國立政治大學資訊管理學系

碩士學位論文

以個人化建構微時刻推薦系統的互動機制

A personalized Interactive Mechanism Framework for Micro-moment Recommender System

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摘要

微時刻概念的出現凸現了情境對人們造成的影響, 而推薦系統應該要順應這樣的趨勢做出改變。為了搜集到足夠的情境資料，微時刻推薦系統必須要有有效的互動機制，讓使用者和系統之間可以方便的互動。本研究採用了支援自治和本體的設計原理，混合不同種類的個人化去設計了四種互動機制，並且將他們實作在一個微時刻推薦應用程式中。本研究的目的是想了解哪一種互動機制最適合微時刻推薦系統的互動機制，根據我們採用的設計原理和微時刻推薦系統的特性，我們認為愈能讓使用者掌控系統和花費較少心力的設計應該會較為適合。我們藉由為期兩週的受測者間實驗去驗證我們的假設。在實驗中我們讓受測者實際使用我們的應用程式，並收集他們的回饋和使用時的紀錄。我們發現在不同的互動機制中存在控制感受的差異，以採用使用者發起和使用者與系統共同發起的個人化的互動機制較高，而且額外的控制不會讓受測者花費多餘的心力。因此我們認為這兩種設計較適合微時刻推薦系統的互動機制。

關鍵詞：微時刻推薦系統，個人化，動機賦能，互動機制

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Abstract

The emergence of the micro-moment concept highlights the influence of context, and the recommender system should be adjusted according to this trend. In order to collect enough contextual information, the micro-moment recommender system (MMRS) have an effective interactive mechanism that allows users to easily interact with the system. This study adopts the design principle of supporting autonomy and promoting the creation and expression of self-identity, mixes different types of personalization to design four types of interactive mechanisms, and implements them in a micro-moment recommender app. The purpose of this study is to understand which interactive mechanism is the most suitable for MMRS. Based on the design principles we adopted and the characteristics of MMRS, we believe that the design that allows users to have more control over the system and uses less effort should be more suitable for supporting micro-moment needs. We tested our hypothesis by a two-week between-subject field study. In the field study, the participants use our app and provide their feedback. We found that there is a difference in perceived active control among different interactive mechanisms, with user-initiated personalized intention and mix-initiated personalized intention personalization mechanisms having higher perceived active control, and the additional control does not cost the participants extra effort. Therefore, we believe that these two designs are more suitable for the MMRS interactive mechanism.

Keywords: Micro-moment recommender system, Personalization, motivational affordance, Interactive mechanism

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Chapter 1 Introduction

While the information on the Internet becomes more various and complicated, users encounter the problem of excessive choices (Hayakawa 2009). With varied options, it is difficult for users to make their decisions for fulfilling their requirements. During the decision process, users need to spend some extra time and effort to make the right choice. Other than that, this situation negatively affects user experience. To improve this circumstance, if users can make proper use of recommender systems that understand the user's preferences and external information, it will help them to save a lot of time and effort to find items that fulfill their needs during the decision-making stage (Schein et al. 2002).

Recently, the prevalent Internet and mobile devices has changed users' behavior patterns. Increased demand for information, resulting in users spending more time searching for information on the Internet without being limited by time and space (Fulgoni 2016). During the search process, user behavior is influenced by many small moments, and user preferences and decisions change frequently, resulting in different user intentions (Bilos et al. 2018). This small moments were called "micro-moment" (Stokes and Harris 2012). In these moments, users often face some dilemma of decision behaviors. Users know what their objectives are, but they don't know how to achieve them. If the appropriate information is provided to users, they will be more likely to accept the information that affects their decisions (Alsalemi et al. 2019).

In the field of recommender systems, changes must be made in response to the emergence of the concept of micro-moments. Unlike traditional recommender systems, users are in a more immediate state during micro-moments and are usually certain to make actions. For instance, in the "I want to buy" moment, the user has determined that the purchase will be performed soon after. Therefore, the recommender system is required to provide the user with information in a limited time to assist the user in purchasing. In addition, the user will encounter different contextual information at different moments, including context, intent and immediacy (Bilos et al. 2018). Different contextual information will give users different needs (Guo et al. 2018),

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and users will expect the system to use contextual information to understand their needs (Bilos et al. 2018). Therefore, the recommender system needs to take the contextual factors into consideration in order to know the user's tendency, so as to improve the correctness of the recommendation and user satisfaction (Liu and Gan 2016).

There is also literature that classifies contextual information into several categories (Zimmermann et al. 2007). For these different information, the recommender system can collect them in different ways, involving explicit and implicit approaches (Adomavicius et al. 2011). The explicit approach means that the system obtains information from the user or relies on the sensor to obtain information from the environment. The implicit approach refers to the inferring of contextual information from other data, such as distinguishing information from past user behavior through models. Through explicit method, the system interacts directly with the user or other data sources to obtain information. This approach is more convenient (Hayakawa 2009) and is not influenced by other factors, such as the performance of the model, so this research focuses on the explicit approach There are many ways to interact with users (Jugovac et al. 2017), no matter what kind of interaction is used in the recommender system, the user interface design plays a very important role in the whole user experience (Knijnenburg et al. 2012), and will even affect the user's acceptance of the recommender system (Pu et al. 2012; Pu and Chen 2007). Therefore, when designing a recommender system for micro-moments (micro-moment recommender system, MMRS), it is also necessary to design a suitable interactive mechanism.

So, how to design a proper interactive mechanism for MMRS? Zhang (2008) mentioned the concept of “motivational affordance”, that is, the system should be designed to meet some of the needs of the user in order to generate motivation for the user to use the system. This paper also divides motivational affordance into several categories and proposes some design criteria for each category. Among them, the psychological category emphasizes the autonomy of users, which we think is consistent with the characteristic that different users have numerous needs in distinct micro-moments in the MMRS, therefore, when designing the interactive

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mechanism of the MMRS, the priority should be to satisfy the autonomy of users.

Personalization is an approach that satisfies the user's autonomy and the self (Zhang 2008b). Personalization can be discussed from many perspectives, and one of them is the subject of personalization, which refers to who leads the process of personalization, and can generally be divided into user-initiated personalized intention and system-initiated personalized intention. We examined the difference between the two types of personalization subjects by using effort-accuracy theory, that is, they require different levels of effort from the user and yield results with different accuracies. Different applications can decide the subject of personalization according to their own needs. The user-initiated personalized intention personalization is used to design the interface of the health app, allowing users to decide which features they want to add to their personal dashboard (Bol et al. 2019). Kim et al. (2005) uses system-initiated personalized intention personalization to design a learning system, which records user behavior and adjusts the design. Therefore, we also evaluated how to use personalization in the interactive mechanism of the MMRS based on the characteristics of the MMRS.

In summary, this study aims to understand what kind of interactive mechanism design is suitable for MMRS, so we combine user-initiated and system-initiated personalization to design the four interactive mechanisms, namely no-personalized intention, user-initiated personalized intention, system-initiated personalized intention, and mix-initiated personalized intention. We developed a micro-moment recommender app, *deleecious*, and conducted a two-week between-subject field study to let the participants actually operate the four designs. A total of 71 participants completed a two-week long experiment. The results show that user-initiated personalized intention and mix-initiated personalized intention provide more control over the system without extra effort, so these two designs are most suitable for use in the MMRS interactive mechanism. In this study, we successfully applied different types of personalization to the design of MMRS interactive mechanism and constructed a development process. In the

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process, we link the context with the user's intention, so that the system can change according to the different contexts. At the same time, the interactive mechanism we use can effectively collect the user's intention to satisfy the requirement of MMRS, so that the system can make recommendation according to the context and the user's intention in real time. In other fields similar to the restaurant recommendation, where people's domain knowledge does not have much difference, the interactive mechanism mentioned in this study can be used to collect users' intentions. Finally, the edit and save functions, which do not increase user effort, can also be used in general recommender systems to help the system understand users better and provide recommendations with higher quality.

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Chapter 2 Literature Review

2-1 Context

In the past, there are different interpretations of context. Abowd et al. (1999) considered that context can be used to describe what the state of a participant in an interaction is. Chen and Kotz (2000) defined context as the environment variable used to describe application behavior and events. Zimmermann et al. (2007) divided context into five categories, which are ’individuality’, ’time’, ‘location’, ’activity’ and ‘relations’. ‘Individuality’ contains all information related to an entity or group of entities. ‘Time’ refers to information related to the state of time, including time zone, present time, etc. ‘Location’ originates from the emergence of mobile devices and represents the real or virtual address of an entity, which can also be distinguished as absolute address and relative address, or quantitative and qualitative address. ‘Activity’ includes all information related to an entity's goals and methods of achieving them. ‘Relations’ is the relationship between an entity and other entities, which can be subdivided into three categories: social, functional, and compositional. Bilos et al. (2018) cut out the entity's intent and immediacy from the context, and call the remaining context with the other two as contextual information. Although slightly different, context is used in these literatures to describe the state of an entity and its environment at the moment, and it changes depending on the state. Such a concept can also be used to describe the different micro-moments we encounter in our lives.

