Relevancy or Diversity?
Recommendation Strategy Based on the Degree of Multi-Context Use of News Feed Users

Wei Wang, Tianjin University of Finance and Economics, China
Shiyong Zheng, School of Business, Guilin University of Electronic Technology, Guilin, China & Management School of Hainan University, Haikou, China & College of Digital Economics, Nanning University, Nanning, China*
Rizwan Ali, Wuhan Technology and Business University, China
Jiaying Li, Guilin University of Electronic Technology, China

ABSTRACT

Reading information in news feed apps has become a kind of popular content consumption in recent years. However, there are contradictory conclusions about the recommendation strategies. Although some previous research has studied the algorithms to improve the accuracy of the combined of relevancy and diversity strategies, how to compromise them according to user attitude and behavior from individual level is limited. This study aims to solve the dilemma at a theoretical level, and the authors find that the degree of multi-context use is a key boundary. Specifically, 1) the location-based recommendation method may lose effectiveness when the degree of a multi-context is high. 2) The users who prefer to use news feed systems in various contexts in their daily life are more likely to read diverse information. The authors suppose that with the increase of the degree of multi-context use, the location-based recommendation may trigger users perceived privacy threat, which will reduce their satisfaction and participation intention.

KEYWORDS

Context-Aware Recommendation System, Degree of Multi-Context Use, News Feed, Participation Intention, Recommendation Methods, Satisfaction

INTRODUCTION

A recommendation system (RS) is an online information service system that suggests appropriate items to users (Kulkarni and Rodd 2020). Generally, RSs employ personalization to improve the effectiveness and efficiency of recommendations. They have been widely used in current online platforms of multiple areas, such as e-commerce (e.g., Amazon), entertainment (e.g., YouTube), and social media (e.g., Weibo)(Liu and Du 2020). In the recommendation process, scholars mainly
focus on developing algorithms to learn users’ preferences and then to find relevant items to users (Kulkarni and Rodd 2020, Zhang and Song 2021). Especially with the development of artificial intelligence (e.g., deep learning techniques), enhanced information retrieval and users’ preferences learning have made RS more effective, so that it can provide more relevant items to users (Zhang et al. 2017, Niu et al. 2018). Therefore, content-diversity is developed to solve this problem (Hou, Pan and Liu 2018, Wu et al. 2020, Szpektor, Maarek and Pelleg 2013). The trade-off between interest-relevancy and content-diversity has also become a classical problem in which attracted many scholars have studied (Javed et al. 2021, Niu et al. 2018, Hou et al. 2018, Panteli and Boutsinas 2021, Smyth and Mcclave 2001, Bag, Ghadge and Tiwari 2019).

With the continuous development of the mobile network, many RSs have integrated mobile techniques with the traditional recommendation methods to improve recommendation effectiveness based on spatial contexts (Wedel and Kannan 2016). And the new system is called the location-based context-aware RS (CARS) (Savage et al. 2012). News feed apps in China, such as Toutiao and Baidu News Feed have all adopted the new system to enhance their service. As for studies on location-based CARS, the context-relevancy method is obviously mostly concerned. It refers to utilizing contexts to improve the quality of the RS, which involves context acquisition, integration, modeling, reasoning, and dissemination (Suhaim and Berri 2021, Nawara and Kashef 2021, Gao et al. 2019, Sojahrood and Taleai 2021). Among them, context integration has attracted much attention from scholars.

Although algorithms that contain contextual information have been developed to meet users’ contextual demands (Setiowati, Adji and Ardiyanto 2018), it is contended that users tend to avoid location-congruent contents because of the privacy concern, sometimes, which may reduce user satisfaction (Kulkarni and Rodd 2020, Mou, Cui and Kurcz 2020). However, few studies have investigated when context-relevancy will cause negative consequences and validate the role of privacy concern. This question is necessary to be explored because CARS can improve user satisfaction by identifying the condition of users’ perception of privacy threat before applying the privacy protection mechanism (Cheng et al. 2017). In addition, given that the privacy threat may be caused by the overpersonalization and oversensitivity of context-relevancy (Bradbury, Jhumka and Leeke 2018), the content-diversity method may also be a potential solution to the privacy issue, which was nonetheless less discussed before (Chen et al. 2021).

Given that it is a comprehensive recommendation process involving multiple recommendation methods, this research tries to integrate three main recommendation methods into the research framework, including interest-relevancy, content-diversity, and context-relevancy. Moreover, it tries to explore the following research questions: (1) What are the general usage patterns of CARS users? (2) What are the impacts of the recommendation methods on user satisfaction and participation? (3) On what condition do the relevancy methods excel or vice versa?

In order to address these questions, the authors chose Baidu News Feed, one of the most popular mobile news apps in China, as the case for further investigation. The researchers collected the through questionnaire surveys and with the help of the structural equation model, and found that: (1) Interest-relevancy and context-relevancy have significantly positive effects on satisfaction, while content-diversity has a marginally negative effect on satisfaction and participation. (2) the degree of multi-context use is a key boundary moderating the relationship between context-relevancy and satisfaction and the relationship between content-diversity and satisfaction. These findings indicate that, if CARS constantly records the changes of users’ locations or scenarios and provides relevant location-congruent contents, users’ perceived threat to privacy will increase and their satisfaction and participation will decrease. In addition, this negative effect will be strengthened when the degree of multi-context use increases. However, the users who prefer to use news feed systems in various contexts in their daily life are more likely to read diverse information.
This study may contribute to the understanding of the role of users’ contextual use habits for compromising the recommendation methods, and gives an idea to solve the trajectory privacy problem in CARS, which is a concern worldwide.

