarded as a serious problem in recommendation systems [2; 5; 6; 7; 8; 22]. Users may regard some recommendations based on their behaviours as a threat to their privacy, because the personal information could be sold to other companies and stolen by employees and hackers [22].

[22] also argued that the widespread adoption of mobile recommendation systems would be hindered by users' privacy rights and the lack of standardization in this area. In the light of the privacy problem, it is difficult to improve the accuracy and effectiveness of recommendations. According to [6], there is great potential for privacy-aware recommendation technologies to overcome the negative influence of the need for privacy on the quality of recommendations. However, at least for now, user experience can be affected by the concern over possible privacy issues. Based on this, a relevant hypothesis is developed below:

H5: Concern over privacy in relation to mobile recommendation systems has a negative effect on the quality of the user experience.

D. Social norms factor

Lastly, the social factor is thought to play an important role. According to [26], social norms are the result of a person's beliefs related to certain behaviours, which come from reference peers. In recent years, social factors have been especially important in mobile recommenders because mobile devices have become the main way of accessing social networks [32]. After they have accessed these networks, the social norms of users can be predicted and analysed based on the data that are easily collected from these networks. [32] suggested that data from social networks should be used to produce more accurate recommendations in order to assist customers. Furthermore, [26] proved that social norms had a direct effect on teenagers' attitudes towards mobile advertising. Therefore, another hypothesis is proposed:

H6: The use of social norms in mobile recommendation systems has a positive effect on the quality of the user experience. Fig. 2 demonstrates the framework including all of the hypotheses developed above.

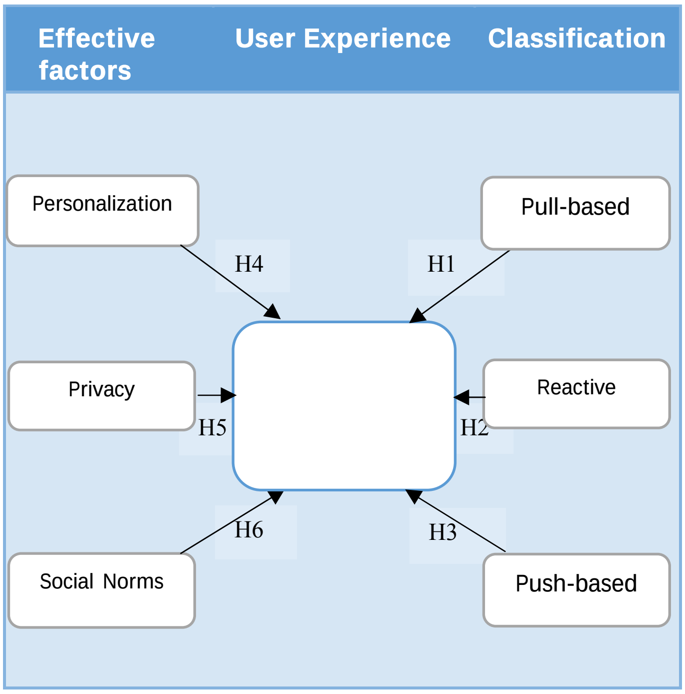

Fig. 1. Conceptual Framework

IV. Possible Methodology

The suggested study will focus on the relationship between various factors and user experience of mobile recommendation systems. As large amounts of data will need to be collected and analysed, a quantitative approach should be used. To enhance user involvement, an online survey should be applied as the main method. The effectiveness of online surveys has been proved in previous similar research. [5] conducted a survey to discuss key issues critical to context-aware mobile recommendations. In another example, an online survey was used to successfully investigate the relationship between users' value perceptions and their intention to use a mobile [30].

According to [4], Asia-Pacific accounts for 61.9% of the global mobile phone market. Furthermore, China accounts for 49.1% of the Asia-Pacific mobile phone market [33]. Therefore, it is reasonable to use the mobile users in China as the sample, and especially those based near Shanghai, the largest Chinese city and a global financial centre. In terms of the age of the respondents, younger adults will be the main focus and the ages will range from 18 to around 40 years old. According to [34], 86% of mobile netizens are in the age range of 30 and under.

