The influence of national culture on the attitude towards mobile recommender systems

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Abstract

This study aimed to identify factors that influence user attitudes toward mobile recommender systems and to examine how these factors interact with cultural values to affect attitudes toward this technology. Based on the theory of reasoned action, belief factors for mobile recommender systems are identified in three dimensions: functional, contextual, and social. Hypotheses explaining different impacts of cultural values on the factors affecting attitudes were also proposed. The research model was tested based on data collected in China, South Korea, and the United Kingdom. Findings indicate that functional and social factors have significant impacts on user attitudes towards mobile recommender systems. The relationships between belief factors and attitudes are moderated by two cultural values: collectivism and uncertainty avoidance. The theoretical and practical implications of applying theory of reasoned action and innovation diffusion theory to explain the adoption of new technologies in societies with different cultures is also discussed.

Keywords: mobile recommender system; theory of reasoned action; user attitude; cross-cultural research.

1. Introduction

Forecasting the adoption of technology in different cultural contexts is pivotal for the success of any organization. As technology grows, presenting users with enhanced features, uncertainty exists as to how such changes will affect consumer attitudes toward these new systems. In particular, consumers with different values and life styles might evaluate new technological features differently and, therefore, develop different attitudes. Extant literature provides abundant evidence that culture influences technological usage [1-5]. However, while these studies emphasize the importance of culture in understanding technology adoption, previous studies have not made clear the effect culture has on user attitudes toward new technologies. The study presented in this paper sought to reveal how cultural values and belief factors intervene in the developmental process relating to user attitudes toward mobile recommender systems (MRSs).

One group of scholars has argued that culture needs to be considered to fully understand how and why societies adopt new innovative technologies. Some scholars have noted that TAM, which was developed to explain the acceptance of systems in USA, is not valid when applied to other cultures [5]. Herbig and Palumbo [3] argued that the diffusion of innovation was different in Japan and the USA because of the differences in cultural attributes between the two countries. Al-Gahtani et al. [1] found that the Unified Theory of Acceptance and Use of Technology (UTAUT) [6], tested in North America, needed to be adjusted for Saudi Arabian culture, because the moderating effect of age and experience was negative in certain cause-effect relationships. Hwang [7] tested whether uncertainty avoidance, an important cultural variable, had a positive relationship with the perceived ease of use in enterprise resource planning (ERP).

Yet, in spite of these initial studies, how other factors differentially shape user attitudes toward new technologies in different cultural contexts has remained largely unexplored. For example, perceived usefulness and social influence are most widely referenced in the

literature as important factors that affect user attitude. However, perceptions of new technology and interpreting social influence are both psychological processes in which an individual's cultural values play a role [8]. It may be inferred that an individual who highly values the group norm could be easily affected by the opinions of others therefore social influence would play a more significant role in a culture in which group norms are highly respected. Identifying the moderating role of culture in user attitudes toward new technologies can thus help predict how new technologies will be received.

This paper aims to reveal the moderating role of culture in the relationships between belief factors and user attitude toward MRSs. User attitude is used in this paper for the following reasons. Firstly, user attitude is one of the important factors that decide the adoption of innovative technologies in multiple theoretical frameworks. Lucas[9] found that attitudes of systems staff toward a computer's potential predicted its use. Karahanna et al.[10] showed that cultural attitudes affected IT adoption and explored how this effect was modified over time.

Understanding how culture plays a role in shaping user attitude toward new technology has wider implications for multiple theoretical frameworks seeking to understand and explain the adoption of new technologies. Secondly, attitudes are one of the most widely studied areas in social psychological domains involving cross-cultural and organizational factors [11]. The adoption of new technologies is also a psychological process in which attitude plays a major role. Thus, the findings of this study are important in interpreting the findings of existing studies in a broader context, including organizational and psychological research disciplines. IT researchers are similarly interested in the relationship between culture and information technologies at the organizational and national levels [12]. Some studies have used attitude as a dependent variable and have shown the influences of diverse constructs influenced by national cultural values of culture on IT adoption and use [13-15].

Focusing on MRS as the target technology is timely, because it is a relatively new technology, and is experiencing gradual global expansion as access to diverse applications and content

services become more important to current users of mobile devices. Unlike desktop or laptop computers, mobile devices have limited features for navigating the Internet, including small display, inconvenient keypad, and short battery life [16, 17]. Thus, the provision of personalized services to mobile users, which reduces the need to navigate with mobile devices, has increased in importance.

This paper first discusses factors influencing user attitudes toward MRSs and then examines the moderating role of cultural values on these influencing factors. We address following research questions.

(1) What features (belief factors) of MRSs are important to user attitudes toward the systems?

(2) Do cultural differences affect the cause-effect relationships between the belief factors and attitude toward MRSs?

To examine the effects of cultural factors, we collect data from the UK, China, and South Korea. We anticipate that an examination of these overlooked factors will help academics understand how personalized systems are accepted by mobile users, and will assist practitioners in strategically focusing resources to increase market share. This study also sheds light on effective methods for predicting the effects of emerging mobile technologies on social change.

This paper is organized as follows. Section 2 provides a review of existing studies on the acceptance of recommender and mobile data services, and the role of culture in that process. Section 3 presents acceptance factors for MRSs and hypotheses about the moderating role of cultures on acceptance factors. Section 4 details the method used to test the research model, and section 5 presents results. Section 6 discusses the theoretical and practical implications of the findings, and section 7 presents conclusions.

2. Conceptual Background

2.1 Mobile Recommender Systems

Recommender systems provide recommendations to a user by a combined analysis of three factors: a profile of the user's preferences or history, profiles of other similar users, and/or an analysis of alternative recommended content [18-22]. MRSs are applications, or the features of applications, that provide personalized recommendations to mobile device users. MRSs can exploit two peculiar characteristics of mobile data services: location awareness and ubiquity [23]. The evolution and advancement of mobile computing have enabled location-based recommender systems [24] that differ from traditional online web recommendations. A key factor contributing to the complexity of MRSs, compared with that of other recommendation systems, is its interface design, given that the small screens of mobile devices render the presentation of sufficient information difficult, compared with the comparative ease of the presentation of such information via desktop or laptop computer [25]. Moreover, fewer input keys and less advanced browsers with limited functionality also render mobile information services less user friendly [26, 27].

Figure 1 presents an example of MRSs available on smart phones. "Appolicious" is a mobile app that provides app recommendations based on previous app purchases and use patterns already present on smart phones (Fig. 1-a). "Genius Playlist" creates music playlists with songs similar to the song used to originate the list (Fig. 1-b). "PrkL8" is a content discovery engine. Users can rate web pages suggested by PrkL8 by touching two buttons on the screen. Increased use of these buttons leads to better suggestions (Fig. 1-c). Many apps which are used on smart phones have recommendation features. These recommender systems can increase the duration of user visits to sites by providing novel and relevant suggestions [28-32]. Recommender systems are popular and widely used [33, 34] by online stores such as Amazon.com and Netflix.com. When MRSs provide more proper recommendations, it affects user attitude positively.

[Fig. 1. Mobile recommender systems]

2.2 Attitudes toward Mobile Data Services and Web-based Recommender Systems

Several theoretical frameworks have been used to explain the adoption and diffusion of new technologies in organizations and societies. The theory of reasoned action (TRA) [35] is one of the fundamental theoretical frameworks to explain human behaviors in general. In TRA, attitude affects behavioural intention, which affects use behaviour. The overall strength of the attitude-intention-behaviour relationship, however, depends in large part on the degree of correspondence between attitudinal and behavioural constructs. TAM [36], based on TRA, is one of the most widely used frameworks to explain the acceptance of wide spectrum of technologies. TAM2 [6] extends TAM by adding social norm construct to increase its explanation power for heterogeneous technologies and user groups. UTAUT [6] integrates multiple theoretical frameworks to increase the explanation power of the acceptance and use behaviour of information technologies. On the other hand, innovation diffusion theory (IDT) [37] explains how innovative idea and technologies are spread in different cultural societies. IDT originally was developed to explain the diffusion of innovative technologies in macro level while the theoretical frameworks explained above explain the adoption of the technologies in individual level. However, in IDT, attitude is the enabler of innovative technologies adoption, and IDT literature has identified general perceptions of product or service adoption that can be identified as belief factors in the construction of user attitude [38].

As the aim of the paper is to reveal how culture influences user attitude toward MRSs, using TRA and IDT as the grounding theoretical frameworks is appropriate. Understanding how belief factors affect attitudes provides insight into the adoption in individual level and macro level.

On the other hand, TRA was used to explain the adoption of mobile marketing systems [39]. This framework confirmed the validity of TRA for explaining consumer behavior in the area of mobile marketing and identified has investigated factors that contributed to attitudes towards mobile data services norms. Social norms had only a slight direct influence on behavioral intentions, but were strong indirect determinants of such intentions via personal

attitudes. Other studies have developed constructs and concepts to be used in research on mobile data services and have investigated factors that contributed to attitudes towards mobile data services [40, 41].