2-2 Micro-moments

The concept of micro-moments originated from (Stokes and Harris 2012). It is a study about different market environments dominated by different people. Such a concept is also applied to many different areas. In the field of mobile web, Google has made a more advanced explanation of this concept. As mobile devices become more and more integrated into people's daily lives, people's lives are cut up into many small interactions, or micro-moments, which are

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the moments where people make decisions and construct preferences based on intent (Ramaswamy 2015). In previous researches, scholars had defined some types of micro-moments, they are the moments implying “I want to know”, “I want to go”, “I want to do”, “I want to buy” (Alsalemi et al. 2019), “I want to show” (Jørgensen 2017), and “I want to remember” (Bilos et al. 2018; Wang et al. 2012). These micro-moments represent the different behaviors that people are about to perform, the different states they are in, and the different environments they are facing. McStay (2017)believed that people are more likely to receive information that is useful to them during these micro-moments, and that many factors influence whether people are ready to receive information. Those factors, including location, preferences, physical state, or even environmental factors such as temperature/weather, describe the micro-moment that people are in at the moment, which are the context of the micro-moment.

2-3 Micro-moment recommender system

With the emergence of the micro-moment concept, traditional recommender systems are becoming more and more unable to meet the needs of users. Traditional recommender systems make recommendations based on the user's preferences without considering the context of the user. However, in the micro-moment perspective, different micro-moments have different contexts, and as mentioned in (Zimmermann et al. 2007), individual preferences are part of the "individuality" in the context, so the preferences of entities are constantly changing. In order to deal with these changing micro-moments, recommender systems need to provide appropriate recommendations for different contexts in order to truly help users (Alsalemi et al. 2019), such a recommender system is called a MMRS.

In a MMRS, in addition to the algorithm that affects the user experience (Burke 2002), there are other factors that also have an impact, and user interface is one of them (Baudisch and Terveen 1999; Bo and Benbasat 2007; Knijnenburg et al. 2012; McNee et al. 2006; Murray and Häubl 2008; Ozok et al. 2010; Ziegler et al. 2005). Therefore, when designing the MMRS,

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besides considering how to make proper use of the context, we also need to make the appropriate user interface design based on the characteristics of the MMRS. When a user uses a MMRS, she needs to let the system know her current context. As mentioned in the introduction section, the explicit approach is more convenient and independent. If the system chooses the explicit method to collect the user's context, it needs a well-designed interactive mechanism to allow the user to interact with the system effectively.

2-4 Motivational affordance

When designing an interactive mechanism, it is important to attract users to use it continuously so that the system can get enough data to perform calculations. To keep users in use, the system must provide them with sufficient motivation. Reeve (2013) mentioned that there are two sources of motivation, internal motives and external events. External events refer to stimuli from the environment, which are less relevant to the design of the system itself. In addition, internal motives refer to the processes within people that can guide and enhance behavior, including physiological need, psychological need, social need, cognition, and emotions. Physiological needs are the inborn bodily demands in biological systems. Psychological needs come from the person's own expectations and will make people want to interact with the environment for psychological vitality, well-being, and growth. Social needs are an inherently generated need that arises out of a person's socialization process and activates a number of emotional responses. Cognition means mental incidents, such as beliefs and expectations. Emotions determine how we respond adaptively to critical issues in our lives. The design of the system should have properties that can improve internal motives in order to allow people to use the system continuously (Jung et al. 2010), these properties are also known as motivational affordance (Zhang 2008a).

Zhang (2008b) mentioned that psychological need, social need, cognition, and emotions are the more relevant internal motives for ICT(Information and communication technology).

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Zhang also proposed corresponding motivational affordance and design principles for these four internal motives. These ten principles can be classified into five categories: psychological, social, social & psychological, cognitive and emotion. Zhang believed that the system design should take these principles into account, and if the system design can have some motivational affordance to meet these motives, it will enhance the motivation. The design of information systems varies according to users, tasks, and contexts (Te'eni et al. 2007), so each system should decide how to adopt the design principle of motivational affordance according to its own characteristics. In the next section, we will discuss which design principles were used in this study to design the interactive mechanism of a MMRS and how they were applied.

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Chapter 3 Research Framework and Development

As mentioned in the previous section, psychological needs make people want to interact with the environment in order to gain psychological vitality, well-being, and growth. When using the MMRS, the accuracy of the recommendations generated by the system is affected by the system's understanding of the user's current intention and context. Expressing the current intention and context is the most important part of the process of using the system. In order to generate good quality recommendations, the system needs to make users willing to interact with the system and communicate their situation to the system. Therefore, we believe that if the psychological needs of users are met, users can be encouraged to use the system and the system can receive sufficient information. Therefore, the interaction mechanism of MMRS should be designed to meet the psychological need of the users.

Psychological needs are related to autonomy and self (Zhang 2008b). Need for autonomy is the need to be able to make decisions on one's own in behavior, rather than having the environment determine the behavior (Miller et al. 1988). The self focuses on the definition and expression of the self (Reeve 2013). If the interactive mechanism of the MMRS can be designed in the direction of satisfying autonomy and the self, it will help users to describe the context to the system. The design principles to meet psychological needs are: supporting autonomy and promoting the creation and expression of self-identity. About supporting autonomy, Zhang (2008b) suggested that if the purpose of the system is to obtain engagement gain, performance gain and encourage self-determined motivation, then the system should have an autonomy-supporting style. The purpose of studying the interactive mechanism of the MMRS is to make the interaction between users and the system more enthusiastic, so that the recommendations generated by the system can better meet the expectations of users. Therefore, we should adopt the design principle of support autonomy to design the interactive mechanism. In addition, regarding the promotion creation and representation of self-identify, the focus of the interactive mechanism of the MMRS is to allow the user to represent the current context, similar to that

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mentioned in (Zhang 2008b), the ability to tell ourselves and others who we are. In addition, it is argued that if people can emphasize their own attributes, it will have a positive impact on the recognition of their identity (Vignoles et al. 2000). Therefore, the second design principle: promote creation and representation of self-identify must also be adopted.

Personalization is a practice that satisfies both design principles (support autonomy, promote creation and representation of self-identify) (Zhang 2008b). Blom (2000) suggests that the personalization of a technology refers to the change of functions, interfaces, information content, or the system itself in order to strengthen the connection with the individual. Blom also compiled some of the motivations that trigger personalization when designing a system, including users seeking different information, accommodating work goals, and accommodating individual differences. If the expected functionality of a system has these motivations, the system can be designed using a personalization approach. All three motivations can exist in a MMRS. When using MMRS, each user is a unique individual who uses the system for their own reasons, and the information they want to get from the system is not always the same. Therefore, we believe that personalization is appropriate for the MMRS interactive mechanism. The following hypothesis is posited.

H1: When designing the interactive mechanism of the MMRS, it is more suitable to adopt the design of personalization than the design without personalization.

The next question is how to add the element of personalization to the interactive mechanism of MMRS? In the past study, four dimensions were used to analyze personalization, namely level, subject, preference learning method, object (Kwon and Kim 2012). First, level means the scope of personalization, which can be divided into 1-to-all, 1-to-n, and 1-to-1. 1-to-all refers to the same design used in all users; 1-to-n refers to the same design used in the same group of users; 1-to-1 refers to each user has its own unique design. Second, the subject means

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who will lead the personalization process, which can be divided into two types: user and system. Third, the preference learning method means how the system learns the user's preferences, which can be divided into two types: explicit and implicit. For example, Kornilova(2012) mentions that the design can be adjusted by getting information from the external environment and users. Finally, object refers to the item to be personalized, which can be a variety of goods or services. Among these four dimensions, the subject is related to the user's degree of perceived active control over the system, while the psychological need in motivational affordance is about the user's ability to control his or her own behavior, and we believe that these two characteristics match each other. Therefore, we believe that when using personalization to design the interactive mechanism of MMRS, we should start from the dimension of subject. Regarding the subject of personalization, although Kwon and Kim (2012) divided it into user-initiated personalized intention and system-initiated personalized intention, but there are many other papers with different interpretations. While these papers are similar, they all have their differences and it is difficult to fully standardize them into a single statement. Blom (2000) sees personalization as a practice that enhances the relationship between systems and users, and separates personalization into user-initiated personalized intention and system-initiated personalized intention (also called customization). Lavie and Meyer (2010) classifies the personalization of systems into four levels. The first is manual, which means that all changes are user-driven. The second, user selection, means that the user selects the changes she wants to make from the choices given by the system. The third type is user approval, which means that the system will first decide what changes to make, and then the user can decide for herself whether to agree or not. And the last one is fully adaptive, which means that all changes are led by the system. Some studies refer to user-initiated personalized intention personalization as adaptable and system-initiated personalized intention personalization as adaptive (Gullà et al. 2015; Peissner and Sellner 2012; Zeidler et al. 2013). Kornilova (2012) refers to changes in the system as adaptations. If the adaptation is decided by the user, it is called simple adaptation; if,

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on the other hand, the system decides how to adapt, it is called self-adaptation.