RESEARCH BACKGROUND

Baidu News Feed

Baidu News Feed, which is also called Baidu Mobile, was first introduced in 2016 and has quickly become a key news feed app since then. It is reported that the monthly active users (MAU) of Baidu Mobile have reached 607 million by September 2021\(^1\). Baidu Mobile is a kind of context-aware recommendation system (CARS) that can provide users with news, articles, photos, and other contents via mobile devices.

Several differences occur between mobile phone-based news feed and traditional personal computer-based media. Firstly, compared with traditional news portal sites, mobile news feed systems can provide different information continuously as users refresh the page. Secondly, traditional news feed mainly adopts a mass personalization system that provides users with customized information based on the average taste of all the users(Wedel and Kannan 2016). However, a mobile news feed can combine mass personalization with individual-level personalization, so that each user can receive personally customized information matching their own tastes and geographical locations(Xu et al. 2015). Thirdly, Baidu News Feed has social functions by which users can like, forward, comment, and reply to the contents and comments. These user participation indexes are important to evaluate the effectiveness of personalization(Iftikhar and Khan 2020). Thus, Baidu News Feed can learn user preferences, adapt the information to users, and evaluate the effectiveness of personalization.

RECOMMENDATION METHODS OF LOCATION-BASED CONTEXT-AWARE SYSTEMS

CARS is a multidimensional (i.e., user, item, and context) system and hence brings a challenge to learn and predict users’ preferences(Suhaim and Berri 2021). The existing studies on CARS mainly concentrate on methods and strategies to improve recommendation accuracy (Kulkarni and Rodd 2020, Morgan, Paun and Ntarmos 2020, Colomo-Palacios et al. 2017, Nawara and Kashef 2021). In general, three CARS methods are mainly discussed in previous research: Interest-relevancy, context-relevancy and content-diversity (Jain, Singh and Dhar 2020, Wu et al. 2020, Werneck et al. 2021).

Interest-Relevancy. This recommendation method refers that RSs can predict users’ interests and push relevant contents by processing and analyzing users’ browsing data or search histories(Figueiredo et al. 2013). This approach has been proven effective in traditional CARS. For instance, Amazon provide items by tracing and analyzing consumers’ online shopping histories(Yun et al. 2018), which improves the sales of product(Bleier and Eisenbeiss 2015). To suggest interest-relevant content to users, three techniques and models are conventionally used: Content-based filtering(Pimenidis, Polatidis and Mouratidis 2018, Liao and Sundar 2021), collaborative filtering (CF) (Sharma, Mitra and Chakraborty 2020, Gai and Klesse 2019) and hybrid approach (Sharma et al. 2020, Ansari, Li and Zhang 2018). Content-based filtering methods recommend similar kind of items to a user based on the past actions of the user. However, collaborative filtering methods recommend items to a new user based on items preferred by other users with similar preferences in the past (Sharma, Mitra and Chakraborty 2020).
Although the performance of RS has been enhanced due to the algorithms, it fails to improve users’ satisfaction for its neglect of users’ preference changes over time (Kotkov, Veijalainen and Wang 2020). Therefore, the content-diversity method is introduced to solve the issue. (Kotkov et al. 2020).

**Content-Diversity.** Content-diversity refers to the degree to which information is different from each other (Nguyen et al. 2014). At present, three kinds of ideas are normally discussed to balance the trade-off between relevancy and diversity in existing literature (Baghi et al. 2021). Firstly, some scholars focused on the criteria aspect and proposed to change the single evaluation criteria to bi-criteria optimization (e.g., MOOP framework and NSGA-II) or multi-objective problem (Baghi et al. 2021, Cheng et al. 2017, Cui et al. 2017). Secondly, algorithms are developed to learn users’ preferences first. Various adjustments will be made later (Lee and Lee 2015, Premchaiswadi et al. 2013, Niu et al. 2018, Hou et al. 2018, Jain et al. 2020). Thirdly, many efforts have been made into the collaborative approach (Panteli and Boutsinas 2021, Bag et al. 2019, Lee and Lee 2015).

In addition to the abovementioned strategies, other recommendation models include contextual factors to increase diversity and are also proven to achieve better effectiveness (Wang et al. 2019, Anelli et al. 2017, Lathia et al. 2010, Dahroug et al. 2019).

**Context-Relevancy.** Context-relevancy method refers to recommending contents to users based on the situations in which they are (Morgan et al. 2020). The contexts include environment-based context (e.g., location, time, weather) and user-based context (e.g., activities, mood) (Suhaim and Berri 2021, Jin et al. 2019). In this study, the authors will utilize the spatial dimension of the context. CARS such as Baidu News Feed can take advantage of geographical techniques to deliver “the right message to the right people at the right time in the right place” (Morgan et al. 2020, Bao et al. 2015). Currently, relevant studies and techniques are centered around five research areas: Context acquisition, integration, modeling, reasoning and dissemination to improve the service quality of RSs (Suhaim and Berri 2021, Nawara and Kashef 2021, Kumar, Jerbi and O’Mahony 2021).

**RESEARCH GAP**

Recommendation accuracy and sensitivity have been improved by geographical and contextual integration techniques (Suhaim and Berri 2021, Jin et al. 2019). However, it is found that users are probably dislike location-congruent contents because of the privacy concern (Kulkarni and Rodd 2020, Pan et al. 2022). Few studies have investigated when context-relevancy loses effectiveness and how to solve this issue. Besides, considering accuracy as a proxy of satisfaction is probably not effective to evaluate the service quality, sometimes (Kulkarni and Rodd 2020).