Findings must be carefully interpreted when the research model is used to examine the adoption of MRSs, due to differences in the functional attributes of the two systems. Unlike general mobile marketing systems, MRSs have recommendation functionality and, therefore, different factors need to be considered in explaining user attitudes toward MRSs. MRSs usually deliver recommendations based on "nearest neighbor" preferences of users. These aspects are distinct from traditional mobile data services [20, 42]. When customers want to get recommended information anytime and anywhere, MRSs need to provide qualified results to users with user preference, locations, and other preferences, whereas traditional mobile data services provide information based only on explicit data or common knowledge with the user search. Thus, previous antecedents of mobile data services do not cover user attitude, nor do they evaluate MRSs considering social influences. Investigation into the specific constructs and factors related to the users' attitude is thus required.

On the other hand, a few studies have identified constructs related to user attitude toward web based recommender systems[19, 43, 44], and perceived usefulness is one of the most commonly used constructs in that literature [20]. It has been reported that users usually perceive e-Commerce sites that provide personalized recommendations to be more useful than those that do not [45]. When recommender systems provide more accurate news recommendations, user satisfaction has been shown to increase [42]. Users' initial level of trust in the recommendation results increased when results were accompanied by justification for outcomes [29].

Accessibility also affected perceived ease of use for mobile data services [46]. Previous studies have suggested that perceived usefulness is the most significant factor in the adoption of mobile data services [40, 47, 48]. Thus, mobile data services should provide functional quality and emotional value to users [49]. Complexity of the technology has also been

suggested as another antecedent for the adoption of mobile data services [50]. Table 1 presents list studies based on user attitudes toward adoption of mobile data services.

[Table 1.Studies on adoption factors of mobile data services]

2.3 The Impact of National Culture on the Attitude of Mobile Data Services and Recommender Systems

The culture has been used with different meanings in many disciplines [51]. Among the definitions of culture, this paper adopts Hofstede's definition as it has been most widely adopted in cultural research in information technologies. Hofstede [48] defines the culture as a group's shared set of distinct basic values which are formed and retained based on their national specifics. He classified the basic values into five cultural dimensions including uncertainty avoidance, individualism/collectivism, masculinity, time orientation, and power distance.

Among those five dimensions, this study focuses on collectivism and uncertainty avoidance (UA) as the two dimensions are closely related with the functionality and the purpose of MRSs. Other dimensions such as masculinity, time orientation and power distance have been used to explain organizational cultures on company and team. Therefore we did not use those dimension by considering user attitude for MRS usage [4, 51, 52]. Collectivism is considered as most of the recommendation functionality is using collaborative recommendation algorithm which uses preferences of a group of people who have similar age, occupations, ethnic background and so on. On the other hand, UA is related with the purpose of MRSs as people use MRSs to reduce alternatives therefore to reduce uncertainty in making purchase decision. Collectivism is defined as the tendency to, and degree to which, people look after themselves and their immediate group solely. Especially, collectivism has been considered to be the important factor appearing cultural differences in previous studies [1, 8, 53]. In addition, UA is defined as the extent to which people feel uncomfortable, or in some cases

threatened, by ambiguous situations. Unstructured situations are different from the norm: they are often described as novel, unknown, or surprising, UA is the effort to minimize the possibility of these situations by enacting strict laws, rules, or safety and security measures. UA is also reinforced by philosophical and religious belief in absolute truth. People with high UA tend to minimize the possibility of uncertain situations by using MRSs that use filters to reduce alternative options [5, 54].

Turel et al. [55] examined the fitness of the structural model for user satisfaction with mobile data services, based on the American Customer Satisfaction Index for four countries: Canada, Singapore, Israel, and Finland. These four countries were selected due to their significant differences with respect to Hofstede's cultural dimensions. Lee et al. [47] reported that the four cultural dimensions (UA, individualism, context, and time perception) affected the antecedents (perceived usefulness, perceived enjoyment, perceived ease of use, and perceived monetary value) of user satisfaction with mobile internet. In addition to variables related to cultural differences, and personal innovativeness [50], the "big five" traits (extraversion, agreeableness, conscientiousness, emotional stability, creativity), cognitive complexity, and cultural influences have also been suggested as personal factors [56, 57]. Table 2 summarizes studies related to culture, mobile environments, and mobile data services.

[Table 2. Cultural factors in the adoption of mobile technologies]

As presented in this discussion, few studies have undertaken the task of explaining the role of cultural differences in new technology adoption, or investigated the interactions between cultural differences and personalized recommender systems. Thus, we have tried to identify the effects of cultural differences on attitudes towards MRSs. We investigated the effects of cultural factors on adopting MRSs by incorporating important determinants related to the adoption of mobile data services and recommender systems identified by previous studies.

3. Research Model

Figure 2 presents the research model employed in this study. The research model is based on TRA, IDT and Hofstede's cultural dimensions of collectivism and UA to identify belief factors that affect attitudes toward MRSs and also to explain how cultural variables play moderating roles in relationships between the belief factors and attitudes.

[Fig. 2. Research model]

In TRA and IDT, user attitude is considered as a function of one's belief that performing the behavior will lead to certain outcomes. Based on the interpretation of the two theories, this paper identifies factors or beliefs that could affect the attitude toward MRSs. After a thorough literature review, we classify the factors that affect the attitudes of users toward MRSs into three dimensions: functional, contextual, and social dimensions. The functional dimension involves how well an MRS meets the needs of users. The contextual dimension is concerned with the mobility of the users when they receive the services. Finally, the social dimension relates to social pressures to use the services.

Hofstede originally measured UA from wider perspective (how members of societies feel about uncertainty and ambiguity). On the other hand, MRSs are used for commercial transactions therefore the UA needs to be applied from transactional context. Thus, this paper defines new construct, called transactional UA (TUA). TUA indicates the extent to which users of MRSs feel uncomfortable or threatened by uncertain and ambiguous situation in the middle of purchase decision making. The feeling of threatened may come from the fact that the user may lose things by making wrong decisions in transactions. One of the reasons why people use MRSs is to receive system recommendations when uncertain as to which products best meet their needs. Therefore, degree of TUA is closely related to attitudes toward MRSs.

On the other hand, in collectivist societies, people are trained from birth to integrate into strong, cohesive in-groups, often extended families, who protect them in exchange for unquestioning loyalty. In these societies, the collectivism dimension is needed because users of MRSs might more readily consider the opinion of others when making purchase decisions and comply more with the general trend of society.

3.1 Beliefs that affect Attitudes toward MRSs

The functionality of mobile services is very important in that many users want to use these services in innovative ways [58]. Many studies have revealed that ease of use is a major factor leading to favorable attitudes toward information systems [36, 48, 49, 58]. Given the difficulty of navigating the web using a mobile device, this paper argues that perceived ease of use is becoming more important in the mobile computing context. Furthermore, using a recommendation service requires a certain level of user input to identify preference data. We hypothesized that user attitude toward an MRS would become more favorable when that MRS was easy to use, and when the user felt comfortable using it. This is because user attitude refers to the degree to which an individual reacts favorably or unfavorably in relation to an object or behavior [59]. As a result, the first hypothesis is derived as follows:

H1: Perceived ease of use will positively influence consumer attitudes toward MRSs.

On the other hand, quality of the information service is frequently cited as a major factor that influences attitudes toward information services [20, 55]. Given that the recommendations forwarded to a mobile user are inferred on the basis of uncertain data, the accuracy of recommendation services is usually worse than that of other information services, such as emails, web browsing, and news feeds. The perceived usefulness of such systems is improved when consumers believe that the decision-making processes and outcomes of

recommender systems are similar to their own [43]. In a MRS context, PRQ (Perceived Recommendation Quality) is considered as perceived usefulness of MRSs. When users want to search for restaurants to visit using their mobile device, they might prefer restaurants nearer to their current location over those more distant. Thus, once users receive high PRQ from MRS, they tend to have positive attitudes toward MRS. Thus, PRQ is becoming more important in that relevant recommendations can be expected to encourage favorable attitudes towards the service.

H2: Perceived recommendation quality will be positively related to attitudes toward MRSs.

Perceived enjoyment is defined as "the extent to which the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use" [60]. Some MRSs have entertainment features such as generating personalized playlists (Apple Genius Mixes) and categorizing users' music preferences (Music Aurora Pro). "Last.fm" generates music playlists based on target users' preferences and other users' listening histories. These recommendations can guide the user to new music. Although accuracy is one of the most important targets of recommendation algorithms, novelty that can bring new products or services to the attention of target users also constitutes an important measure of the performance of recommendation algorithms given that this can provide users with an enjoyable experience [18]. As a user accumulates experiences with a recommender system, the user may enjoy using its functions, and have more favorable feelings toward the service in general [47, 61].

H3: Perceived enjoyment will positively influence consumer attitudes toward MRSs.