These papers all describe the differences in the subjects of systems during personalization. It can be seen that the common point of these papers is that they all divide the subject of personalization into user-initiated personalized intention and system-initiated personalized intention. The biggest impact of different subjects on the user is how much extra effort she needs to put into the system. If user-initiated personalized intention personalization is used, it will take more effort and time for the user to learn how to use the system, but the user will have more perceived active control over the system and understand it better (Fischer 1993; Gullà et al. 2015). If system-initiated personalized intention personalization is used, the system will adjust itself according to the situation, so the user can spend less effort, even if the system is complex, the user can still use it easily (Hook 1998; Trumbly et al. 1994). However, this approach may not be able to fully meet the user's imagination for personalization, giving the user the feeling of not being able to control the system (Barkhuus and Dey 2003; Weld et al. 2003).

When comparing the degree to which user-initiated personalized intention and system-initiated personalized intention personalization can satisfy psychological needs, the former should be higher because the user can operate the system exactly as he or she wants, i.e., the system can present the user's thoughts more correctly. If user-initiated personalized intention personalization is applied to the MMRS interactive mechanism, users should be able to express their preferences in the current context more effectively. Therefore, we can posit the second hypothesis.

H2: Although user need to spend more effort, user-initiated personalized intention personalization is more suitable for designing the interactive mechanism for MMRS than system-initiated personalized intention personalization.

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In addition to distinguishing between user-initiated personalized intention and system-initiated personalized intention personalization, it is argued that both practices should co-exist in a system (Blom 2000). There is also literature that suggests that users and systems participate in the process of personalization together (Kornilova 2012). This approach not only provides users with control, but also relies on system's assistance, making it easier for users to use. So, we propose the third and the fourth hypothesis.

H3: Mix-initiated personalized intention personalization (mixed user-initiated personalized intention and system-initiated personalized intention) is more suitable for designing interactive mechanism for MMRS than user-initiated personalized intention personalization.

H4: Mixed personalization (mixed user-initiated personalized intention and system-initiated personalized intention) is more suitable for designing interactive mechanism for MMRS than system-initiated personalized intention personalization.

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Chapter 4　Methodology

In the previous paragraphs, we argued that personalization is suitable for designing the MMRS interactive mechanism. It was also hypothesized that among the personalization of different subjects, mix-initiated personalized intention personalization would be more suitable than user-initiated personalized intention personalization, and user-initiated personalized intention personalization would be more suitable than system-initiated personalized intention personalization. To test the validity of these hypotheses, four different interactive mechanisms were designed in this study. Through the experiment, users were allowed to operate our designs in a MMRS, and then some subjective and objective metrics were used to compare the advantages and disadvantages of these designs. The four designs are no-personalized intention, user-initiated personalized intention, system-initiated personalized intention, and mix-initiated personalized intention. More details about the experiment and the participants will be described in the subsequent paragraphs.

4-1　Dataset

For the experiment, we constructed a dataset of restaurants. We collected information of 939 restaurants from google map and openRice[1]. These restaurants are located in Daan District, Wenshan District, and Xinyi District. The information includes name, address, latitude and longitude, business hours, cuisine type, google rating, services offered (for here or to go), and price range.

4-2　Tasks

Preference elicitation is an important section in the recommender system, and this study focused on this part of the interface design to achieve customization and adaptive. Knijnenburg

[1] OpenRice is a restaurant review website.

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and Willemsen (2009) verified that the user's domain knowledge affects the applicable preference elicitation method. Therefore, in order to remove the influence caused by domain knowledge, we chose the restaurant recommendation where all participants have domain knowledge as the experimental domain. Therefore, in the field study, participants had to deal with a dining situation by using our micro-moment recommender app, *deleecious*.

Table 1. Context categories.

Categories	**values**
weather	Good, bad
time	Day, night
Weekdays & weekends	Weekday, weekend

Figure 1. The current context in the interface.

Micro-moment contains three important elements, context, intent, and immediacy (Biloš et al. 2018). Therefore, participants need to express their intention of restaurants in the preference elicitation stage in a timely manner according to the current context. In order to avoid adding redundant operations to the participants, *deleecious* uses only contexts that can be automatically detected by the phone, including weather, time, and weekdays & weekends (see Table 1.). For example, if it is sunning at 10am on a Monday morning, the screen will show that it is now a good weather weekday day (see Figure 1.). After obtaining the participant's intention, *deleecious* will generate appropriate restaurant recommendations based on the participant's long-term preference and intention. Each participant will be required to use

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deleecious for a period of two weeks. During the process, participants are encouraged to use *deleecious* as many times as possible and to explore the features inside.

4-3 Recommendation algorithm

We modified and adopted the recommendation algorithm mentioned in the previous literature to fit the experimental context (Zeng et al. 2016). Zeng's algorithm is to generate recommendations by calculating the cosine similarity between the restaurant cuisine and the participant's preferred cuisine (see Formula 1). If the result of the calculation is larger, it means that the restaurant is more in line with the user's preferences and is suitable to be recommended to the user. There are 21 types of cuisines in total[2]. To facilitate the calculation, we need to present both the restaurant's cuisines and the participants' preferred cuisines in an array of 0 and 1.

First, the restaurant cuisine f can be obtained from the dataset, if the restaurant a belongs to the j^{th} cuisine, then $f_{aj} = 1$. The participants' preferred cuisine, i.e., their preference vector p, can be obtained from the on boarding survey (see Appendix B). In the survey, participants are asked which cuisines they prefer in order to create a preference vector. The content of the preference vector is not related to the context, but represents the long-term preference of the participant for the restaurant cuisine. If participant b prefers the i^{th} cuisine, then $p_{bi} = 1$.

$$Similar(Pu, f) = cos(Pu, f) = \frac{\sum_{i=1}^{n} P_i f_i}{\sqrt{\sum_{i=1}^{n} {P_i}^2} \times \sqrt{\sum_{i=1}^{n} {f_i}^2}} \qquad (1)$$

The preference vector is not constant. The system also updates the participant's preference vector according to the restaurant he or she chooses each time. For example, if a participant chooses a Taiwanese restaurant, the field of Taiwanese cuisine in the participant's preference vector will be increased by 1, indicating that the participant prefers Taiwanese restaurants over other cuisines (see Figure 2.). After that, the system will use formula 2 to normalize the

[2] Including Taiwanese, Chinese, Korean, Hong Kong style, Thai, Vietnamese, Italian, French, American, German, European, Southeast Asia, Japanese, Indian, Mexican, Russian, Middle Eastern, Hawaiian, drinks, coffee, Bar/Bistro.

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participants' preference vector, to make sure that the value will still between 0 and 1. This allows the system to be more closely matched to the participant's preferences when generating recommendations later.

$$Norm(p_i) = \frac{p_i}{\sum_{j=0}^{n} p_j} \tag{2}$$

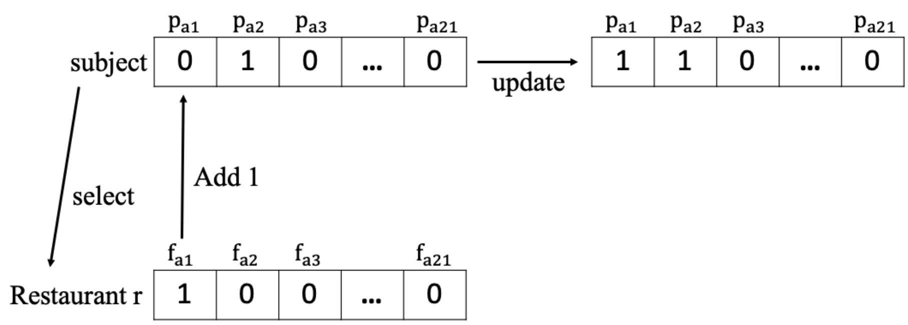

Figure 2. The process of updating participant's preference vector.

4-4 App system

For this research, we developed an android app *deleecious*. We used flutter to develop the app because it also meets the requirements of iOS version. We chose firebase firestore as the backend database. The firebase firestore stores data in json format, which allows us to store the data we need in a very flexible way. The firebase firestore also has query syntax, so we can add, delete, query, and modify data to the firebase firestore through flutter in a timely manner.