In order to fill these research gaps and given that it is a comprehensive recommendation process involving multiple recommendation methods, the authors have proposed a comprehensive framework to explore the influence of different recommendation methods on user satisfaction and participation directly.

**RESEARCH MODEL AND HYPOTHESES DEVELOPMENT**

Drawing on Sharma et al.’s framework (Item-User-Action). (Sharma et al. 2020), the authors will investigate the impacts of recommendation methods on user satisfaction from the item perspective. Furthermore, they will also examine user participation from the action perspective. The authors will also introduce the degree of multi-context use into the research model to examine the boundary of the effects of the recommendation methods. The research model is shown in Figure 1.
User Satisfaction

Based on Expectation-confirmation Theory (ECT), consumers’ satisfaction towards a product or service means it has met their initial expectations (Tam, Santos and Oliveira 2020). Many researchers have discussed about the antecedent factors leading to satisfaction in transportation service (Fu, Zhang and Chan 2018), online shopping (Wahab and Khong 2019), and online corporation Web site (Eveleth, Baker-Eveleth and Stone 2015), but discussions on news feed are limited. When users read contents...
in news feeds, they generally have utilitarian and hedonic motives. On the one hand, they expect their utilitarian value needs to be met (e.g., enriching knowledge by reading). On the other hand, users also expect their hedonic value demands can be met by reading the topics (e.g., sport, film, pet, and food) that can bring pleasure to their lives (Hasan, Jha and Liu 2018). In order to satisfy these motives and expectations of users, Baidu Mobile needs to learn users’ interests as accurately as possible and provide relevant contents. When Baidu Mobile suggests an item to users, it can collect data on users’ liking, which indicates they are satisfied with the item. Users ignoring the content that is irrelevant to their interest indicates their dissatisfaction with the recommendation (Eveleth et al. 2015).

**INTEREST-RELEVANCY**

Previous studies have proven that interest-relevant information would enhance user satisfaction and interaction (Filieri and McLeay 2013, Kim et al. 2017, Murthi and Sarkar 2003, Chen and Tseng 2011, Belém et al. 2016). Zhang et al. (Zhang et al. 2018) argued that, if brand followers perceive a high level of relevancy between a brand microblog and themselves, they would be more likely to develop positive attitudes towards the brand. Similarly, Filieri and McLeay (2013) affirmed a positive relationship between information relevancy and travelers’ adoption of information from online review sites. Kim et al. (2017) proved that the relevancy of tourism information in social media is positively associated with the cognitive and affective site images of tourists. Tucker (Tucker 2013) verified that the advertisements targeting at an individual’s interests were effective on Facebook. In news feed context, users consume information services. Information service should satisfy the demand of interest (Fu et al. 2018). Users have initial or stable preference, and the relevant information is able to match their interest, thereby promote satisfaction. Thus, the authors hypothesize the following:

**Hypothesis 1 (H1):** Interest-relevancy is positively associated with user satisfaction.

**CONTEXT-RELEVANCY**

The context in CARS refers to the environment in which the interaction between users and applications takes place (Suhaim and Berri 2021) and location is one of the most important contexts paid a lot of attentions (Hu et al. 2021). Many lines of evidence have indicated that context-relevant content may promote user satisfaction in CARS. Ghose et al. (Ghose, Goldfarb and Han 2013) validated that the messages of the store that are located in close proximity to a user’s home are more likely to be
read. Users may prefer the restaurants recommendation related to their tourist destinations (Renjith, Sreekumar and Jathavedan 2020, Kulkarni and Rodd 2020, Kolahkaj et al. 2020). Some scholars have also found that users tend to have stronger relationships with their local friends in social networks (Valverde-Rebaza et al. 2018, Bao et al. 2015). Therefore, location-based recommendation is more likely to adapt users’ changing requirements and expectations in different places, which may also have a positive effect on satisfaction (Meyners et al. 2017). Therefore, the authors assume that a high level of context-relevant information will easily satisfy users by meeting their demands in a certain context. Thus, the authors suggest the following:

**Hypothesis 2 (H2):** Context-relevancy is positively associated with user satisfaction.

**CONTENT-DIVERSITY**

Although numerous studies have discussed and verified the effectiveness of content-diversity through regarding the indicators (e.g., click-through rate) as proxies of user satisfaction to CARS, studies from a psychological perspective by testing user satisfaction directly are relatively limited (Kulkarni and Rodd 2020).

Overpersonalization was not effective as it might narrow the contents over time (Nguyen et al. 2014, McSherry 2002, Zeng et al. 2010). Based on the motive theory and ECT, it is reasonable to infer that reading a mass of homogeneous contents in Baidu Mobile may cause boredom in users and promote their variety-seeking motivations, which may lead to their expectations of diverse content (Eveleth et al. 2015). Diverse content will broaden users’ horizon, help them find new interests and meet their expectations, thereby accelerating their satisfaction (Kotkov et al. 2020). For example, it is proved that recommendation users consume more content-diverse movies or music than non-recommendation users in the long run (Anderson et al. 2020, Nguyen et al. 2014). Therefore, the authors hypothesize the following:

**Hypothesis 3 (H3):** Content-diversity is positively associated with user satisfaction.

**THE MODERATING ROLE OF THE DEGREE OF MULTI-CONTEXT USE**

The degree of multi-context of app use in this study refers to the number of contexts (or scenes and activities) in which a user is usually engaged when they use CARS like news feed in daily life (Suhaim and Berri 2021, Nawara and Kashef 2021, Carlarne 2011, Dey 2001). For example, a user who is used to reading news feed during commuting, work break, meals and before sleep has a higher multi-context degree than a user who only does it at meals. The users with a higher degree of multi-context tend to obtain information across different places and time (Zhang, Chow and Li 2014). As Table 1 shows, although existing literature includes a number of works on recommendation strategies, the consideration of consumer browsing habit of the degree of multi-context use is limited.