The second dimension concerned with the context of the service is use. Mobility refers to the ability to access services while moving using various devices such as laptops, smart phones, and mobile phones [62]. The benefit of mobile services is that users are able to have access to services at any time or place, thereby overcoming the traditional barriers of access to these services. Users have typically used mobile services in unstable environments (low usability) and in various use contexts such as traveling via subway, looking for unfamiliar restaurants or walking in certain places. It can be inferred that the more users appreciate the value of mobility, the more the users will value the MRS [48]. Thus, the following hypothesis is derived:

H4: Mobility will positively influence consumer attitudes toward MRSs.

The third dimension is concerned with social influences that are defined as the way in which the opinions and attitudes of one or more persons affect those of others [63]. Various studies including TRA and TPB, have suggested that social influences affect user attitudes towards MRSs by serving as subjective norms [35, 41, 59].The term subjective norms refers to individual perceptions of the social pressure to perform a particular behavior, such as using MRSs [64]. Although some variables, such as expectancy or fascinating condition, are important aspects of system usages, MRSs need to be especially focused on social norms because MRSs generate recommendations using similar user preferences. Therefore, users consider social relationships or interactions on MRSs more than expectancy or fascinating conditions. This external or interpersonal influence includes reputation or word-of-mouth among users. Many users are able to access recommender systems on mobile devices, and friends, colleagues, and similar users can positively influence their attitudes [40, 57].

H5: Social influence will positively influence consumer attitudes toward MRSs.

3.2 The fit of cultural technology to MRSs

According to the culture-technology fit theory [47], user perceptions of an IT system are dependent on their individual cultural characteristics. The majority of recommender systems use user characteristics, product features, and the behavior of similar users as input for preparing recommendations [65]. User characteristics and behavior reflect the impact of culture on recommender systems. In the context of intracultural similarities and differences, the majority of users in a given culture can be less expressive in their preferences and yet receive recommendations based on the greater expressiveness of others in the same culture. Indeed, the cultural profiles of users shape users' views of the world. For example, users from a particular cultural group tended to notice certain information and to ignore other information [66], resulting in differences in ratings. These differences, created by diverse cultural lenses, were used to interpret the importance of MRS features and thus affected the criteria used to determine whether to adopt an MRS.

As collectivism enables individuals to reach more definite decisions via social interactions, it can strengthen the relationship between social influence and user attitudes [47]. Highly hierarchical and collectivist cultures, such as Korea and Japan, emphasize the interdependence, sociability, and equality of in-group members [54]. These collectivists construe themselves as interdependent with others and desire harmony within their groups.

Social influence enables users to consider information and reach decisions with others [64]. An individual may respond to opinions from referral sources in the context of social pressure to homogenize attitudes. Indeed, social influence is related to the characteristics of collective groups that lead them to accept information from similar groups [40]. Mobile users usually receive recommendations for MRSs from users with similar preferences. For example, collaborative filtering recommends items based on the preference similarities of customers because it automates the process by which the preferences of others generate

recommendations. Thus, we hypothesized that collectivists will be more affected than individualists by social influence.

H6: The positive effect of social influence on attitudes will be stronger in collectivist than in individualistic users.

Lee et al. [67] and Choi et al. [68] have suggested that UA affects the adoption of mobile data services. Groups with high levels of UA exhibit a greater need to articulate technology, detailed information, and clear decision-making rules [68]. These groups tend to avoid uncertain situations by seeking stability and usual behaviors. Users with low TUA accept uncertainty without much discomfort, take risks more readily than users high in TUA, and tolerate different opinions and unfamiliar situations. However, users high in TUA have a strong need to control environments and situations. Thus, individuals who exhibit high TUA should place greater importance than those who exhibit low TUA on the quality of recommendations. We hypothesized that perceptions of the quality of recommendations would be more important to those high in TUA than to those low in TUA.

H7: The positive impact of perceived recommendation quality on attitudes will be stronger in users with higher TUA than in those with lower TUA.

4. Method

We conducted online surveys in the UK, China, and South Korea to test the hypotheses. The questionnaire consisted of 29 items rated on a 7-point Likert scale. Each item in the questionnaire was derived from existing literature as described in Table 3. In particular, we adopted the measurement items for TUA from Choi et al. [68] as they defined the items for mobile commerce context therefore in line with the definition of TUA in this paper. This

study checked face validity and content validity by making face-to-face interviews with three professors and fifteen Ph.D. students to evaluate the questionnaire validity before data collection. The survey questions were developed in English in the beginning. One of the authors working in the UK then had a focused group interviews with five Ph. D. students who are working in IS research field. The focused group interview was to validate if all interviewees have the common understanding on the questions to measure each construct. Other two authors of the paper then translated the English questionnaire into Korean version. The authors also had a focused group interview with two professors in Marketing research field and five MSc students in IS field for the same reason. For Chinese questionnaire, a Korean researcher in China had translated the Korean version into Chinese one. After that translation, one Chinese professor and five graduate students in IS research field checked the translated survey items to verify the meanings from original survey items. Finally, we asked the Chinese professor to translate the Chinese questionnaire into English to make sure that the translation process did not change the meanings of the questions.

[Table 3. Constructs and related studies]

This research involved 310 respondents from South Korea ('Smartphone café', cafe.naver.com/bjphone), 105 from China (undergraduates and graduate school students), and 104 from the UK (Coolsmartphone Forum, http://forum.coolsmartphone.com/; and PC Advisor Customer Forum, http://www.pcadvisor.co.uk/forums/24/mobile/). Participants were recruited from smart phone user groups as described above in three countries in exchange for a 10% chance of winning a U.S. $10 gift card for the iTunes store. We selected smart phone user groups which discussed the functions and issues on smart phones and shared their personal experiences with smart phones. We posted article on the user groups to explain the purpose of the survey and the incentive along with the URL of the survey web site. Before responding to the survey, participants had to read a description and view pictures of mobile

recommender systems and push the check button to confirm that they understood the concept of mobile recommender systems. If they did not push the check button, the survey was ended without any further responses. Survey questions were presented in Korean, Chinese, and English, respectively, in three countries. Korean and Chinese survey questions were translated from English by professors and graduate students in each country. All participants voluntarily participated in the online survey. Table 4 presents a summary of the descriptive statistics for the participants.

Table 4. Descriptive statistics of participants

The data showed that 297 Korean (95.8%), 87 Chinese (82.9%), and 77 UK (74%) respondents had experience using smart phones. The most frequently used smart-phone OS was Apple iOS (Korean = 72.2%, Chinese = 42.9%, UK = 44.2%), and 196 respondents from Korea (63.2%), 39 from China (37.1%), and 64 from the UK (64%) reported using recommendation services on the mobile web. The most frequently used apps by respondents from Korea and the UK related to entertainment, utilities, social networking, and music. On the other hand, most Chinese participants used apps for entertainment, music, news, and weather.

The questionnaires used in this study were reliable as evidenced by Cronbach's α values of at least 0.7 for all dimensions. We also checked the statistical power based on Cohen (1998) [69]. The number of total sample size was 92 and actual power was 0.804 while the number of respondents was 297 in this study. After testing statistical power and exploratory factor analysis, we confirmed the factors identified by checking the convergent and discriminant validities with confirmatory factor analysis (CFA) using PLS software (smartPLS). After identifying validity for constructs, we tested research model with multiple regression. In the research model, we considered all items as reflective measures to test convergent and discriminant validities for constructs. The use of a formative measure is well known for

producing misleading outcomes and for its weakness in model estimation [70, 71]. Convergent validity was evaluated using the criterion that construct reliability needed to exceed 0.70 and that the average variance extracted (AVE) by each construct had to exceed the variance due to measurement error for that construct (i.e., the AVE should exceed 0.50) [72]. Table 5 shows a summary of the composite reliability and AVE according to these criteria. The composite reliability for the data was 0.902–0.959 (i.e., much greater than 0.70). Additionally, the AVE for the data ranged from 0.733 to 0.853, well above 0.5. These results supported the adequate composite reliability and AVE of the data from the three countries.

Table 5. Scale properties of data

To check the discriminant validity of the data, we confirmed that the square root of each construct's AVE was greater than the correlation of the construct with other latent variables [73]. The results in Table 6 support the discriminant and convergent validity of the data set. The extent of common method bias was evaluated through Harman's single-factor test [74]. All variables were loaded into a principal component factor analysis and the unrotated factor solution conducted. The seven factors which have above 1 (Eigen value) were extracted. Although one factor accounted for 38% of the total variance, it was not concluded that neither a single factor emerged from the factor analysis or one general factor accounted for the majority of the covariance among the measures [74].

[Table 6. Correlations matrix]

5. Results

Table 7 shows the results of the regression analysis for all participants with respect to the proposed model. As shown in the table, H1, H2, H3 and H5 were accepted indicating that all the identified factors except mobility had positive effects on attitudes toward MRSs. In

particular, social influence (coefficient 0.275, $p<0.01$), perceived enjoyment (coefficient 0.272, $p<0.01$), and perceived quality of recommendation (coefficient 0.258, $p<0.01$) exerted stronger effects than ease of use (coefficient 0.091, $p<0.05$).