After the sample has been chosen, a questionnaire consisting of around 20 questions will be designed according to the hypotheses that have been developed in this paper. Questions will be organized into four sections. In the first section, basic information about the respondents and the usage of mobile phones will be collected. The second section will start to test the respondents' understanding of mobile recommendations. The third section will look into the four factors mentioned in the hypotheses, and the respondents will be provided with some well-known examples so that they can understand the questions. Finally, one or two open-ended questions will be designed to collect some unexpected opinions. Ideally, 300 to 400 responses will need to be collected. Mobile phones and personal computers with the Internet will be used as the main way of collecting data. Mobile phones are a reliable way to conduct a survey given that phone ownership reached 56% of adults in 2013 [35]. After the data have been collected, SPSS will be used for data analysis.

V. Conclusion and Future Research

This paper focuses on mobile recommendation systems, rather than traditional recommenders, from the user's perspective. By identifying the most significant factors affecting user experience, the gap between the designers and users of mobile recommendation systems has been partly bridged. The proposed conceptual framework is intended to be used to guide the future development and design of mobile recommendation systems. Moreover, this framework can also help users to balance their needs when choosing a suitable mobile recommender.

Future work can achieve a deeper understanding of the interrelationships of the factors identified in this paper. In other words, this conceptual framework may be expanded to better explain the user experience issues in the designing of mobile recommenders. One possible extension lies in the connection between the basic classification and the other factors. The effects of other factors, including personalization, privacy and social norms, may differ in different kinds of recommendation systems. For example, recommendations in pull-based systems can be more personalized than those in push-based systems because of the high user involvement. Hence, pulled-based systems may be more heavily affected by the personalization factor.

The relationships between personalization, social norms and privacy can also be added to this framework. Although these factors refer to totally different concerns, there is likely to be some correlation in how they affect recommendations. To be specific, excessive personalization of recommendations will cause privacy problems, and social network information can work with personalized information to improve the user experience. However, further research will need to verify and quantify these possible relationships.

References

[1] Pathak, B., Garfinkel, R., Gopal, R., Venkatesan, R. & Yin, F. (2010) Empirical Analysis of the Impact of Recommender Systems on Sales. *Journal of Management Information Systems*, Vol. 27 Issue 2, p159-188.

[2] Pu, P., Li C. & Hu, R. (2012) Evaluating recommender systems from the user's perspective: survey of the state of the art. User Modeling & User-Adapted Interaction, Vol. 22 Issue 4/5, p317-355.

[3] Bobadilla, J., Ortega, F., Hernando, A. & Gutierrez, A. (2013) Recommender systems survey. *Knowledge-Based Systems*, Vol. 46, p109.

[4] MarketLine Industry Profile (2014) Profile Global Mobile Phones April 2014. Mobile Phones Industry Profile: Global, p1-34.

[5] Liu, Q., Ma, H., Chen, E. & XIONG, H. (2013) A survey of context-aware mobile recommendations. International Journal of Information Technology & Decision Making, Vol. 12 Issue 1, p139-172.

[6] Konstan, J. & Riedl, J. (2012) Recommender systems: from algorithms to user experience. *User Modeling & User-Adapted Interaction*, Vol. 22 Issue 1/2, p101-123.

[7] Knijnenburg, B., Willemsen, M., Gantner, Z., Soncu, H. & Newell, C. (2012) Explaining the user experience of recommender systems. User Modeling & User-Adapted Interaction, Vol. 22 Issue 4/5, p441-504.

[8] Polatidis, N. & Georgiadis, C. (2014) Factors Influencing the Quality of the User Experience Ubiquitous Recommender in Systems. *In Distributed, Ambient, and Pervasive Interactions*, pp. 369-379.

[9] Gallego, D., Woerndl, W. & Huecas, G. (2013) Evaluating the impact of proactivity in the user experience of acontext-aware restaurant recommender for Android smartphones. Journal of Systems Architecture, Vol. 59 Issue 9, p748.

[10] Park, D.H., Kim, H.K., Choi, I.Y. & Kim, J.K. (2012) A literature review and classification of recommender systems research. *Expert Systems with Applications*, Vol. 40, p10059-p10072.

[11] Shani, G. & Gunawardana, A. (2013) Tutorial on application-oriented evaluation of recommendation system. *AI Communications*, Vol. 26 Issue 2, p225-236.

[12] Liu, J., Zhou, T., Zhang, Z., Yang, Z., Liu, C. & Li, W. (2014) Promoting cold-start items in recommender systems. Publication: eprint arXiv:1404.4936. Available From: http://arxiv.org/abs/1404.4936 [Accessed 7 November 2014].

[13] Pu, P., Li C. & Kumar, P. (2008) Evaluating product search and recommender systems for E-commerce environments. Electronic Commerce Research, Vol. 8 Issue 1/2, p1-27.