As a MMRS for restaurant, *deleecious* allows participants to get recommended restaurants by following the steps below.

Login. In the onboarding survey, participants are asked to provide their email, which they can use to log in to *deleecious*.

Express current intention. The participant will first see the current context when he/she enters *deleecious* (see Figure 1.). Then the participants were asked to use interactive mechanism to express their intention to choose a restaurant. Baltrunas et al. (2013) listed some of the

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contextual factors that can be applied to tourist attraction recommendations. Liu and Gan (2016) compiled some of the most frequently occurring restaurant feature factors from customer reviews. Some of these factors can be used to filter different types of restaurants, so we believe that these factors can be used as the intentions of the participants. This study combined two studies we mentioned above to compile five intention factors. Other factors are considered to be too subjective and difficult to be standardized across participants, and therefore not suitable for our study. The detail of the intention factors is shown in Table 2.

Table 2. The intention factors.

intention factor	**values**
service	no limit / for here / to go
consumption	no limit / $ / $$ / $$$ / $$$$
time	no limit / < 1 hours / 1-2 hours
distance	no limit / < 1000m / 1000-2500m
rating	no limit / > 4 stars

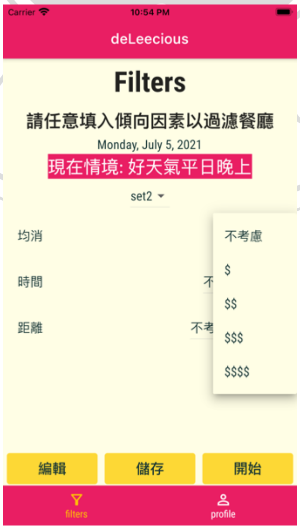

Figure 3. The drop-down menu to determine the value of intention factors.

The participants can determine the value of the intention factors through a drop-down menu (see Figure 3). By relying on these intention factors, *deleecious* can know exactly what

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kind of restaurant the participant needs at the moment.

There are four different kinds of interactive mechanisms in *deleecious*, and they allow the participants to perform different operations. The difference between the four types of interactive mechanisms lies in the subject of personalization they use. In deleecious, personalization is applied to the intention factor used by the participants, and variations in the subject of personalization can have different effects on the intention factor.

The first one is no-personalized intention, which means that no personalization is used in the design. No matter what kind of context a participant encounter, he or she will only receive a fixed set of intention factors, that is, a set of five factors, and the participants cannot modify the intention factor set. Only the Start button will be available in the interface (see Figure 4.).

Figure 4. The interface of no-personalized intention interactive mechanism.

The second one is user-initiated personalized intention, a design that adopts the user as the subject of personalization. The first time a participant uses *deleecious*, he or she will get the complete intention factor set containing five intention factors. There are edit button and save button on the interface (see Figure 5.). The participant can edit the factors, or save the adjusted set. When saving, the participant can also save the selected values together. Later, when using *deleecious*, participants can select the set they want to use from all the intention factor sets.

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The third one is system-initiated personalized intention, a design that adopts the system as the subject of personalization. *Deleecious* provides the participants corresponding default intention factor set based on the current context. Before the field study started, we conducted a preliminary survey (see Appendix A) to find out which intention factor people would like to use to select a restaurant in different contexts. The default intention factor set for each context is shown in Table 6. After the participant receives the corresponding default intention factor set according to the current context, it is not possible to adjust these intention factor sets. They can only use the default intention factor set to express their intentions, and there is only a start button in the interface (see Figure 6.).

Figure 5. The interface of user-initiated personalized intention interactive mechanism. From left to right. (a) Edit button and save button. (b) Interface of edit function. (c) Interface of save function.

The fourth one is mix-initiated personalized intention, a design in which both the user and the system are used as the subjects of personalization. *deleecious* will provide the participants with the corresponding default intention factor set according to the current context. The participants can edit the factors or save the adjusted set and the selected values by pushing the edit button and the save button in the interface (see Figure 7.). When saving the adjusted set,

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the current context will also be saved. Later, when the same context is encountered, *deleecious* will provide all the sets belonging to this context to the participant to choose.

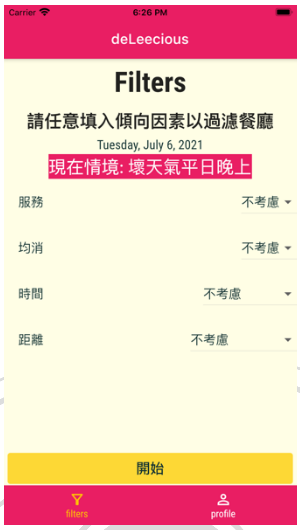

Figure 6. The interface of system-initiated personalized intention interactive mechanism.

Figure 7. The interface of mix-initiated personalized intention interactive mechanism. From left to right. (a) Edit button and save button. (b) Interface of edit function. (c) Interface of save function.

Generate recommendation. After deciding the value of the intention factor through the drop-down menu, the participant can click the Start button to let *deleecious* start the calculation. First, we will use Zeng's recommendation algorithm to find out the restaurants that match the

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participants' cuisine preferences from all the restaurants (Zeng et al. 2016). We then use the intentions provided by the participants to perform post filtering to filter out the restaurants that match the participants' intentions. These restaurants are then used as the final recommendation for participants to choose from. For example, if the participant prefers a restaurant that offers carry-out service, restaurants that offer in-house service will be filtered out. The participant can confirm his choice by clicking on the select restaurant button (see Figure 8.). After pressing the select restaurant button, the complete recommendation process is finished.

Figure 8. The recommendation interface with select restaurant button.

4-5 Design & procedure

This study started with a preliminary survey to collect the default intention factor set used in *deleecious*. The formal part of the experiment began after the preliminary survey was completed. This study was organized as a between-subject experiment, and included three phases: (1) Onboarding surveys, (2) a field study, and (3) a post survey. Because of the current covid-19 situation, all interactions with participants were conducted online. Participants first read a description of the experiment and then completed an on-boarding survey, which took about 5 minutes. The participants were then be notified by email that the field study has begun.

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In addition to the tutorials for downloading the app, there were also some instructions for using the app in the letter. The instructions varied depending on the experimental group to which the participant belongs. Participants were required to complete at least 20 recommendations in the next two weeks in order to be eligible for a lottery. After that, all participants filled out a post survey (about 5 minutes). The details of each part of the experiment are described below.

Preliminary survey. The main purpose of the preliminary survey is to investigate which factors most people would like to use to filter the restaurant when faced with different contexts. The combination of these factors is the default intention factor set that will be used in *deleecious*. We ask participants whether they would choose a specific intention factor (e.g., average spending per person at a restaurant) as the basis for their choice of restaurant in day, night, weekday, weekend, good weather, and bad weather (see Appendix A). The intention factors are shown in Table 2. In each context, as long as more than 70% of the participants choose the intention factor as the basis for restaurant selection, we will add that intention factor to the default intention factor set of the corresponding context.

Onboarding survey. Onboarding survey can be divided into two parts, cuisine preference and recommender system usage habits. First of all, in the section of cuisine preference, we ask the participants which cuisine they like (see Appendix B). There are 21 types of cuisine, and all 939 restaurants in the dataset are included in these 21 types of cuisine. Participants can choose one or more favorite cuisines as they like. The results of their choices are stored in the database in an array of 0s and 1s. It is used as a preference vector to assist in the calculation of the recommendation algorithm.

The next part is the recommender system usage habit. We asked the participants how often they would use their cell phones to look up information, and whether they would use the mobile recommender system to look up information, and how often they would do so (see Appendix B). The purpose was to find out whether the participants had the habit of using mobile recommender system in the past, and check whether the participants' different usage habit will

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affect their feelings towards *deleecious* during the experiment.

Field study. After completing the onboarding survey, participants were randomly assigned to an experimental group to begin a two-week field study. The study was conducted in a between-subject manner, and there were four experimental groups (see Table 3.). Participants are randomly assigned to one of the groups, and we make sure that the number of people in each group is approximately the same.

Table 3. The experimental groups.

Groups	description
NP	This group is a control group, and it used the no-personalized intention interactive mechanism.
UI	This group uses the user-initiated personalized intention interactive mechanism.
SI	This group uses the system-initiated personalized intention interactive mechanism.
MI	This group uses the mix-initiated personalized intention interactive mechanism.

During the process, the participant's actions will be recorded. Each user action of editing, saving, starting recommendation, selecting a restaurant and the session time are saved as log data in the database for later analysis.