H4, which concerned the impact of mobility on attitudes, was not supported in that its t-value was 1.968 and significance was set at 0.05.

[Table 7. Regression analysis results for the proposed research model]

To test H6-H7, the moderating effects of collectivism and TUA were examined. The moderating effect is the result of qualitative or quantitative variables, which affect the direction or strength of the relationship between independent and dependent variables [75]. Dependent variables in a moderating model are determined through the interaction between the independent variable and moderator. In particular, this model shows how the size of interacting effect is increased, as well as whether the interaction with the moderator was positive or negative. Thus, the path coefficient can be increased through an independent variable * moderator [76-78].

[Table 8. Moderating effects of collectivism and TUA]

Table 8 presents confirmation that collectivism (COLL) fully moderated the positive relationship between social influence (SI) and attitudes (ATT). Collectivism as an independent variable was also significant at $p<0.01$. Additionally, the interaction involving SI*COLL was supported at $p=0.01$. Thus, H6 was accepted.

Perceived recommendation quality (PRQ) was examined in terms of moderating effect of TUA. The relationship between PRQ and ATT was partially moderated by TUA. Although, TUA was not significant as an independent variable, the interaction (PRQ*UA) was

supported at $p<0.05$. Thus, H7, which related to the moderating effect of UA, was supported.

Cultural differences among the participants from the three countries are shown in Tables 9 and 10. We conducted an ANOVA and a Duncan's multiple range test [79] as a *post hoc* analysis for data from Korea, China and the UK, to identify the effects of collectivism and TUA. As shown in the results from the Duncan test (table 10), Korea has a higher level of collectivism than China or the UK, and China has a higher level of collectivism than the UK. The values for TUA were greater in China and Korea than in the UK. The levels of TUA in China and Korea were similar.

[Table 9. Cultural differences among Korea, China and the UK]

[Table 10. Cultural Differences among the three countries]

The results of the regression analyses for the three countries are presented in Table 11. Enjoyment and social influence significantly affected the attitudes of respondents from all three countries, whereas mobility did not have a significant effect on the attitude of those from any of the countries. All variables in the functional dimension were significant among Korean respondents. PEOU, PRQ and ENJOY were significant with path coefficients 0.122($p < 0.01$), 0.290 ($p < 0.05$), and 0.246 ($p<0.01$), respectively. Among Chinese participants, PRQ was not significant (0.150, p = 0.058), whereas the other function-related variables, PEOU and ENJOY, showed significant effects on attitudes according to the path coefficient: 0.177 ($p < 0.05$) and 0.298 ($p < 0.00$) respectively. In particular, enjoyment emerged as the most important factor contributing to user attitude.

Among those from the UK, the significance of PEOU was not supported with a path coefficient of 0.075 ($p > 0.1$), whereas the other functional variables, PRQ and ENJOY, were significantly related to attitudes. According to the results obtained from respondents from the

three countries, it cannot be said that mobility is a significant belief factor that affects attitudes toward MRSs, and the significance of PEOU and PRQ for attitude varied among nations.

[Table 11. Regression analysis for Korea, China and the UK]

In addition, multi-group comparisons were conducted, through regressions with dummy variables, in order to identify differences among the three models for each country (see Table 12). This study takes into account the presence of multi-group structure data, implying the estimation of the same model for different groups. In the regression analysis framework, the most widely adopted statistical methods for comparing regression models are based on the comparison of the estimated model parameters [80, 81]. In the comparison between Korea and China, all path coefficients proved to be not significantly different. For Korea and the UK, the path coefficients for PEOU→ATT, ENJOY→ATT and SI→ATT were significantly different between the two countries. For China and U.K, the path coefficients of Enjoy→ATT and SI→ATT were significantly different between the two countries. Therefore, we identified that each country had differences in their belief factors for MRSs.

[Table 12. Multi-group comparisons for Korea, China and the UK]

6. Discussion

The theoretical contribution of this paper is threefold.

Firstly, to the authors' knowledge, this paper is one of the first studies demonstrating the moderating role of cultural variables for relationships between belief factors and attitudes toward new technologies based on data from three culturally diverse countries. Though existing studies have revealed that technology adoption models need cultural adjustments in

different countries [1, 5, 7], it was previously unknown how cultural values specifically affected attitude-building processes. This study extends our understanding of how culture plays a role in building attitudes toward new technologies by including the cultural dimension in the research model. It also shows how cultural variables moderate the cause-effect relationships between belief factors and attitudes toward new technologies. Collectivism moderates the relationship between social influence and attitudes, just as TUA moderates the relationship between perceived recommendation quality and attitudes. The findings thus provide scholars with insights for applying TRA and IDT to explanations of new technology adoption and diffusion. For TRA, belief factors that affect attitude toward new technologies have different impacts on attitudes in different cultures. The role of culture in applying TRA was one of the main research issues investigated by scholars. For example, Park [2000] found that individual attitude had a stronger impact on behavior intention than social attitude in Korea, while the opposite result was obtained in a US study [82]. The moderating role of culture in the relationships between purchase intention and its causal factors was also reported [83]. This paper is one of only a few empirical studies reporting that attitudes can be differently shaped through different belief factors, depending on a society's dominant cultural values. In Rogers' IDT, technology adopters are classified into five categories: innovators, early adopters, the early majority, the late majority, and laggards. Adopters in each category are reported to have different characteristics, including that of attitude [37].

While features of innovative technologies, including radicality and scope, affect the extent and the speed of innovation diffusion [84], it was not fully understood why or how some new technologies diffused in some countries quicker than in other countries. This study demonstrated that collectivism and TUA moderate the relationships between belief factors and attitudes and this may explain why some technologies more quickly diffuse in some countries in which collectivism is more highly valued. For example, Korea is one country where mobile and broadband technologies diffused faster than any other. This may be explained by high collectivism that facilitates favorable attitudes toward technologies. The

cultural variables are also expected to affect the distribution of five categories of adopters, and, therefore, generate different shapes of diffusion curves in these countries.

Secondly, this paper identified the belief factors that affect attitudes toward MRSs. MRSs include multiple features stemming from two individual systems: a recommender system and a mobile application. The findings from this study have confirmed that user attitudes toward MRSs need to be understood by considering belief factors for the two individual systems. Previous studies reported that perceived recommendation quality and perceived ease of use influenced attitudes toward both mobile data services and recommender systems [23, 28, 42, 43]. These studies reported perceived ease of use as one of the most important contributors to the adoption of recommender systems [6] and mobile data services [43]. The impact of perceived ease of use on attitudes toward MRSs was confirmed in this study as well. In particular, users in Korea and China, with a higher tendency for TUA, noted the importance of this factor with respect to MRSs. Given that social influence has been noted as among the most important factors for using mobile data services [40], it seems reasonable that this factor would also be applicable to MRSs, which have inherited the general characteristics of mobile data services. From the perspective of recommender systems, the concept of social presence, the "psychological connection formed between a website and its visitors," differed from social influence, and was one of the most important factors influencing the adoption of MRSs [19]. Although the data collected from the three countries supported the direct relationships between all identified belief factors (with the exception of mobility), attitudes toward MRSs, the perceived quality of recommendation, enjoyment from the functional dimension, and social influence exerted the greatest impacts on attitude. Thus, we need to understand MRSs in the context of mobile data services and recommender systems rather than as simply another mobile data service or recommender system.

Thirdly, this study did not find a significant relationship between mobility and attitude toward

MRSs. Mobility or responsiveness has been considered to be one of the factors affecting attitudes toward mobile data services [85, 86]. This may be explained by rapid advances in mobile telecommunications technologies, which have now became a part of the everyday life of users. Most wireless service companies in the three countries surveyed provided reliable 3G or 4G networks that offered appropriate speed for mobile web users. Thus, it may be inferred that users may take it for granted that they have access to the Internet on the move. Given that users of mobile data services need information according to their location while they are moving, it is not surprising that users expressed concerns about the mobility of mobile data services during the early days of mobile wireless networks. This assertion needs to be verified in future studies.

The results of this study have the following practical implications.

Firstly, belief factors were found to have a different impact on attitudes toward MRSs depending on the cultural characteristics of the target societies. This suggests that practitioners should consider the impact of culture on the functional and social dimensions of new technologies incorporating mobility and recommender systems. Countries differ with regard to the optimal way in which recommendations should be displayed by MRSs. Service providers can reflect users' characteristics, including collectivism and TUA, in their recommendations and their explanations of those recommendations. For example, in countries where collectivism is a cultural feature, like South Korea and China, it may be expected that MRSs using collaborative filtering methods [87] , which consider other similar users' purchase decisions as well as the user's past purchasing history, could increase favorable attitudes toward MRSs. Korean and Chinese consumers, who value social rules highly, tend to appreciate other users' opinions in order to minimize their risks of wrong purchases when they are not certain of their preferences for target products. Secondly, the findings from this study indicate that MRS providers need to pay special attention to enjoyment in the recommendation process for Korean and Chinese users, as these users tend to value

enjoyment more highly than do UK users.