[14] Dabrowski, M. & Acton, T. (2013) The performance of recommender systems in online shopping: A user-centric study. Expert Systems with Applications, Vol. 40 Issue 14, p5551.

[15] Aldrich, S. E. (2014) Recommender Systems in Commercial Use. *AI Magazine*, Vol. 32 Issue 3, p28-34.

[16] Hostler, R.E., Yoon, V.Y. & Guimaraes, T. (2012) Recommendation agent impact on consumer online shopping: The Movie Magic case study. *Expert Systems with Applications,* Vol. 39 Issue 3, p2989.

[17] Polatidis, N. & Georgiadis, C.K. (2013) Mobile Recommender Systems: An Overview of Technologies and Challenges. *In Informatics and Applications (ICIA), Second International Conference on IEEE*, p282-287.

[18] Gavalas, D., Konstantopoulos, C., Mastakas, k. & Pantziou, G. (2014) Mobile recommender systems in tourism. *Journal of Network & Computer Applications*, Vol. 39, p319-333.

[19] Joon, Y.C., Hee, S.S. & Soung, H.K. (2007) MCORE: a context-sensitive recommendation system for the mobile Web. *Expert Systems*, Vol. 24 Issue 1, p32-46.

[20] Xia, X., Wang, X., Li, J. & Zhou, X. (2014) Multi-objective mobile app recommendation: A system-level collaboration approach. *Computers & Electrical Engineering*, Vol. 40 Issue 1, p203.

[21] Jannach, D. (2011) Recommender systems: an introduction. *Cambridge University Press*, New York.

[22] Owusu, T.D. & Hoffman, C. (2014) The personaliztion and prediction innovation of mobile recommender systems. *Issues in Information Systems*, Vol. 15 Issue 2, p168-174.

[23] Gao, H., Wang, S., Yang, B. & Yang, H. (2014) User Preference-oriented Collaborative Recommendation Algorithm in E-commerce. *Journal of Software*, Vol. 9 Issue 7, p1886.

[24] Kabassi, K. (2010) Personalizing recommendations for tourists. Telematics and Informatics, Vol. 27 Issue 1, p51–66.

[25] Bauer, H. H. et al. (2015) Driving consumer acceptance of mobile marketing: a theoretical framework and empirical study. *Journal of Electronic Commerce Research*, Vol. 6, p181-192.

[26] Hor-Meyll, L.F., Correia, L.M. & Brantes Ferreira, J. (2014) Why Should I Accept Ads on my Mobile Phone? Factors Affecting the Acceptance by Brazilian Teenagers. *Brazilian Business Review (English Edition),* Vol. 11 Issue 4, p130-150.

[27] Sultan, F.; Rohm, A.; Gao, T. (2009) Factors affecting consumer acceptance of mobile marketing: a two-country study of youth markets. *Journal of Interactive Marketing*, Vol. 23, p308-320.

[28] Zhang, J.; Mao, E. (2008) Understanding the acceptance of mobile SMS advertising among young Chinese consumers. *Psychology & Marketing*, Vol. 25, Issue 8, p787-805.

[29] Tsang, M. M., Ho, S. C. & Liang, T. P. (2004) Consumer attitudes toward mobile advertising: an empirical study. *International. Journal of Electronic Commerce*, Vol. 8, p65-78.

[30] Shen, X., Sun, Y & Wang, N. (2013) Recommendations from Friends Anytime and Anywhere: Toward a Model of Contextual Offer and Consumption Values. *CyberPsychology, Behavior & Social Networking*, Vol. 16 Issue 5, p349-356.

[31] Tintarev, N. & Masthoff, J. (2012) Evaluating the effectiveness of explanations for recommender systems. *User Modeling & User-Adapted Interaction*, Vol. 22 Issue 4/5, p399-439.

[32] Oulasvirta, A., Ratternbury, T. & Raita, E. (2012) Habits make smartphone use more pervasive. Personal and Ubiquitous Computing, vol. 16, Issue 1, p105-114.

[33] MarketLine Industry Profile (2012) Mobile Phones in China September 2012. *Mobile Phones Industry Profile*: China, p1-35.

[34] Lu, J., Yu, C. & Liu, C. (2010) Mobile data Service demographics in urban China. *Journal of Computer Information Systems*, Vol. 50 Issue 2, p117-126.

[35] Cook, W.A. (2014) Is mobile a reliable platform for survey taking? Defining quality in online surveys from mobile respondents. *Journal of Advertising Research*, Vol. 54 Issue 2, p141-148.