In addition to the expectations of accuracy and diversity of recommendations, privacy is also a concern due to users’ fear for the leak of their personal data, especially personal trajectory during the use of mobile news feeds apps (Kulkarni and Rodd 2020). Thus, there are two trade-offs among the expectations (Panteli and Boutsinas 2021): One is relevancy-seeking and variety-seeking; the other is spatial relevancy-seeking and privacy. However, an important question has not been well answered: How does CARS compromise on users’ expectations for a better recommendation? That is, on which condition should CARS consider interest-relevancy, context-relevancy or content-diversity more to improve users’ satisfaction? This paper considers that the degree of multi-context use may be a factor moderating the effects of the recommendation methods on users’ satisfaction. To be more specific, first, interest-relevant contents may achieve the expectation that users’ interest will be met. Then,
users may be satisfied. However, interest-relevancy strategy could narrow consumers’ interest over time and various places, which means that this strategy may lose effectiveness for satisfaction as the degree of multi-context use rises (Kotkov et al. 2020). Second, users also have the need for safety for RS. Some consumers have strong privacy security awareness in their mobile device uses. If the system always provides them accurate information matched the locations as their shifts of various places, they may have higher perceived privacy leaks of trajectory (Bradbury et al. 2018), which will reduce their satisfaction. Therefore, the negative effect of the context-relevancy method on user satisfaction might be strengthened with the rise of the degree of multi-context use. Third, content-diversity may not bring overpersonalization, information cocoons and privacy problems (Nguyen et al. 2014). In addition, users’ preferences can change with time and context, which may lead to user’s variety-seeking behavior (Kotkov et al. 2020). Therefore, content-diversity strategy may meet user’s variety-seeking demand could not trigger user privacy concern, and further improve their satisfaction for the high degree of multi-context users. Thus, the authors hypothesize the following:

**Hypothesis 4 (H4):** The degree of multi-context weakens the relationship between interest-relevancy and user satisfaction.

**Hypothesis 5 (H5):** The degree of multi-context weakens the relationship between context-relevancy and user satisfaction.

**Hypothesis 6 (H6):** The degree of multi-context strengthens the relationship between content-diversity and user satisfaction.

**USERS PARTICIPATION INTENTION IN NEWS FEEDS**

CARS such as Baidu News Feed is not only a content-oriented application but also one of the most popular communication tools for many people because of the interaction functions. It is mentioned that user participation refers to the activities users perform during system development (Barki and Hartwick 1994). By this definition, social media studies have identified two types of participation behaviors, namely content contribution and user participation. Content contribution refers to users’ original creation generated by users, such as articles, videos, photos, and other initiative content forms. User participation refers to the social interaction among users online (Xu and Li 2015). However, lurking is also an important form of participation to be considered. Certain scholars elucidated that there exist numerous passive members who read and browse the information but rarely post messages (or comments) or communicate with others (Preece, Nonnecke and Andrews 2004). Shao and Guosong (Shao and Guosong 2009) regarded this type of behavior as a content assumption. In this study, the authors focus on user participation in Baidu News Feed. In addition to entertainment and communication, users also focus on information acquisition (Hall-Phillips et al. 2016).

Some researchers have studied the relationship between participation and satisfaction. They have found that greater consumer participation would bring more satisfaction and trust (Dabholkar and Sheng 2012, Li et al. 2018). Besides, Khan (Khan 2017) studied the motivation of user participation on YouTube. Zhang et al. (Zhang et al. 2018) investigated the factors that affect participation and brand loyalty on microblogs. However, satisfaction (attitude) may also influence participation (behavior). Chan and Chan (Chan and Chan 2010) found that wheelchair users’ satisfaction could improve their intention of community participation. In news feed context, the motive of a user to “like”, “comment” the contents or interact with other users is that the contents meet their demands and interest. Users will ignore the information that does not satisfy their preferences. Therefore, satisfaction will promote participation in news feed systems. Thus, the authors hypothesize the following:

**Hypothesis 7 (H7):** Satisfaction has a positive influence on user participation intention.
METHODOLOGY

Questionnaire Design

The authors used the questionnaires to collect the sample data. Since the original questionnaires were written in English, so the authors invited three Ph.D students from the Department of Marketing and Information System who were proficient both in English and Chinese to translate the original version into Chinese and then back-translated it into English (Lu and Chen 2021, Xu et al. 2022). Next, the authors invited three professors from the Department of Information System to discuss the questionnaire with the research team. They also invited the professors to compare the translated version with the original version after the suggestions were applied to ensure the consistency between the two versions. Then, an offline pilot survey was conducted with 50 students from a public university in China in order to evaluate the effectiveness of the questionnaires (Akram et al. 2021). Finally, the questionnaires were refined based on the participants’ feedback and suggestions.

DATA COLLECTION

The authors posted the questionnaires on Wenjuanxing, a famous and professional questionnaire distribution platform in China. The link to the questionnaires was shared on mainstream social media in China (e.g., Weibo, WeChat, and QQ). Data collection took place from December 30th, 2021 to January 25th, 2022.