7. Conclusion

This paper revealed the moderating effect of cultural values on relationships between belief factors and attitudes toward MRSs. More specifically, based on TRA, this paper identified belief factors relating to MRSs, taking into consideration functional, contextual, and social dimensions, and tested the cause-effect relationships between these factors and attitudes using data collected in three culturally diverse countries: the UK, South Korea, and China. This paper also confirmed that the relationship between social influence and attitude was moderated by the collectivism variable, and that the relationship between perceived recommendation quality and attitude was moderated by the TUA variable. The findings of the study should help scholars understand how cultural values impact user attitudes when new technology is introduced into a society. The findings should also help policy makers and technology providers, who may consider the cultural values of target markets when making marketing and policy decisions.

The limitations in this study include followings. Firstly, the proposed research model was tested in the context of MRSs therefore the cultural influence on user attitude toward different information technologies which have different purposes and functionalities may be different from the findings in this paper. Secondly, the research model was tested on data collected from three culturally distinct countries in Europe and Far East. Thus the managers in different region need to be cautious in interpreting the findings. In addition, the compared groups had a difference in that Korea and UK samples were web forums whereas Chinese data were from college students. Therefore, Chinese data might have subtle differences from the results for Korea and UK. However, the participants in Korea and UK also were mainly in their 20s and smartphones are heavily used by young generations. Third, though the three countries have different cultures in terms of collectivism and uncertainty avoidance, the countries are not representative for the cultures. Thus, the generalization of the results in this study is limited.

The future research directions include testing the models in more countries including other regions of the globe to increase the generality of the findings. Also, it would be interesting to see how cultural values moderate the speed and shape of innovation diffusion based on IDT based on experimental setting.

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References

[1] S.S. Al-Gahtani, G.S. Hubona, J. Wang, Information technology (IT) in Saudi Arabia: Culture and the acceptance and use of IT, Information & Management, 44 (2007) 681-691.

[2] P.A. Herbig, J.C. Miller, The Effect of Culture upon Innovativeness: A Comparison of United States and Japan Sourcing Capabilities, Journal of International Consumer Marketing, 3 (1991) 1-57.

[3] P.A. Herbig, F. Palumbo, The effect of culture on the adoption process: A comparison of Japanese and American behavior, Technological Forecasting and Social Change, 46 (1994) 71-101.

[4] R. Rothwell, H. Wisseman, Technology, Culture, and Public Policy, Technovation (Netherlands), 4 (1986) 91-115.

[5] D.W. Straub, M. Keil, W. Brenner, Testing the Technology Acceptance Model across Cultures: A Three-Country Study, Information & Management, 33 (1997) 1-11.

[6] V. Venkatesh, M.G. Morris, G.B. Davis, F.D. Davis, User Acceptance of Information Technology: Toward a Unified View, MIS Quarterly, 27 (2003) 425-478.

[7] Y. Hwang, Investigating enterprise systems adoption: uncertainty avoidance, intrinsic motivation, and the technology acceptance model, Eurupean Journal of Information Systems, 14 (2005) 150-161.

[8] K. Bandyopadhyay, K.A. Fraccastoro, The Effect Of Culture On User Acceptance Of Information Technology, Communications of the Association for Information Systems, 19 (2007) 522-543.

[9] H.C. Lucas, Jr. , Why information systems fail, Columbia University Press, New York, 1975b.

[10] E. Karahanna, D.W. Straub, C. N.L., Information Technology Adoption Across Time: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs, MIS Quarterly, 23 (1999) 183-213.

[11] R.S. Bhagat, S.J. McQuaid, Role of Subjective Culture in Organizations: A Review and

Directions for Future Research, Journal of Applied Psychology Monograph, 67 (1982) 653-685.
[12] D.E. Leidner, T. Kayworth, A Review of Culture in Inforamtion Systems Research: Toward a Theory of Information Technology Culture Conflct, MIS Quarterly, 30 (2006) 357-399.
[13] G.M. Rose, R. Evaristo, D. Straub, Culture and Consumer Responses to Web Download Time: A Four-Continent Study of Mono and Polychronism, ITEM, 50 (2003) 31-43.
[14] B. Shore, A.R. Venkatachalam, E. Solorzano, J.M. Burn, S.Z. Hassan, L.J. Janczewski, Softlifting and Piracy: Behavior Across Cultures, Technology in Society, 23 (2001) 563-581.
[15] P.Y.K. Chau, M. Cole, A.P. Massey, M. Montoya-Weiss, R.M. O'Keefe, Cultural Differences in the Online Behavior of Consumers, Communications of the ACM, 45 (2002) 138-143.
[16] M. Dunlop, S. Brewster, The challenge of mobile devices for human computer interaction, Personal and Ubiquitous Computing, 6 (2002) 260-268.
[17] H.J. Lee, J.Y. Choi, S.J. Park, Context-Aware Recommendations on the Mobile Web, in: OTM Workshops 2005, LNCS 3762, 2005, pp. 142-151.
[18] J.L. Herlocker, J.A. Konstan, L.G. Terveen, J.T. Riedl, Evaluating Collaborative Filtering Recommender Systems, ACM Transactions on Information Systems, 22 (2004) 5-53.
[19] N. Kumar, I. Benbasat, The Influence of Recommendations and Consumer Reviews on Evaluations of Websites, Information Systems Research, 17 (2006) 425-429.
[20] B. Xiao, I. Benbasat, E-commerce Product Recommendation Agents: Use, Characteristics, and Impact, MIS Quarterly, 31 (2007) 137-209.
[21] B. Xiao, I. Benbasat, Product-related Deception in e-Commerce: A Theoretical Perspective, MIS Quarterly, 35 (2011) 137-209.
[22] J.Y. Choeh, H.J. Lee, Mobile Push: Personalization and User Experience, AI Communications, 21 (2008) 185-193.
[23] F. Ricci, Mobile Recommender Systems, International Journal of Information Technology and Tourism, 12 (2011) 1-24.
[24] T.F. Stafford, M.L. Gillenson, Mobile commerce: what it is and what it could be, Communications of the ACM, 46 (2003) 33-34.
[25] S.Y. Ho, S.H. Kwok, The Attraction of Personalized Service for Users in m-Commerce: An Empirical Study, ACM SIGecom Exchanges, 3 (2003) 10-18.
[26] G. Buchanan, S. Farrant, M. Jones, H.W. Thimbleby, G. Marsden, M.J. Pazzani, Improving mobile internet usability, in: the tenth international world wideweb conference, 2001, pp. 673–680.
[27] C.Y. Kim, J.K. Lee, Y.H. Cho, D.H. Kim, Viscors: A Visual-Content Recommender for the Mobile Web, IEEE Intelligent Systems, 19 (2004) 32-39.
[28] S. Al-Natour, I. Benbasat, R. Cenfetelli, The Adoption of Online Shopping Assistants: Perceived Similarity as an Antecedent to Evaluative Beliefs, Journal of the Association for Information Systems, 12 (2011) 347-374.
[29] W. Wang, I. Benbasat, Recommendation Agents for Electronic Commerce: Effects of Explanation Facilities on Trusting Beliefs, Journal of Management Information Systems, 23 (2007) 217-246.
[30] G. Shani, A. Gunawardana, Recommender Systems Handbook: Evaluating Recommendation Systems, Springer, 2011.
[31] S.R. Hill, I. Troshani, Factors Influencing The Adoption of Personalisation Mobile Services: Empirical Evidence from Young Australians, International Journal of Mobile Communications, 8 (2010) 150-168.
[32] J.Y. Choi, H.S. Song, H.S. Kim, MCORE: A Context-sensitive Recommendation System for The Mobile Web, Expert Systems, 24 (2007) 32-46.
[33] O. Arazy, N. Kumar, B. Shapira, A Theory-Driven Design Framework for Social Recommender Systems, Journal of the Association for Information Systems, 11 (2010) 455-490.
[34] J. Choi, H.J. Lee, Y.C. Kim, The Influence of Social Presence on Customer Intention to Reuse Online Recommender Systems: The Roles of Personalization and Product Type,