Post survey. At the end of the field study, the participant was asked to fill out a post survey (see Appendix C). The questions in the survey can be divided into three parts. First, the participants were asked about the degree of perceived active control over the intention factor set when using *deleecious* (Bol et al. 2019). Then, the participants were asked about the degree of effort they feel when using *deleecious* (Lewis 1995). The third part is the MMRS anticipation. The participants were asked about their anticipation of the MMRS. The purpose is to see if their

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anticipation of the MMRS meet the motivations of personalization, and if they do, the MMRS is suitable to be designed with personalization (Blom 2000).

4-6 Participants

For the preliminary survey, a total of 64 participants were recruited through online bulletin board. Because the participants do not know the content of the formal part of the experiment during the preliminary survey, they can continue to participate in the formal part of the experiment even after completing the preliminary survey.

Table 4. The participant demographics.

Characteristic	**Type**	**NP (16)**	**UI (19)**	**SI (16)**	**MI (20)**	**frequency**
Gender	Female	8	9	9	11	37
	Male	8	10	7	9	34
Age	< 20	6	3	4	5	18
	21 – 30	10	16	12	15	53
Education	High school	1	0	0	0	1
	Collage	12	16	8	15	51
	Graduate school	3	3	8	5	19
Total						71

For the formal part of the experiment (including onboarding survey, field survey, and post survey), a total of 114 participants were recruited through online bulletin board, and these participants were randomly assigned to four experimental groups (NP: 29, UI: 28, SI: 28, MI: 29). The experiment was conducted in a between-subject manner, during which the participants were not informed about the other groups to ensure that they would not be influenced by the other groups. Participants who did not conduct the field study and did not complete the post survey were removed from the experiment. A total of 71 participants completed the experiment

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(NP: 16, UI: 19, SI: 16, MI: 20). The demographic information of these participants is shown in Table 4.

Table 5. The hypothesis and metrics.

Hypothesis	**Metrics**
H1: When designing the interactive mechanism of the MMRS, it is more suitable to adopt the design of personalization than the design without personalization.	Post survey
H2: Although user need to spend more effort, user-initiated personalized intention personalization is more suitable for designing the interactive mechanism for MMRS than system-initiated personalized intention personalization.	App log • Execute time Post survey
H3: Mix-initiated personalized intention personalization is more suitable for designing interactive mechanism for MMRS than user-initiated personalized intention personalization.	App log • Execute time • Ratio of edit and save • Saved set used ratio Post survey
H4: Mixed personalization is more suitable for designing interactive mechanism for MMRS than system-initiated personalized intention personalization.	App log • Execute time Post survey

4-7 Hypothesis and statistic method

This study aims to understand what kind of interactive mechanism design is suitable for MMRS. We adopted the concept of motivational affordance and used the principles of support autonomy and promotion creation and representation of self-identify to design the interactive mechanism using personalization. We also proposed four hypotheses for the four interactive

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mechanisms we designed.

For the hypotheses, we use some metrics to check their validity (see Table 5.). We believe that when using the MMRS, the participants should prefer some personalization of the system. This is because personalization may give the participant a greater perceived active control. In addition to the perceived active control, because the MMRS needs to give recommendations promptly before the user takes action, the more effort-saving interactive mechanism is more suitable. In the three groups that have used personalization, participants in the MI group should spend less time than those in the UI group, use fewer edit and save functions, and yet feel the same level of control. Compared to participants in the SI group, participants in the MI group felt a greater perceived active control while spending about the same amount of time. Therefore, we believe that the MI group would have the best performance among the four groups and would be most suitable for the interactive mechanism in the MMRS.

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Chapter 5 Analysis and result

In order to understand what kind of interactive mechanism design is more suitable for MMRS, we divided the experiment into four groups, namely NP, UI, SI, MI.

The analysis results of preliminary survey, onboarding survey, app log, and post survey are described in this section. First of all, the preliminary survey can show what intention factor most people will choose as the basis for restaurant selection in a particular context. Then, in the onboarding survey, we can understand more about the background of the participants, as well as their preferred cuisine and their habits of using the recommender system. Next, in the app log section, we analyzed the log data to understand the differences in the behavior of each group of participants. Finally, we analyze the data from the post survey to verify whether our proposed hypothesis is valid.

Figure 9. The intention factor selected ratio in each context.

5-1 Analysis of preliminary survey

In the survey, we asked the participants whether they would choose a specific intention factor as a basis for choosing a restaurant in each context. We collected a total of 64 results.

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The results of the survey are shown in Figure 9, with the x-axis showing the six contexts and the y-axis showing the ratio of participants who had selected a particular intention factor in each context. In each context, as long as over 70% of the participants had selected a specific intention factor, we added that intention factor to the default intention factor set of the corresponding context.

There are five intention factors in the experiment. Firstly, 71.8% of the participants chose restaurant service when the weather was bad. Secondly, 73.4% of the participants chose consumption during weekdays. Third, 71.8% of the participants chose time during weekdays. Fourth, 84.3% and 79.6% of the participants chose distance during bad weather and weekdays respectively. Finally, during holidays, 96.8% of the respondents chose the rating of restaurants. By consolidating the above results, we can compile the default intention factor set in each context (see Table 6.).

Table 6. The default intention factor sets.

Context set	**Intention factors**
Good weather weekday day.	Consumption, time, distance
Good weather weekday night.	Consumption, time, distance
Good weather weekend day.	Rating
Good weather weekend night.	Rating
Bad weather weekday day.	Service, consumption, time, distance
Bad weather weekday night.	Service, consumption, time, distance
Bad weather weekend day.	Service, rating
Bad weather weekend night.	Service, rating

5-2 Analysis of onboarding survey

In the survey, we asked the participants which cuisines they preferred and their usage

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habits of the recommender system in order to understand them better. We collected a total of 114 results. However, among these 114 participants, only 71 had completed the field study and post survey, so we only analyzed the results of these 71 participants.

Among all 21 cuisines, the five most popular cuisines were Taiwanese, Japanese, American, Drinks, and Chinese, and the percentages of participants who preferred these cuisines were 85.9%, 85.9%, 71.8%, 67.6%, and 63.3%, respectively. The complete results of the preferred cuisines are shown in Figure 10.

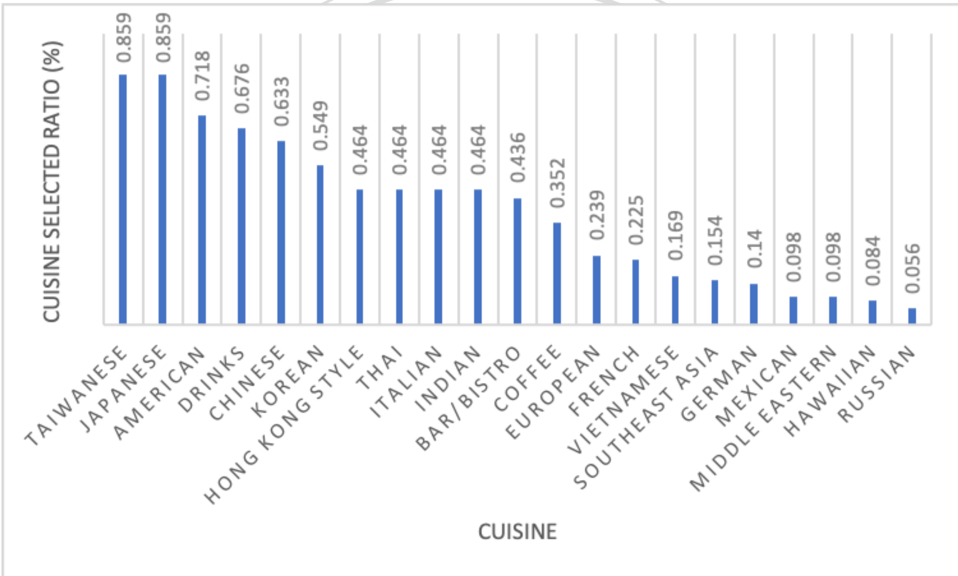

Figure 10. Participants' preferred cuisine.

Regarding the habit of using the recommender system, all participants usually use their cell phones to check information, but the frequency varies slightly, with the highest percentage using multiple times a day (see Figure 11(a)). Among all the participants, 91.5% have used the recommender system and 8.5% have not used the recommender system. However, when asked how often they usually use the mobile recommender system, 12.6% of the participants said that they never used it. We believed that the difference between the two is that some participants may have only used the web version of the recommender system and not the mobile version of the recommender system. The percentages of the frequency of the participants using the mobile

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recommender system are shown in the Figure 11(b). Summing up the above results, we can see that most of the participants have the experience of using the mobile recommender system.