A question that “which mobile news app is the one you use most recently” was asked first (Akram et al. 2021, Lu and Chen 2021). Then these participants were instructed to answer the other questions based on their recent reading experience of this app. It should be noted that to attract participants and increase the response rate, RMB 20 was paid to those who completed the survey.

The authors eventually obtained 985 questionnaires in total, of which 512 were valid. (In the data analyzing process, the authors excluded from the dataset the participants who had not reported that Baidu Mobile was the news application they had used most recently, on account of potential confounding factors. The researchers also excluded the participants whose app use experience was less than one month, on account of their unstable reading habits and behaviors, which might have biased their results (Akram et al. 2021)). The demographic characteristics of the samples (Table 2) were consistent with the results of the Baidu’s report (360 doc)2.

MEASURES

The authors adopted the the measurement items of the constructs in their research model from extant literature. Table 3 and 4 list the measurements of these constructs. The authors introduced slight modifications to ensure that their validity and fit the context of this study. Except for the demographic variables and information on the app use, they measured all constructs on a seven-point Likert scale from 1 as “strongly disagree” to 7 as “strongly agree”. The degree of multi-context of the app use in this study refers to the number of contexts (or activities) in which a user is usually engaged when they read news feed in daily life (Suhaim and Berri 2021, Nawara and Kashef 2021, Carlarne 2011, Dey 2001). Therefore, in this study, the authors focused on the user’s daily routines to study the degree of multi-context, which is consistent with the previous studies (Jin et al. 2019, Porter et al. 2010). The authors accumulated the contexts where the users choose to use the app (Table 4) in their questionnaires to measure the degree of multi-context use. If the candidate \( i \) chooses the context \( J_j \), then the authors obtain the following,
Table 2. Demographic characteristics of the samples

| Variable                     | Value          | n   | %   |
|------------------------------|----------------|-----|-----|
| Gender                       | Female         | 246 | 48.0|
|                              | Male           | 266 | 52.0|
| Age                          | <18            | 6   | 1.2 |
|                              | 18–24          | 141 | 27.5|
|                              | 25–34          | 226 | 44.2|
|                              | 35–44          | 104 | 20.3|
|                              | 45–54          | 28  | 5.4 |
|                              | >55            | 7   | 1.4 |
| Education level              | Middle school  | 3   | 0.6 |
|                              | High school    | 48  | 9.4 |
|                              | Junior college | 180 | 35.2|
|                              | Bachelor       | 174 | 34.0|
|                              | Master         | 91  | 17.8|
|                              | PhD            | 16  | 3.1 |
| Job                          | Student        | 190 | 37.2|
|                              | General staff  | 156 | 30.4|
|                              | Manager        | 42  | 8.3 |
|                              | Self-employed  | 105 | 20.6|
|                              | Retiree        | 14  | 2.5 |
|                              | Others         | 5   | 1.0 |
| Income (CNY) per month       | <2000          | 82  | 16.1|
|                              | 2000–3000      | 133 | 25.9|
|                              | 3001–5000      | 150 | 29.2|
|                              | 5000–8000      | 106 | 20.8|
|                              | 8000–12000     | 26  | 5.1 |
|                              | >12000         | 15  | 2.9 |
| Mobile phone system          | Android        | 323 | 63.1|
|                              | IOS            | 170 | 33.2|
|                              | Others         | 19  | 3.7 |
| Experience of using news feeds app | 1–3 months | 31  | 6.0 |
|                              | 3–6 months     | 62  | 12.1|
|                              | 6–9 months     | 106 | 20.7|
|                              | 9–12 months    | 174 | 34.0|
|                              | 12–18 months   | 80  | 15.6|
|                              | 18 months      | 59  | 11.5|

continued on following page
\[ I_{j}^{i}(x) = \begin{cases} 1 & \text{if the candidate } i \text{ choose the context } J_{j}, \\ 0 & \text{otherwise.} \end{cases} \]  

(1)

where \( J_{j} \) presents the context \( j \). Thus, the measure of the degree of multi-context of a candidate can be estimated by Equation (2):

\[ M_{\text{multi-context}}^{i} = \sum_{j=1}^{n} I_{j}^{i}(x) \]  

(2)

In this paper, the authors take \( n=9 \) (Table 4). The contexts considered in this study are referenced from previous studies and the suggestions from Baidu experts (Jin et al. 2019, Porter et al. 2010, Wilson 2012).

**DATA ANALYSIS AND RESULTS**

Data analysis tools including SPSS 22 and AMOS 22.0 were applied for statistical analysis.

**MEASUREMENT MODEL**

First, confirmatory factor analysis was employed to examine the validity of the model variables. It was found that all the fit indices were acceptable and met the threshold value, as follows: \( \chi^2=167.760, \chi^2/df = 1.864<3.00, \text{SRMR}=0.038<0.05, \text{RMSEA}=0.021<0.05, \text{CFI} = 0.986>0.90, \text{TLI}=0.965>0.90. \) These values are within the required limits and demonstrate the satisfactory fit of the measurement model with the data.

Then, the authors further employed composite reliability and Cronbach’s alpha to examine the reliability of the instruments. Table 5 shows that Cronbach’s alpha values are all in the range of 0.902–0.988, thereby satisfying the minimum requirement of 0.70. All the CR results are shown in Table 6, with each exceeding 0.847. Based on the results, all the measurements are reliable in this study (Akram et al. 2021).