International Journal of Electronic Commerce, 16 (2011) 129-153.
[35] M. Fishbein, I. Ajzen, Belief Attitude, Intention, Behavior: An Introduction to Theory and Research, Addison-Wesley, MA, 1975.
[36] F.D. Davis, Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, MIS Quarterly, 13 (1989) 319-339.
[37] E.M. Rogers, Diffusion of Innovations, 5th ed ed., Free Press, New York, 2003.
[38] G.C. Moore, I. Benbasat, Integrating Diffusion of Innovations and Theory of Reasoned Action models to predict utilization of information technology by end-users, in: K. Kautz, J. Pries-Heje (Eds.) Diffusion and Adoption of Information Technology, Chapman & Hall, London, 1996.
[39] H.H. Bauer, T. Reichardt, B. S.J., M.M. Neumann, Driving consumer acceptance of mobile marketing: a theoretical framework and empirical study, Journal of Electronic Commerce Research, 6 (2005) 181-195.
[40] S.J. Hong, K.Y. Tam, Understanding the Adoption of Multipurpose Information Appliances: The Case of Mobile Data Services, Information Systems Research, 17 (2006) 162-179.
[41] J.K. Park, S.J. Yang, X. Lehto, Adoption of Mobile Technologies for Chinese Consumers, Journal of Electronic Commerce Research, 8 (2007) 196-206.
[42] T. Liang, H. Lai, Y. Ku, Personalized Content Recommendation and User Satisfaction: Theoretical Synthesis and Empirical Findings, Journal of Management Information Systems, 23 (2007) 45-70.
[43] S. Al-Natour, I. Benbasat, R.T. Cenfetelli, The Effects of Process and Outcome Similarity on Users' Evaluations of Decision Aids, Decision Sciences, 39 (2008) 175-211.
[44] S.Y.X. Komiak, I. Benbasat, The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents, MIS Quarterly, 30 (2006) 941-960.
[45] K.Y. Tam, S.Y. Ho, Web Personalization As A Persuasion Strategy: An Elaboration Likelihood Model Perspective, Information Systems Research, 16 (2005) 271-291.
[46] P. Meso, P. Musa, V. Mbarika, Towards a model of consumer use of mobile information and communication technology in LDCs: the case of sub-Saharan Africa, Information Systems Journal, 15 (2005) 119–146.
[47] B. Lee, B. Choi, J. Kim, S. Hong, Culture-Technology Fit: Effects of Cultural Characteristics on the Post-Adoption Beliefs of Mobile Internet Users, International Journal of Electronic Commerce, 11 (2007) 11-51.
[48] M. Pagani, Determinants of Adoption of Third Generation Mobile Multimedia Services., Journal of Interactive Marketing, 18 (2004) 46-59.
[49] K. Yang, L.D. Jolly, Value-added Mobile Data Services: The Antecedent Effects of Consumer Value on Using Mobile Data Service, International Journal of Mobile Marketing, 1 (2006) 11-17.
[50] F. Parveen, A. Sulaiman, Technology Complexity, Personal Innovativeness and Intention to Use Wireless Internet Using Mobile Devices in Malaysia, International Review of Business Research Papers, 4 (2008) 1-10.
[51] V. Taras, J. Rowney, P. Steel, Half A Century of Measuring Culture: Review of Approaches, Challenges, and Limitations based on the Analysis of 121 Instruments for Quantifying Culture, Journal of International Management, 15 (2009) 357-373.
[52] G. Hofstede, Attitudes, Values and Organizational Culture: Disentangling the Concepts, Organization Studies, 19 (1998) 477-492.
[53] G. Hofstede, Culture's Consequences (2nd ed.), Sage Publications, Thousand Oaks, CA, 2001.
[54] K.Y. Ng, L. Van Dyne, Culture and Minority Influence: Effects on persuasion and originality, Blackwell, Oxford, UK, 2001.
[55] O. Turel, A. Serenko, B. Detlor, M. Collan, I. Nam, J. Puhakainen, Investigating the determinants of satisfaction and usage of mobile IT services in four countries, Journal of Global Information Technology Management, 9 (2006) 6-25.
[56] D. Goren-Bar, I. Graziola, F. Pianesi, M. Zancanaro, The Influence of Personality Factors on Visitor Attitudes Towards Adaptivity Dimensions for Mobile Museum Guides,

User Model and User Adapted Interaction, 16 (2006) 31-62.
[57] J. Van Biljon, P. Kotze, Cultural Factors in A Mobile Phone Adoption and Usage Model, Journal of Universal Computer Science, 14 (2008) 2650-2679.
[58] J. Gebauer, M.J. Shaw, Success factors and impacts of mobile business applications: Results from a mobile e-procurement study, International Journal of Electronic Commerce, 8 (2004) 11-17.
[59] I. Ajzen, TheTheory of Planned Behavior, Organizational Behavior Human Decision Processes, 50 (1999) 179-211.
[60] F.D. Davis, Perceived Usefulness, Perceived Ease of Use and User Acceptance of Information Technology, MIS Quarterly, 13 (1989) 319-340.
[61] D.J. Xu, The Influence of Personalization in Affecting Consumer Attitudes Toward Mobile Advertising in China, Journal of Computer Information Systems, 47 (2006) 9-19.
[62] K. Lyytinen, Y. Yoo, Research Commentary: The Next Wave of Nomadic Computing, Information Systems Research, 13 (2002) 377–388.
[63] R. Martin, M. Hewstone, Social-influence processes of control and change: Conformity, obedience to authority and innovation, Sage, London, 2003.
[64] V. Venkatesh, M.G. Morris, Why don't men ever stop to ask for directions? Gender, social influence and their role in technology acceptance and user behavior, MIS Quarterly, 24 (2000) 115–139.
[65] R. Nikolaeva, S. Sriram, The Moderating Role of Consumer and Product Characteristics on the Value of Customized On-line Recommendation, International Journal of Electronic Commerce, 11 (2006) 101-123.
[66] J.W. Overby, S.F. Gardial, R.B. Woodruff, French versus American consumers' attachment of value to a product in a common consumption context: A cross-national comparison, Journal of the Academy of Marketing Science, 32 (2004) 437–460.
[67] Y. Lee, J. Kim, I. Lee, H. Kim, A Cross-cultural Study on the Value Structure of Mobile Internet Usage: Comparison between Korea and Japan, Journal of Electronic Commerce Research, 3 (2002) 227-239.
[68] B. Choi, I. Lee, J. Kim, Culturability in mobile data services: a qualitative study of the relationship between cultural characteristics and user-experience attributes, International Journal of Human–computer Interaction, 20 (2006) 171–206.
[69] J. Cohen, Statistical Power Analysis for the Behavioral Sciences, 2nd ed., Lawrence Erlbaum Publishing, NJ, 1998.
[70] G. Kim, B. Shin, V. Grover, Investigating Two Contradictory Views of Formative Measurement in Information Systems Research, MIS Quarterly, 34 (2010) 345-365.
[71] A. Diamantopoulos, J.A. Siguaw, Formative Versus Reflective Indicators in Organizational Measure Development: A Comparison and Empirical Illustration, British Joural of Management, 17 (2006) 263-282.
[72] E. Garbarino, M.S. Johnson, The Different Role of Satisfaction, Trust, and Commitment in Customer Relationships, Journal of Marketing, 63 (1999) 70-87.
[73] C. Fornell, D.F. Larcker, Evaluating Structural Equation Models with Unobservable Variables and Measurement Error, Journal of Marketing Research, 18 (1981) 39-50.
[74] P.M. Podsakoff, S.B. MacKenzie, J. Lee, N.P. Podsakoff, Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies, J. Appl. Psychol., 88 (2003) 897-903.
[75] R.M. Baron, D.A. Kenny, The Moderator-mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Consideration, Journal of Personality and Social Psychology, 51 (1986) 1173-1182.
[76] W.W. Chin, B.L. Marcolin, P.R. Newsted, A Partial Least Squares Latent Cariable Modeling Approach for Measuring Interaction Effects: Results from A Monte Carlo Simulation Study and Voice Mail Emotion/Adoption Study, in: Procedings of the Seventeenth International Conference on Information Systems, Cleveland, Ohio, 1996.
[77] J. Henseler, G. Fassott, Testing Moderating Effects in PLS Path Models: An Illustration of Available Procedures, in: V. Esposito Vinzi, W.W. Chin, J. Henseler, H. Wang (Eds.) Handbook of Partial Least Squares, Springer Handbooks of Computational Statistics, 2010,