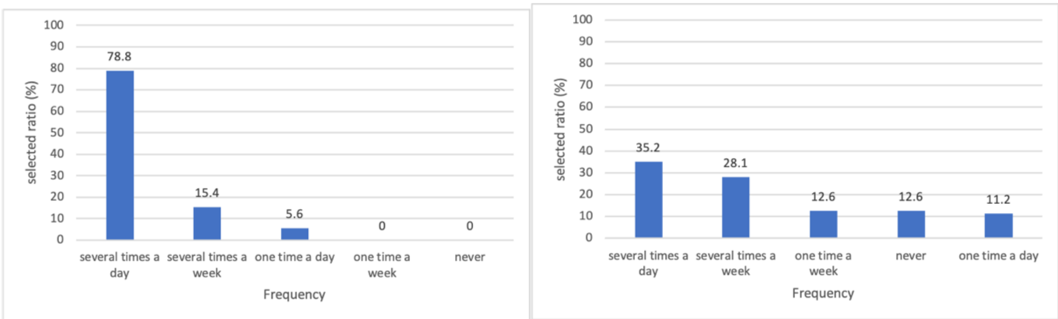

Figure 11. (a) The frequency of using cellphone to get information. (b) The frequency of using mobile recommender system to get information.

Table 7. The definitions of measurements.

Measurement	**Definition**
Average execute time (sec)	The average time it takes for a participant to complete a recommendation.
Edit count (times)	Total number of times participants used the edit function.
Save count (times)	Total number of times participants used the save function
Edit ratio (%)	Among the total number of recommendations completed by the participant, the number of times the edit function was used.
Save ratio (%)	Among the total number of recommendations completed by the participant, the number of times the save function was used.
Saved set used ratio (%)	Among the total number of recommendations completed by the participant, the number of times the saved intention factor sets were used.

5-3 Analysis of app log

After two weeks of field study, 71 participants completed a total of 2308

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recommendations. Each recommendation could be subdivided into different steps. In the NP and SI groups, the participants filled in the intention factor first and then chose the restaurant they were interested in after receiving the recommendations. In the UI and MI groups, the participants can also edit and save the intention factor set when they fill in the intention factor. The operations of these participants are recorded in the database. We used a number of measurements to examine whether the participants' behavior met our expectations (see Table 7). The mean and standard error of the measurements are shown in Table 8.

Table 8. The mean and standard error of the measurements.

Action	**NP (16)**	**UI (19)**	**SI (16)**	**MI (20)**	**All**
Average Execute time (sec)	30.73±5.23	38.95±7.17	29.99±5.21	38.88±6.64	34.78±3.08
Numbers of recommendation	25.00±3.39	31.74±6.71	46.75±10.28	27.85±4.40	32.51±3.26
Edit count		7.37±1.39		6.40±1.18	6.87±0.90
Numbers of save		2.58±1.33		3.50±0.65	3.05±0.72
Edit ratio (%)		0.28±0.06		0.43±0.12	0.36±0.07
Save ratio (%)		0.24±0.10		0.23±0.06	0.23±0.06
Saved set used ratio (%)		0.13±0.05		0.24±0.06	0.19±0.04

For average execute time, the time taken by the participants for each recommendation represents the actual effort they need, so we can examine whether there is a difference in the effort required by each experimental group by analyzing average execute time. The average execute time is the sum of the time required by the participant to complete each recommendation, divided by the total number of recommendations completed by the participant. We used Kruskal-Wallis one-way ANOVA to analyze the average execution time. There was

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no significant difference between execute time in four groups (Chi square = 1.588, p = .662, df = 3), with a mean rank 29.13 for NP, 33.06 for UI, 28.20 for SI, and 35.40 for MI, which means that the distribution of average execute time was the same among the four experimental groups. That is, the participants in the four groups spend the same amount of effort when using the app, which implies that even if the participants in the UI and MI groups need to perform additional edit and save operations, the amount of effort they spend will not increase significantly.

Edit count refers to the total number of times each participant performed the edit function during the two-week field study. Save count refers to the total number of times each participant performed the save function during the two-week field study. For both edit count and save count, we conducted Kruskal-Wallis one-way ANOVA. There is no significant difference between two groups in the distribution of edit count (Chi square = 0.319, p = .572, df = 1), with a mean rank 21.05 for UI, 19.00 for MI. On the contrary, there is significant difference between two groups in the distribution of save count (Chi square = 5.705, p = .017, df = 1), with a mean rank 15.61 for UI, 24.18 for MI. Although there is a significant difference between the UI and MI groups in terms of save count, the average number of completed recommendations is different for these two groups. Therefore, we analyzed the edit ratio and save ratio, i.e., the proportion of all recommendations completed by the participants that they used the edit and save functions.

Edit ratio is the total number of times the participant used the edit function divided by the total number of times he made a recommendation. Save ratio is the total number of times the participant used the save function divided by the total number of recommendations he made. For edit ratio and save ratio, we also conducted Kruskal-Wallis one-way ANOVA. In the UI and MI experimental groups, there are functions of editing and saving intention factor sets, but it is not mandatory for the participants to use these two functions, the participants can decide whether to use them according to their own needs. We originally thought that in the MI group, all the intention factor sets would be filtered by the system using context once before allowing

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the participants to choose. Therefore, the MI group should have less need to use the edit and save functions. However, according to the results of the analysis, there is no significant difference between two groups in the distribution of edit ratio (Chi square = 0.495, p = .482, df = 1), with a mean rank 18.68 for UI, 21.25 for MI, also no significant difference between two groups in the distribution of save ratio (Chi square = 1.875, p = .171, df = 1) with a mean rank 17.45 for UI, 22.43 for MI. This is not quite the same as we had expected.

Saved set used ratio is the proportion of saved intention factor sets used among all recommendations completed by the participant. We divided the number of times the participant used the saved intention factor sets by the number of times they completed the recommendations, and conducted Kruskal-Wallis one-way ANOVA to see if there's difference between UI and MI groups. There is significant difference between two groups in the distribution of saved set used ratio (Chi square = 4.927, p = .026, df = 1), with a mean rank 15.92 for UI, 23.88 for MI. According to Table 8, with respect to the saved set used ratio, the mean of participants in the MI group was higher than the mean of participants in the UI group.

Table 9. Mean and SE of three Factors for four groups.

Group / Factor	NP	UI	SI	MI	All
	N = 16	N = 19	N = 16	N = 20	N = 71
Perceived active control	4.05±0.30	5.66±0.19	4.06±0.28	5.78±0.23	4.97±0.16
Effort	5.11±0.25	5.75±0.25	5.46±0.23	5.99±0.18	5.61±1.12
MMRS anticipation	5.40±0.23	5.68±0.21	5.67±0.26	5.85±0.17	5.66±0.11

5-4 Analysis of post survey

In the survey, we asked the participants how they felt about the app after experiencing the field study in two weeks, in order to understand whether the participants in different experimental groups really felt the difference in the design of the interactive mechanism. Only

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71 participants' responses were collected. We used a 7-point Likert scale to express participants' feeling (1 = Strongly disagree, 7 = Strongly agree). The survey consisted of three main aspects, namely, perceived active control, effort, and MMRS anticipation.

The perceived active control refers to the degree of control that users feel when using the app (Bol et al. 2019; Voorveld et al. 2011). The questions related to perceived active control are shown in Appendix C, with higher mean scores indicating that participants felt they had more control over the intention factor set. Effort refers to the degree of difficulty participants felt when using the intention factor set in the app, i.e., the less effort the participants had to spend. The questions related to effort are shown in Appendix C. The higher the average score, the easier the participants found the intention factor set to be to use. The MMRS anticipation is concerned with whether or not the participant's anticipation of MMRS will satisfy personalization motivations (Blom 2000). The questions related to the MMRS anticipation are shown in Appendix C. The higher the average score, the more suitable the app is for personalization design. The results of the survey are shown in Table 9.

Table 10. The reliability and validity of perceived active control and effort.

Factor	Cronbach's alpha	Composite reliability	AVE
Perceived active control	0.858	0.894	0.587
Effort	0.895	0.918	0.653

We conducted an outer model analysis for the questions of perceived active control and effort in the post survey to determine that the survey has reliability and validity. According to Table 10, both factors have Composite reliability > 0.7 (perceived active control: 0.894, effort: 0.918) and Cronbach's alpha > 0.7 (perceived active control: 0.858, effort: 0.895), indicating that they have internal consistency and reliability. In terms of validity, the AVE of both factors were higher than 0.5 (perceived active control: 0.587, effort: 0.653), which means that both factors have convergent validity. Finally, according to Table 11, both factors had discriminant

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validity.

With respect to the assumption of homogeneity of variance, Levene's test was not significant for any of the questions; thus, they are at the significant level (see Table 12.). Next, we conducted a Normality test to verify whether the results of perceived active control, effort, and MMRS anticipation were normally distributed. According to Table 13, only the results of effort are normally distributed, while perceived active control and MMRS anticipation are not normally distributed.