Factor loadings and AVE are evaluated with confirmatory factor analysis to test the convergent and discriminant validity. The authors initially tested the convergent validity of the constructs meeting the Fornell and Larcker’s criteria (1981). Table 6 shows that all AVE values fall in the range of 0.735–0.816, which are above the minimum criterion of 0.50 (Akram et al. 2021). Therefore, the convergent validity of our measurement instrument is verified. The values of square roots of AVE are
compared with the correlations between paired constructs to check the discriminant validity. Table 7 shows that all the square roots of AVE are more significant than the inter-construct correlations, thereby demonstrating the discriminant validity.

Table 3. List of the measures of research constructs

| Variable         | Item | Description                                                                 | Source                                           |
|------------------|------|-----------------------------------------------------------------------------|--------------------------------------------------|
| Interest-relevancy (IR) | IR1  | The information from this mobile news app is consistent with my values.      | (Shen et al. 2010)                               |
|                  | IR2  | The information from this mobile news app is consistent with my preferences.|
| Context-relevancy (CR)  | CR1  | This mobile news app provides relevant information to match the changes of my location in a timely manner. | (Xu and Chow 2016)                              |
|                  | CR2  | The information from this mobile news app is based on my spatial preferences.|
| Content-diversity (CD) | CD1  | This mobile news app can provide different contents on one topic.           | (Ziegler et al. 2005)                            |
|                  | CD2  | This mobile news app can provide information on rich topics.                |
|                  | CD3  | This mobile news app can help me discover new interests.                    |
|                  | CD4  | This mobile news app can help me discover new places or activities.         |
| Satisfaction (SA)  | SA1  | I am satisfied with the reading experience of this mobile news app.          | (Shokouhyar, Shokoohyar and Safari 2020)         |
|                  | SA2  | I am satisfied with the interaction experience of this mobile news app.      |
|                  | SA3  | I am satisfied with the information quality of this mobile news app.         |
| Participation Intention (PI) | PI1  | I will read the information from this mobile news app carefully.            | (Zhang et al. 2018)                              |
|                  | PI2  | I will forward information from this mobile news app.                       |
|                  | PI3  | I will assign likes to the information from this mobile news app.           |
|                  | PI4  | I will comment on the information on this mobile news app with my friends.  |

Table 4. Contexts of Baidu Mobile use in daily life

| Variable                     | Item                        | n    | %  |
|------------------------------|-----------------------------|------|----|
| Contexts of Baidu Mobile use in daily life. | Commuting (In transport). | 224  | 43.8|
|                              | Work break.                 | 241  | 47.1|
|                              | During work.                | 197  | 38.5|
|                              | Before meals.               | 171  | 33.4|
|                              | At meals.                   | 305  | 59.6|
|                              | After meals.                | 250  | 48.8|
|                              | After getting up.           | 106  | 20.7|
|                              | Before sleep.               | 270  | 52.7|
|                              | Walking on the road.        | 73   | 14.3|
The structural equation model and hypotheses are tested in this section. First, all the structural model fit indices indicated a good fit between the data and the model ($\chi^2=163.872$, $\chi^2/df = 1.707<3.00$).

### Table 5. Reliability analysis of overall factors

| Construct                  | Number of questions | Cronbach’s alpha |
|----------------------------|---------------------|------------------|
| Interest-relevancy (IR)    | 2                   | 0.951            |
| Context-relevancy (CR)     | 2                   | 0.913            |
| Content-diversity (CD)     | 4                   | 0.959            |
| Satisfaction (SA)          | 3                   | 0.902            |
| Participation Intention (PI)| 4                  | 0.988            |

### Table 6. Outer loading on overall factors

| Construct                  | Item      | Factor loading | CR$^1$ | AVE$^2$ |
|----------------------------|-----------|----------------|--------|---------|
| Interest-relevancy (IR)    | IR1       | .861           | .847   | .735    |
|                            | IR2       | .854           |        |         |
| Context-relevancy (CR)     | CR1       | .896           | .878   | .782    |
|                            | CR2       | .873           |        |         |
| Content-diversity (CD)     | CD1       | .905           | .940   | .794    |
|                            | CD2       | .899           |        |         |
|                            | CD3       | .886           |        |         |
|                            | CD4       | .874           |        |         |
| Satisfaction (SA)          | SA1       | .884           | .930   | .816    |
|                            | SA2       | .884           |        |         |
|                            | SA3       | .787           |        |         |
| Participation Intention (PI)| PI1     | .898           | .929   | .765    |
|                            | PI2       | .898           |        |         |
|                            | PI3       | .852           |        |         |
|                            | PI4       | .849           |        |         |

Notes: 1) = composite reliability, 2) = average variance extracted

### Table 7. Analysis of discriminant validity

| Construct                  | Mean      | SD     | 1     | 2     | 3     | 4     | 5     |
|----------------------------|-----------|--------|-------|-------|-------|-------|-------|
| Interest-relevancy (IR)    | 5.152     | 1.019  | .857  |       |       |       |       |
| Context-relevancy (CR)     | 5.642     | .985   | .607**| .884  |       |       |       |
| Content-diversity (CD)     | 4.785     | .996   | .589**| .612**| .891  |       |       |
| Satisfaction (SA)          | 5.898     | 1.143  | .638**| .502**| -.564**| .903  |       |
| Participation Intention (PI)| 5.046   | .897   | .717**| .609**| -.634**| .721***| .875  |

### STRUCTURAL EQUATION MODEL AND RESULTS

The structural equation model and hypotheses are tested in this section. First, all the structural model fit indices indicated a good fit between the data and the model ($\chi^2=163.872$, $\chi^2/df = 1.707<3.00$,}
SRMR=0.041<0.05, RMSEA=0.037<0.05, CFI=0.936>0.90, TLI=0.928>0.90 (Hu and Bentler 1999).