pp. 713-735.
[78] J. Henseler, W.W. Chin, A Comparison of Approaches for the Analysis of Interaction Effects Between Latent Variables Using Partial Least Squares Path Modeling, Structural Equation Modeling: A Multidisciplinary Journal, 17 (2010) 82-109.
[79] D.B. Duncan, Multiple range and multiple F tests, Biometrics, 11 (1955) 1-42.
[80] C.C. Clogg, E. Petkova, A. Haritou, Statistical methods for comparing Regression Coefficients between Models, The American Journal of Sociology, 100 (1995) 1261-1293.
[81] K. Han, R.J. Kauffman, B.R. Nault, Returns to Information Technology Outsourcing, Information Systems Research, 22 (2010) 824-840.
[82] H.S. Park, Relationships among Attitudes and Subjective Norms: Testing the Theory of Reasoned Action across Cultures, Communication Studies, 51 (2000) 162-175.
[83] H.S. Park, T.R. Levine, The theory of reasoned action and self-construal: Evidence from three cultures, ComM, 66 (1999) 199-218.
[84] H. Lee, K.G. Smith, C.M. Grimm, The Effect of New Product Radicality and Scope on the Extent and Speed of Innovation Diffusion, Journal of Management, 29 (2003) 753-768.
[85] S.J. Hong, J.Y.L. Thong, J.Y. Moon, K.Y. Tam, Understanding the Behaviour of Mobile Data Services Consumers, Information Systems Frontiers, 10 (2008) 431-445.
[86] D. Huiying, L. Tingjie, A.B. Whinston, L. Jiale, An Empirical Study of Consumer Adoption on Mobile Data Services (MDS) in China, Multimedia and Information Technology 1(2010).
[87] M. Balabanovic, Y. Shoham, Fab: Content-based, Collaborative Recommendation, Communications of the ACM, 40 (1997) 66-72.
[88] R. Negi, Determining customer satisfaction through perceived service quality: A study of ethiopian mobile users, International Journal of Mobile Marketing, 4 (2009) 31-38.
[89] J.W. Jun, S. Lee, Mobile Media Use and Its Impact on Consumer Attitudes Toward Mobile Advertising, International Journal of Mobile Marketing, 2 (2007) 50-58.
[90] C. Nam, J. Yi, D. Lee, J. Lim, Factors of Adoption of M-payment Service, International Telecommunications Policy Review, 12 (2005) 91-117.
[91] V. Venkatesh, Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model., Information Systems Research, 11 (2000) 342-365.
[92] T.R. Hill, M. Roldan, Toward Third Generation Threaded Discussions for Mobile Learning: Opportunities and Challenges for Ubiquitous Collaborative Environments, Information Systems Frontiers, 7 (2005) 55-70.

1 Table 1.Studies of mobile data services

Literature	Study Field	Research Constructs	Methodology
Negi [88]	Antecedents of adopting mobile data services	SERVQUAL, Satisfaction	Survey, Regression
Jun and Lee [89]		Mobility, Fashion, Information, Entertainment, Functionality, Multimedia service, Sociability, Attitude, Intention	Survey, Structural Equation Modeling(SEM)
Xu [61]		Entertainment, Informativeness, Irritation, Credibility, Personalization, Attitude, Intention	Survey, ANOVA, PLS
Pagani [48]		Price, Knowledge, Perceived innovation, Enjoyment, Attitude, Intention to use	Phone interview Survey, Adaptive conjoint analysis
Dunlop and Brewster [16]		Mobility, Pervasiveness, Limitations in input/output facilities, Context	Conceptual study
Yang and Jolly [49]	Value classifications of mobile data services	Functional value, Emotional value, Social value, Monetary value, Attitude	Online survey, SEM (AMOS)
Gebauer and Shaw [58]		Technology and task characteristics by function, usage, impact	Case study
Lee et al. [67]		Functional value, Emotional value, Social value, Monetary value, Satisfaction, Preferred service	Web survey (Korea and Japan), Regression
Yang and Jolly [49]		Functional value, Emotional value, Social value, Monetary value, Gender, Age, Intention to use	SEM
Wang and Benbasat [29]	Influencing factors to intentions to use of mobile data services	Decision strategy, Perceived quality, Explanation, Perceived cognitive effort, Perceived restrictiveness, Intentions to use	Experiment, PLS
Hong and Tam [40]		Five sets of factors related to adoption	Survey, SEM (LISREL)
Bauer et al. [39]		Usefulness, Perceived utility, Knowledge, Social utility, Perceived risk	Online survey, SEM (LISREL)
Meso et al. [46]		Mobility, Cultural influence, Age, Gender, Business Use of mobile technology	Survey, PLS
Venkatesh et al. [6]		Unified theory of acceptance and use of technology	SEM

Table 2. Cultural factors in mobile environments

Literature	Cultural factors		Results	Methodology
Choi et al. [68]	Cultural	Contextuality, Individualism/Collectivism, Uncertainty avoidance	Found cultural differences among Korea, Finland, and Japan	Interview
	User experiences	GUI, Information architecture, Content		
Lee et al. [47]	Uncertainty avoidance, Individualism, Context, Time perception		Found cultural dimensions regarding Korea, Taiwan and Hong Kong	SEM, MANOVA & ANOVA
Xu [61]	Creditability, Personalization, Informativeness, Entertainment, Irritation		Analysis of mobile user attitudes according to personalization	SEM
Park et al. [41]	Moderator: Gender, Age, Usage Experience of IT Social influence, Attitude toward using mobile data services		Suggested factors affecting attitudes toward mobile devices Performance expectation, Effort expectation, Social influence Facilitating condition was not significant	SEM
Parveen and Sulaiman [50]	Perceived usefulness, Perceived ease of use, Technology Complexity Personal Innovativeness Intention to adopt WIMD		New strategies and plans to increase the usage of WIMD in Malaysia	Correlation analysis
Goren-bar et al. [56]	Five personality traits of mobile users (Extraversion, Agreeableness, Conscientiousness, Emotional stability, Creativity)		Suggested BIG5 traits by Experiment	Regression
Nam et al. [90]	Relative advantages, image, safety, personal characteristics, propensity to use the mobile internet, personal payment environment, perception of advantages of mobile communication)		Adoption of M-payment	Regression and clustering analyses
Van Biljon and Kotze [57]	Cultural influence Mediators: Demographic, Socioeconomic, Personal factors		Suggested human nature (motivational human needs)	Personal factors mediated proposed model
Turel et al. [55]	Perceived quality, Prior expectations Cultural dimension according to Hofstede's constructs regarding customer satisfaction		Extended the marketing-based American model Conducted in various areas of Canada, Singapore, and Finland	SEM

Table 3. Constructs and related studies

Construct	Literature	Survey Item
Perceived recommendation quality	Venkatesh [91] Hong and Tam [40]	I think that mobile recommendations are a good source for my decisions about purchasing products.
		Mobile recommendations provide me with the recommended results I need.
		Mobile recommender systems provide proper items for me.
		Recommended items are suited to my interests.
Perceived ease of use	Davis [60] Hong and Tam [75]	I expect that learning how to use mobile recommender systems would be easy for me.
		I expect that my interactions with mobile recommender systems would be clear and understandable.
		I would find mobile recommender systems to be easy to use.
		I expect that it would be easy for me to become skillful at using mobile recommender systems.
Mobility	Hill and Roldan [92]	I use a cell phone because I can use it anywhere.
		I use a cell phone because I can use it whenever I want.
		I use a cell phone because I can use it while I am doing anything else.
		I use a cell phone because I can move from place to place while I am using it.
Attitude	Xu [61]	Generally, I find recommendations a good thing.
		I appreciate receiving recommendation messages via the mobile phone.
		I like the idea of using mobile recommender systems.
		Using mobile recommendation is a wise idea.
Enjoyment	Xu [61] Hong and Tam [40]	I expect that using mobile recommender systems would be enjoyable.
		I expect that using mobile recommender systems would be pleasurable.
		I expect to have fun using mobile recommender systems
		I expect that using mobile recommender system would be interesting.
Social influence	Venkatesh and Morris [64]	People who influence my behavior think that I should use the mobile recommender system for purchase.
		People who are important to me think that I should use the mobile recommender systems for purchase.
		In general, the same interest group has supported the use of the mobile recommender systems for purchase.
Collectivism	Choi et al. [68] Hofstede [52, 53]	I want to know others' interests and take comfort in having such knowledge.
		I take pleasure in sharing other people's interests with others.
		I will maintain or develop relationships by sharing interests with others.
Uncertainty avoidance	Choi et al. [68] Hofstede [52, 53]	I worry about losing things in ambiguous situations.
		I feel safe when following the opinions of experts or peers.
		I prefer situations and events that are familiar, predictable and stable.

Table 4. Characteristics of participants

Country	Korea	China	UK
Demographics	*n* (%)	*n* (%)	*n* (%)
Gender			
Male	294(94.8)	79(75.2)	57(54.8)
Female	16(5.2)	26(24.8)	47(45.2)
Age			
Below 18	27 (8.7)	10(9.5)	1(1.0)
18-25	63 (20.3)	57(54.3)	30(28.8)
26-30	93 (30.0)	28(26.7)	35(33.7)
31-35	78(25.2)	6(5.7)	15(14.4)
36-40	33(10.6)	3(2.9)	11(10.6)
41-45	15(4.8)	1(1.0)	6(5.8)
46-50	0(0.0)	0(0.0)	2(1.9)
Above 51	1(0.3)	0(0.0)	4(3.8)
Smartphone experience			
Yes	297(95.8)	87(82.9)	77(74.0)
No	13(4.2)	18(17.1)	27(26.0)
Used OS for smart phone			
Windows Mobile	64(20.6)	18(17.1)	0(0.0)
iOS	224(72.2)	45(42.9)	46(44.2)
Android	1(0.3)	8(7.6)	7(6.7)
Symbian	9(2.9)	15(14.3)	1(1.0)
BlackBerry	6(2.0)	2(1.9)	24(23.1)