Therefore, we can use one-way between-subject ANOVA to see if there is a significant difference between the four experimental groups in terms of effort, as for perceived active control and MMRS anticipation, we choose to use Kruskal-Wallis one-way ANOVA to analyze them.

Table 11. Factor loadings of all the items.

Items	**Perceived active control**	**Effort**
Perceived active control 1	**0.805**	0.468
Perceived active control 2	**0.833**	0.485
Perceived active control 3	**0.650**	0.575
Perceived active control 4	**0.784**	0.351
Perceived active control 5	**0.653**	0.123
Perceived active control 6	**0.847**	0.465
Effort 1	0.392	**0.667**
Effort 2	0.429	**0.756**
Effort 3	0.467	**0.859**
Effort 4	0.461	**0.891**
Effort 5	0.436	**0.909**
Effort 6	0.372	**0.735**

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Table 12. The results of Levene's test.

	Levene Statistic	p-value
Perceived active control	1.260	0.295
Effort	0.733	0.536
MMRS anticipation	0.316	0.814

* significant at p < 0.05, ** significant at p < 0.01, *** significant at p < 0.001

Table 13. The result of Normality test.

	Kolmogorov-Smirnov	df	p-value
Perceived active control	0.151	71	< 0.001***
Effort	0.095	71	0.184
MMRS anticipation	0.196	71	< 0.001***

* significant at p < 0.05, ** significant at p < 0.01, *** significant at p < 0.001

Table 14. The post-hoc test result of perceived active control.

Comparison	Test statistics	SE	p-value
SI - NP	0.281	7.288	0.969
SI - UI	25.910	6.994	< 0.001***
SI - MI	-28.744	6.914	< 0.001***
NP - UI	-25.628	6.994	< 0.001***
NP - MI	-28.462	6.914	< 0.001***
UI - MI	-2.834	6.604	0.688

* significant at p < 0.05, ** significant at p < 0.01, *** significant at p < 0.001

A Kruskal-Wallis one-way ANOVA was conducted to compare the effect of perceived active control in four experimental groups. There was a significant difference between

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perceived active control in four groups (Chi square = 30.843, $p < .001$, df = 3), with a mean rank 21.19 for NP, 46.82 for UI, 20.91 for SI, and 49.65 for MI. The MI group (Mdn = 6.00) performed significantly better than the NP (Mdn = 4.42) and SI (Mdn = 4.42) groups, and although the MI group also performed better than the UI (Mdn = 5.67) group, there was no significant difference between the MI and UI groups. Other than that, there were no significant differences between the SI and NP groups. This result is similar to our expectation because both the MI and UI groups have the ability to edit and save the intention factor set, and the participants may feel the same level of control. There was no significant difference between the NP and SI groups because neither group had the ability to edit and save the intention factor set.

Therefore, based on the post-hoc tests results, we can tell that the function of editing and saving the intention factor set does allow the participant to feel a higher degree of control. The results of the post-hoc tests are shown in Table 14.

A one-way between-subjects ANOVA was conducted to compare the effect of effort in four experimental groups. There was no significant effect of at the $p < .5$ level for the four groups [$F(3, 67) = 2.712$, $p = 0.052$]. We originally thought that participants in the UI, MI groups would find it more difficult to use the system. However, there is no significant difference between the four experimental groups. In addition, according to Table 9, we can see that the mean of all four groups is greater than 5 (NP: 5.11, UI: 5.75, SI: 5.46, MI: 5.99), which means that generally, all participants found the intention factor set easy to use. Although this result is not in line with our original expectation, we still think it is reasonable. Since smartphones are now well-developed and common, and 87.4% of our participants have previous experience with mobile recommender systems (see Figure 11(b)). They are already used to operating smartphones, resulting in a decrease in the overall perceived difficulty of operating the intention factor set, which means the less effort the participants need to spend.

A Kruskal-Wallis one-way ANOVA was conducted to compare the effect of MMRS anticipation in four experimental groups. There was a significant difference between perceived

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active control in four groups (Chi square = 2.609, $p < .456$, $df = 3$), with a mean rank 29.19 for NP, 36.82 for UI, 36.84 for SI, and 40.00 for MI. Moreover, according to Table 9, the average of all four groups is greater than 5 (NP: 5.40, UI: 5.68, SI: 5.67, MI: 5.85), this means that the MMRS is expected to have personalization motivations regardless of the experimental group. This is because regardless of the group of participants, they all face the same situation, i.e., they need to tell the system their intentions in order to obtain recommendations, which do not vary from one experimental group to another.

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Chapter 6 Discussion and conclusion

6-1 Discussion

The purpose of this study is to understand what kind of interactive mechanism is more suitable for MMRS. We also developed a micro-moment restaurant recommender app for the participants to use to observe their behavior. Throughout the study, we conducted a preliminary survey, onboarding survey, field study, and post survey. The results showed that the UI, MI group with user-initiated personalized intention personalization had better control and was able to help the participants with design principles of support autonomy and promotion creation and representation of self-identification. From the results of the analysis, we can summarize several main findings.

MMRS has personalization motivations. Blom (2000) mentioned three personalization motivations, including enable access to information content, accommodate work goals, and accommodate individual differences. If the system has these motivations, then personalization should be adopted. From the results of the post survey, we can see that almost all the participants expected that MMRS has these three personalization motivations. The recommender system is originally designed to meet the needs of each individual, and the MMRS emphasizes that users can express their own unique intentions according to the situation they face. Therefore, we can infer that our proposed hypothesis 1 is accepted. When designing the interactive mechanism of the MMRS, it is more suitable to adopt the design of personalization than the design without personalization.

Edit and save functions do not increase user effort. We originally assumed that because of the additional operations to be performed, the UI, MI group of participants might have to spend more effort. However, according to the log data analysis, there was no significant difference in the time spent by the four groups, indicating that they actually spent the same amount of effort. In addition, according to the post survey analysis, we can find that there is no significant difference between the four groups in terms of the degree of effort felt by the

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participants. Therefore, it is clear that adding the edit and save functions does not make the app difficult to use. We think the reason is that people are now very familiar with operating cell phones and pressing a few more buttons will not increase their effort. In addition, almost all of our participants have used the recommender system on cell phones, and the functions of edit and save are not particularly innovative, so they don't need to spend extra effort to learn how to use it. The productions after the participants use the save function is called saved sets. The purpose of saved sets is to allow participants to directly use the previously edited intention factor sets when manipulating the intention factor set. We expected that the use of saved sets would reduce the participants' effort, but according to the log data and post survey, there was no significant difference between UI, MI groups and the other two groups in terms of the actual effort spent and the perceived effort. We believe that the reason may be in our app, the execution of various operations are mostly click-driven, the operation of various functions do not differ much, even if the participants are not directly using the saved set to generate recommendations, there is no need to perform too many additional actions. In addition, we would like to understand the status of saved set usage between the UI and MI groups, so we compared the saved set used ratio of the two groups. We found that the average saved set used ratio of the MI group was larger than that of the UI group, and there was a significant difference between the two groups. We believe that the reason is because MI group is using mix-initiated personalization, and the intention factor sets provided to the participants are in line with the current context. It is easier for participants to choose the intention factor set they want to use, so that they will be more willing to use those saved sets.

Edit and save functions can increase perceived active control. In both the UI and MI groups, participants could edit and save the intention factor set, and we believe that these two features give participants more control over the system because they can decide which intention factors they want to use instead of only using the ones provided by the system. According to the results of the post survey, these two groups of participants did feel more control than the

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other two groups after two weeks of field study. Based on the two arguments that edit and save functions can increase perceived active control and will not increase user effort, we can infer that our hypotheses 2 and 4 are accepted. That is, user-initiated personalized intention personalization is more suitable for use in MMRS than system-initiated personalized intention personalization, and mix-initiated personalized intention personalization is more suitable for use in MMRS than system-initiated personalized intention personalization. Because both user-initiated personalized intention personalization and mix-initiated personalized intention personalization can give more control to users without increasing user effort, they are more suitable for interactive mechanism in MMRS.

The interactive mechanism with mix-initiated personalized intention personalization does not make participants to use the edit and save functions less often. According to the analysis results of log data, there is no significant difference in the distribution of edit ratio and save ratio between UI and MI groups, and the median of edit ratio and save ratio of MI group is higher than that of UI group. We believe that the reason for this is that the system filters the intention factor set according to the context in the MI group, so that the participants may repeatedly edit or save the same intention factor set in different contexts, which increases the edit ratio and save ratio. However, since the edit and save functions do not increase the effort of participants, the edit ratio and save ratio do not affect our evaluation of user-initiated personalized intention personalization and mix-initiated personalized intention personalization. These two types of personalization can bring more control to the participants without increasing their effort. Therefore, we can say that our hypothesis 3 is rejected, and both types of personalization are suitable for application in MMRS.