Table 8 and Figure 2 summarize the results of the authors’ hypotheses. The standardized parameter estimates reveal that user satisfaction is significantly affected by interest-relevancy (β=0.562, t=5.601, p<0.001), context-relevancy (β=0.686, t=3.299, p=0.001). Thus, hypotheses H1 and H2 are supported. Content-diversity has a marginally negative effect on user satisfaction (β=-0.201, t=-1.649, p=0.098). The moderating effect of the degree of multi-context use between content-diversity and satisfaction is positive and significant (β=1.186, t=3.098, p=0.002). The moderating effect of the degree of multi-context on the relationship between context-relevancy and user satisfaction is negative and significant (β=-0.921, t=-2.620, p=0.009). However, the authors could not find a significant moderating effect of the degree of multi-context on the relationship between interest-relevancy and user satisfaction (β=-0.129, t=-0.576 p=0.571). Finally, satisfaction has a positive and significant influence on participation (β=.891, t=10.142 p<0.001).

Considering the data collection using a self-reported survey, the authors assessed the common method bias (CMB) before testing the structural model. The authors also tested Harman’s one-factor test according to previous research (Podsakoff et al. 2003). The exploratory factor analysis (EFA) results show that not a single factor accounts for a large portion of the variance; the most prominent factor explains 34.92% of the variance in the data, which is below the recommended threshold of 50% (Podsakoff et al. 2003). Thus, common method bias is not an issue in this study.

Table 8. Results of the structural model analyses

| Path | Path Coefficient | p-Value | t-Value | Hypothesis |
|------|------------------|---------|---------|------------|
| H1: IR→SA | .562 | .000 | 5.601 | Supported |
| H2: CR→SA | .686 | .001 | 3.299 | Supported |
| H3: CD→SA | -.201 | .098 | -1.649 | Not supported |
| H4: IR × The degree of multi-context use→SA | -.128 | .571 | -0.576 | Not supported |
| H5: CR × The degree of multi-context use→SA | -.921 | .009 | -2.620 | Supported |
| H6: CD × The degree of multi-context use→SA | 1.186 | .002 | 3.098 | Supported |
| H7: SA→PI | .891 | .000 | 10.142 | Supported |

Figure 2. Path coefficients of the research model
CONCLUSIONS
Discussion of Findings

This research has examined the relationship between the recommendation methods and user satisfaction and participation using Baidu News Feed as the case. Generally, the findings corroborate that the relevancy recommendation methods are positively associated with user satisfaction. This finding is consistent with the prior research on the brand community in microblogs (Kim et al. 2017, Zhang et al. 2018) and recommendation algorithms (Szpektor et al. 2013, Wang et al. 2019). The authors validate that context-relevancy also positively influences user satisfaction, which supports the viewpoint that the popular recommendation method based on users’ geographical location is an effective approach to attract users’ attention and promote their activity in news feeds (Morgan et al. 2020, Ketelaar et al. 2017, Rahimi, Far and Wang 2021). However, the authors did not find strong evidence that content-diversity has a positive effect on user participation, in this research. This result is inconsistent with previous findings that diversity has a positive effect on the recommendation quality (Anderson et al. 2020, Nguyen et al. 2014). One possible reason is that the positive effect may only appear with overpersonalization. Otherwise, users generally prefer the contents relevant to their interests and contexts, however it is subject to further examination.

The most interesting finding in this study is that while there is a dilemma between the three recommendations, the degree of multiple-context can provide a good trade-off. The results verify that the degree of multi-context weakens the relationship between context-relevancy and user satisfaction, which means that, if the system provides the location-based information continuously as the degree of multi-context rises, users will probably perceive privacy threat and not prefer the location-congruent contents. This supports the existence of users’ privacy concern in using news feeds across different scenarios (Kulkarni and Rodd 2020). However, this study proves that the degree of multi-context will strengthen the relationship between content-diversity and user satisfaction and participation. Therefore, it might be argued that the user with a high degree of multi-context will read diverse contents, when in various contexts. The finding is aligned with previous research that users’ preferences can also change with the spatial context (Kotkov et al. 2020) and suggests that the content-diversity method is probably a solution to the privacy issue. In conclusion, these findings indicate that, there is a dark side of context-relevancy when the degree of multi-context is high, which goes contrary to the previous viewpoint that the more users’ locations and the contents are consistent, the better (Ketelaar et al. 2017, Suhaim and Berri 2021). Besides, content-diversity may be a method to ameliorate this negative effect when the degree of multi-context if the user is high.

THEORETICAL IMPLICATIONS

This research makes three theoretical contributions to the studies on the recommendation strategies. Firstly, this study has solved the trade-off issues among the recommendation methods. It is well known that there is a trade-off between content-relevancy and content-diversity due to overpersonalization. This paper reveals there is also a trade-off between context-relevancy and content-diversity. Specifically, most existing studies hold that location-based recommendation is better compared with non-personalization (Ketelaar et al. 2017, Suhaim and Berri 2021). Nevertheless, some evidences indicate users may also avoid context-relevant, especially location-congruent contents, sometimes, which means location-based recommendation is not always effective (Kulkarni and Rodd 2020). However, the discussions on the reasons behind these inconsistent conclusions are limited. In this study, the authors found that the degree of multi-context use is a key boundary moderating the effect of spatial context-relevancy and content-diversity on user satisfaction. To be more specific, when the degree of multi-context use is low, the location-congruent content may meet users’ contextual demands. Instead, when the degree is high, spatial context-relevancy may be a negative effect on user satisfaction, because the oversensitivity of location tracking may increase users’ privacy concern.
and reduce their satisfaction with CARS (Kulkarni and Rodd 2020). Therefore, the content-diversity method involving irrelevant contents may be better on such an occasion.