Country	Korea	China	UK
Demographics	*n* (%)	*n* (%)	*n* (%)
Used Applications			
Books	44(14.8)	**65(61.9)**	16(15.4)
Business	69(23.2)	14(13.3)	10(9.6)
Education	44(14.8)	18(17.1)	17(16.3)
Entertainment	**172(57.9)**	**47(44.8)**	**37(35.6)**
Finance	15(5.1)	16(15.2)	6(5.8)
Healthcare & Fitness	26(8.8)	5(4.8)	13(12.5)
Lifestyle	**97(32.7)**	14(13.3)	20(19.2)
Medical	4(1.3)	6(5.7)	4(3.8)
Music	**104(35.0)**	**53(50.5)**	**32(30.8)**
News	41(13.8)	**51(48.6)**	22(21.2)
Weather	44(14.8)	**45(42.9)**	9(8.7)
Photo	38(12.8)	13(12.4)	4(3.8)
Reference	65(21.9)	27(25.7)	**36(34.6)**
Social networking	**105(35.4)**	26(24.8)	15(14.4)
Sports	15(5.1)	17(16.2)	15 (14.4)
Travel	41(13.8)	14(13.3)	19(18.3)
Utilities	**115(38.7)**	3(2.9)	17(16.3)
Recommendation experiences			
On mobile & fixed web	196(63.2)	39(37.1)	40(38.5)
Only on fixed web	68(21.9)	36(34.3)	24(23.1)
Never	46(14.8)	30(28.6)	40(38.5)

Table 5.Scale properties of data

Items	AVE	Construct Reliability	Cronbach's α
PEOU	0.757	0.926	0.893
PRQ	0.853	0.959	0.942
Enjoy	0.807	0.944	0.920
Mobil	0.733	0.916	0.878
SI	0.853	0.946	0.914
COLL	0.736	0.893	0.822
UA	0.653	0.847	0.753
ATT	0.769	0.930	0.899

Table 6. Correlations matrix

	PEOU	PRQ	ENJOY	MOBIL	SI	COLL	UA	ATT
PEOU	**0.870**							
PRQ	0.419	**0.924**						
ENJOY	0.602	0.668	**0.898**					
MOBIL	0.330	0.270	0.323	**0.856**				
SI	0.384	0.547	0.543	0.211	**0.923**			
COLL	0.260	0.353	0.313	0.256	0.284	**0.858**		
UA	0.204	0.222	0.197	0.223	0.159	0.276	**0.808**	
ATT	0.491	0.644	0.669	0.307	0.613	0.270	0.196	**0.877**
AVE	**0.757**	**0.853**	**0.807**	**0.733**	**0.853**	**0.736**	**0.653**	**0.769**

Table 7.Results of the regression analysis of the proposed research model

R^2	F	Sig.	Path	β	t	Sig.
0.576	139.586	0.000	PEOU → ATT	0.091	2.480	0.013
			PRQ → ATT	0.258	6.384	0.000
			ENJOY→ ATT	0.272	6.046	0.000
			MOBIL→ ATT	0.061	1.968	0.050
			SI → ATT	0.275	7.655	0.000

Table 8. Moderating effects of collectivism and uncertainty avoidance

		Variables	R^2	F	Sig.	β	t	Sig.
SI * COLL → ATT	1	SI	0.372	306.070	0.000	0.610	17.495	0.000
	2	SI	0.381	159.014	0.000	0.581	16.114	0.000
		COLL				0.101	2.808	0.005
	3	SI	0.389	109.446	0.000	0.224	1.573	0.116
		COLL				-0.147	-1.441	0.150
		SI*COLL				0.497	2.600	0.010
PRQ * UA → ATT	1	PRQ	0.412	362.798	0.000	0.642	19.047	0.000
	2	PRQ	0.415	182.850	0.000	0.633	18.430	0.000
		UA					1.455	0.146
	3	PRQ	0.420	124.519	0.000	0.356	2.779	0.006
		UNCER				-0.184	-1.674	0.095
		PRQ*UA				0.402	2.239	0.026

Table 9. Differences among Korea, China and the UK along cultural dimensions

Cultural Factors	Country	N	Mean	*S.E.*	F	Sig.
Collectivism	Korea	310	5.686	0.051	30.340	0.000
	China	105	5.406	0.131		
	UK	104	4.686	0.145		
Uncertainty Avoidance	Korea	310	5.114	0.058	5.145	0.006
	China	105	5.152	0.124		
	UK	104	4.724	0.130		

Table 10. Cultural Differences among the three countries

	Country	1	2	3
Collectivism	Korea	5.686		
	China		5.406	
	UK			4.686
Uncertainty Avoidance	Countries	1	2	
	China	5.152		N/A
	Korea	5.114		
	UK		4.724	

Table 11. Regression analysis for Korea, China and the UK

Countries	R^2	F	Sig.	Path	β	t	Sig.
Korea	0.601	91.611	0.000	PEOU→ATT	0.122	2.578	0.010
				PRQ→ ATT	0.290	5.810	0.000
				ENJOY→ ATT	0.246	4.320	0.000
				MOBIL→ ATT	0.068	1.744	0.082
				SI→ ATT	0.246	5.146	0.000
China	0.709	48.351	0.000	PEOU→ATT	0.177	2.621	0.010
				PRQ→ ATT	0.150	1.919	0.058
				ENJOY→ ATT	0.298	3.743	0.000
				MOBIL→ ATT	0.054	0.880	0.381
				SI→ ATT	0.431	6.501	0.000
UK	0.411	13.684	0.000	PEOU→ATT	-0.075	-0.706	0.482
				PRQ→ ATT	0.289	2.268	0.026
				ENJOY→ ATT	0.294	2.065	0.042
				MOBIL→ ATT	0.041	0.481	0.631
				SI→ ATT	0.205	2.266	0.026

Table 12. Multi-group Comparison for Korea, China and the UK

Path	Comparison	R^2	F	Sig.	β	t	Sig.
PEOU → ATT	KOR-CHN	0.299	58.298	0.000	0.022	0.216	0.829
	KOR-UK	0.265	49.276	0.000	0.237	2.432	0.015
	CHN-UK	0.216	18.826	0.000	0.215	1.638	0.103
PRQ → ATT	KOR-CHN	0.441	108.192	0.000	0.086	1.115	0.265
	KOR-UK	0.414	96.403	0.000	0.154	1.804	0.072
	CHN-UK	0.624	43.579	0.000	0.068	0.645	0.520
Enjoy → ATT	KOR-CHN	0.484	128.374	0.000	-0.048	-0.617	0.537
	KOR-UK	0.437	106.052	0.165	2.000	2.126	0.034
	CHN-UK	0.436	52.795	0.000	0.212	2.124	0.035
Mobil → ATT	KOR-CHN	0.126	19.824	0.000	-0.062	-0.531	0.596
	KOR-UK	0.086	12.922	0.000	0.156	1.509	0.132
	CHN-UK	0.120	9.331	0.000	0.218	1.649	0.101
SI → ATT	KOR-CHN	0.435	105.415	0.000	-0.159	-1.958	0.051
	KOR-UK	0.349	73.352	0.000	0.212	2.708	0.007
	CHN-UK	0.389	43.500	0.000	0.371	3.630	0.000

1 APPENDIX 1. The explanation for Mobile Recommender Systems for the survey

Instruction

Mobile Recommendation

- Personalized recommendation is acknowledged as one of important features of a business-to-consumer website since it provides the suitable contents or services segmented each customer's preference on PCs or mobile phones.
- Recommendations are based on the customer's preferences, purchase histories, and similar users, and then recommended items are delivered with the aim of helping customers make decisions from a variety of choices.
- Mobile service providers operate various location-based services, such as suggesting recommendations about nearby restaurants and 'searching friends', to notify users about where their friends are.This way can reduce customers' search efforts and increase satisfaction on mobile commerce.

Figure 1) Purchase of Mobile Applications

Figure 1 is recommendations of mobile applications. Recommendations are based on previous purchases and the reasons of recommendation were shown as "Based on _(previously purchased app)_".

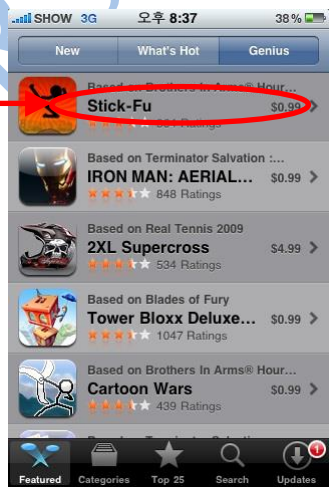
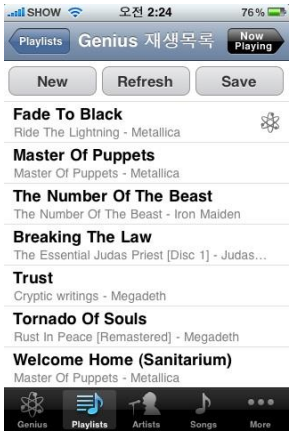


Figure 2 is recommendations for music playlist for mobile users. It makes the recommendation from favorite songs of the user and his or her listening habit. information.

Figure 2) Music Recommendation using Habits for Listening Style for Music



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