Secondly, this study may contribute to the context integration strategies of CARS. Previous studies on the context integration strategies normally look at algorithms (e.g., pre-filtering and post-filtering) and aim at answering when to incorporate the context data into the recommendation process for a certain recommendation list (Kulkarni and Rodd 2020). Instead of examining the issue from the technical perspective, in this research the authors adopted a comprehensive perspective and the item-user-action framework to explore how to incorporate the context-relevancy method into the traditional recommendation methods (i.e., interest-relevancy and content-diversity) based on the users’ using habits of CARS. The authors argue that the CARS may consider the degree of multi-contextual application use as a factor to compromise and integrate the three recommendation methods to improve the overall user satisfaction and participation.

Thirdly, this study may contribute to the research on the recommendation evaluation of CARS. Compared with previous studies on CARS considering accuracy as the proxy of user satisfaction (Suhaim and Berri 2021), in this research, the authors examined user satisfaction directly and considered user participation as an indicator to assess users’ behavioral intention (Hu, Zhang and Luo 2016, Jung and Sundar 2016). Nowadays, most CARS such as Baidu Mobile are bidirectional systems that can provide users with content and receive their feedback (e.g., “like”, “comment”) (Johnson, Saldaña and Kaye 2021). The participatory feedback can not only reflect users’ attitudes and evaluation of the content provided by CARS, but also enhance their stickiness to the system (Johnson et al. 2021).

**PRACTICAL IMPLICATIONS**

The study offers two important implications for the practitioners. First, this research promotes practitioners’ understanding of the strategies for the trade-off between context-relevancy and users’ privacy concerns. Prior researchers argued that users may dislike the contextual-related contents, especially the location-congruent contents when they perceive privacy threats (Kulkarni and Rodd 2020). In this paper, the authors chose Baidu News Feed as the case study and investigated when users would be aware of the privacy leak of the context-relevancy method and how to solve it. In the authors’ view, if Baidu News Feed can provide the real-time location-congruent content for users in various scenarios sensitively, the sensitivity and accuracy of RS response may enhance users’ perception of location privacy leak and reduce their satisfaction and participation (Johnson et al. 2021). The research findings verified these ideas. In addition, the study also suggests that the RS should incorporate diversified content to improve users’ user satisfaction and participation. The study may also provide a theoretical basis for the optimization of the contextual recommendation algorithms for developers.

Second, this research suggests that practitioners pay more attention to privacy issues in location-based CARS. With the enactment of the General Data Protection Regulation (GDPR) in the European Union, western scholars have paid much attention to privacy issues (Mohammed and Tejay 2017, Goddard 2017). The enactment of Information Security Technology—Personal Information Security Specification in China, it is indicated that privacy problem has also become more and more important in China (Wang Han and Munir 2018, Wu et al. 2022). Western developers and researchers have proposed some techniques (e.g., cryptographic approaches and federated learning) to protect users’ private data (Chen et al. 2021, McMahan et al. 2017, Yakoubov et al. 2014). However, users privacy concern may be in conflict with their demands for location-congruent information, which is an issue that should be addressed (Suhaim and Berri 2021). This study mainly focused on how to utilize users’ location change information properly in order to reduce their perceived privacy threat from a user psychological perspective, and provided as solution taking the degree of multi-context use into consideration. Thus, this research may contribute to how CARS can be enhanced in service quality.
LIMITATIONS AND FUTURE RESEARCH

This study has several limitations and certain directions for future research. Firstly, the results might have limited generalizability because the data were from one app Baidu News Feed only. Thus, the authors can extend this study to other news feed applications (e.g., Weibo) in future research. Indeed, Baidu News Feed is an informational app but Weibo is a relational app that focuses more on interaction, which may obtain different results. Secondly, the survey data may have certain limitations in terms of the representativeness of the samples. Therefore, future research can also attempt to use secondary data and method of mathematical modeling to capture and identify the users’ characteristics and preferences and validate the findings of this study or explore other boundaries. Thirdly, the survey data were based on the research subjects’ perceived preferences. Conducting it with revealed preferences may enhance the validity of the results, which is worthy of an examination in the future.

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CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

ETHICS STATEMENT

This study has been approved by the Institutional Review Board committee and has therefore been performed in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki. All participants who completed the survey signed a consent form prior to participating in the study.
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**ENDNOTES**

1  https://www.163.com/dy/article/GP18E6FD0519U3I5.html

2  http://www.360doc.com/content/17/0928/15/14853527_690861468.shtml
Wei Wang is an assistant professor at School of Business, Tianjin University of Finance and Economics. She got Ph.D. of Marketing, at School of Economics and Management, Wuhan University. Her research interest is network marketing and information system.

Shiyong Zheng is an Associate professor at School of Business, Guilin University of Electronic Technology. His research interest is network marketing and information system.

Rizwan Ali is an assistant professor of marketing at School of Electronic Commerce, Wuhan Technology and Business University. He obtained Ph.D. degree at Economics and Management School, Wuhan University in 2018. His research interest is brand relationship and word of mouth. His work has appeared in Computers in Human Behaviors.