6-2 Theoretical implications

In the past studies, there are few papers related to MMRS. In our study, we not only discuss the characteristics of MMRS, but also develop a micro-moment recommender app that

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allows us to observe people's behavior when facing micro-moments. In our app *deleecious*, we successfully applied different types of personalization to the design of the interactive mechanism and constructed a development process for the MMRS. Restaurant recommendation is a field that fits the characteristics of micro-moment recommendation, because the current context and intentions have a great influence on human choices. In other domains with similar characteristics, such as music recommendation, a MMRS can be developed by following the development process proposed in this study. When designing the app, we used context factor to compose the current context, and then collected different factors that people would consider in different contexts through a survey to link the context with people's intention and organize some default intention factor set. This approach can be used to quickly build systems with system-initiated personalized intention features in less complex contexts.

6-3 Practical implications

After our research, we found that the interactive mechanism of user-initiated and mix-initiated personalization is more suitable to be used in the restaurant's micro-moment recommender system. In addition, we also found that the control provided to the participants through edit and save functions does not necessarily increase their effort, so in practice, these two functions can be used more often, not only in the micro-moment recommender system, but also in the general recommender system. General recommender systems often try to simplify the operation process in order to save users' effort, but this practice also affects the quality of recommendations. Therefore, general recommendation system can be improved if more edit and save functions are employed.

Restaurant recommendation is a field where people's domain knowledge does not differ much, and everyone has a certain degree of domain knowledge about the characteristics of restaurants. The interactive mechanism we use in our field study can effectively collect all the users' intention. In other domains where domain knowledge does not have a large difference,

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the interactive mechanism used in this study can also be useful to help the system collect user intentions.

6-4 Limitations and future work

In this study, we actually developed a micro-moment recommender app, and through field study and post survey, we summarized that user-initiated personalized intention and mix-initiated personalized intention personalization are more suitable for designing the interactive mechanism of MMRS. However, there are some limitations in the experimental process of this study. First of all, we recruited the participants through a student-only online bulletin board, resulting in almost all of the participants were students. Although students had the same need to go to restaurants, the behavior among students was more limited. In addition, because of the covid-19 epidemic, the frequency of going out was greatly reduced, so the frequency of the participants using the app was also reduced. We were also unable to confirm that the participants actually went out to restaurants when using the app. All these reasons may lead to bias in our findings. In the future, we can improve on these limitations and continue our research. We can recruit participants from more diverse channels and add a mechanism to the app to ensure that the participants actually went to the restaurant. In addition, the micro moment recommender system can be used not only in the field of restaurant recommendation, but also in other areas. In the future, based on our research results, we can continue to study other aspects of the MMRS.

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Appendix A - Preliminary survey

English version.

Instruction: We would like to know if context affects how people choose a restaurant. You may choose one or more answers to the following questions.

Q1 In the following context, would you choose a restaurant based on the services it offers (in-house/takeaway)?

- During the day, I would choose a restaurant based on the service it offers (in-house or carry-out).
- During the night, I would choose a restaurant based on the service it offers (in-house or carry-out).
- During the weekday, I would choose a restaurant based on the service it offers (in-house or carry-out).
- During the weekend, I would choose a restaurant based on the service it offers (in-house or carry-out).
- When the weather is good, I would choose a restaurant based on the service it offers (in-house or carry-out).
- When the weather is bad, I would choose a restaurant based on the service it offers (in-house or carry-out).

Q2 In the following context, would you choose a restaurant based on the average consumption?

- During the day, I would choose a restaurant based on the average consumption.
- During the night, I would choose a restaurant based on the average consumption.
- During the weekday, I would choose a restaurant based on the average consumption.
- During the weekend, I would choose a restaurant based on the average consumption.
- When the weather is good, I would choose a restaurant based on the average

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consumption.

- When the weather is bad, I would choose a restaurant based on the average consumption.

Q3 In the following context, would you choose a restaurant based on the time you have?

- During the day, I would choose a restaurant based on the time I have.
- During the night, I would choose a restaurant based on the time I have.
- During the weekday, I would choose a restaurant based on the time I have.
- During the weekend, I would choose a restaurant based on the time I have.
- When the weather is good, I would choose a restaurant based on the time I have.
- When the weather is bad, I would choose a restaurant based on the time I have.

Q4 In the following context, would you choose a restaurant based on the distance?

- During the day, I would choose a restaurant based on the distance.
- During the night, I would choose a restaurant based on the distance.
- During the weekday, I would choose a restaurant based on the distance.
- During the weekend, I would choose a restaurant based on the distance.
- When the weather is good, I would choose a restaurant based on the distance.
- When the weather is bad, I would choose a restaurant based on the distance.

Q5 In the following context, would you choose a restaurant based on the restaurant's rating?

- During the day, I would choose a restaurant based on the restaurant's rating.
- During the night, I would choose a restaurant based on the restaurant's rating.
- During the weekday, I would choose a restaurant based on the restaurant's rating.
- During the weekend, I would choose a restaurant based on the restaurant's rating.
- When the weather is good, I would choose a restaurant based on the restaurant's rating.
- When the weather is bad, I would choose a restaurant based on the restaurant's rating.

Mandarin version.

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介紹：我們想知道情境是否會影響人們對餐廳的選擇。針對下列問題您可以選擇一個或多個選項。
Q1 請問您在下列的情境中，您會不會依據餐廳提供的服務（內用/外帶）來選擇餐廳？ • 在白天的時候，我會以餐廳提供的服務（內用或外帶）作為我選擇餐廳的依據。 • 在晚上的時候，我會以餐廳提供的服務（內用或外帶）作為我選擇餐廳的依據。 • 在平日的時候，我會以餐廳提供的服務（內用或外帶）作為我選擇餐廳的依據。 • 在假日的時候，我會以餐廳提供的服務（內用或外帶）作為我選擇餐廳的依據。 • 在天氣好的時候，我會以餐廳提供的服務(內用或外帶)作為我選擇餐廳的依據。 • 在天氣不好的時候，我會以餐廳提供的服務（內用或外帶）作為我選擇餐廳的依據。
Q2 請問您在下列的情境中，您會不會依據餐廳的個人平均消費來選擇餐廳？ • 在白天的時候，我會以餐廳的個人平均消費作為我選擇餐廳的依據。 • 在晚上的時候，我會以餐廳的個人平均消費作為我選擇餐廳的依據。 • 在平日的時候，我會以餐廳的個人平均消費作為我選擇餐廳的依據。 • 在假日的時候，我會以餐廳的個人平均消費作為我選擇餐廳的依據。 • 在天氣好的時候，我會以餐廳的個人平均消費作為我選擇餐廳的依據。 • 在天氣不好的時候，我會以餐廳的個人平均消費作為我選擇餐廳的依據。
Q3 請問您在下列的情境中，您會不會依據您擁有的用餐時間來選擇餐廳？ • 在白天的時候，我會以我擁有的用餐時間作為我選擇餐廳的依據。 • 在晚上的時候，我會以我擁有的用餐時間作為我選擇餐廳的依據。 • 在平日的時候，我會以我擁有的用餐時間作為我選擇餐廳的依據。 • 在假日的時候，我會以我擁有的用餐時間作為我選擇餐廳的依據。 • 在天氣好的時候，我會以我擁有的用餐時間作為我選擇餐廳的依據。 • 在天氣不好的時候，我會以我擁有的用餐時間作為我選擇餐廳的依據。

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Q4 請問您在下列的情境中，您會不會依據與餐廳的距離來選擇餐廳？

- 在白天的時候，我會以與餐廳的距離作為我選擇餐廳的依據。
- 在晚上的時候，我會以與餐廳的距離作為我選擇餐廳的依據。
- 在平日的時候，我會以與餐廳的距離作為我選擇餐廳的依據。
- 在假日的時候，我會以與餐廳的距離作為我選擇餐廳的依據。
- 在天氣好的時候，我會以與餐廳的距離作為我選擇餐廳的依據。
- 在天氣不好的時候，我會以與餐廳的距離作為我選擇餐廳的依據。

Q5 請問您在下列的情境中，您會不會依據餐廳的評分來選擇餐廳？

- 在白天的時候，我會以餐廳的評分作為我選擇餐廳的依據。
- 在晚上的時候，我會以餐廳的評分作為我選擇餐廳的依據。
- 在平日的時候，我會以餐廳的評分作為我選擇餐廳的依據。
- 在假日的時候，我會以餐廳的評分作為我選擇餐廳的依據。
- 在天氣好的時候，我會以餐廳的評分作為我選擇餐廳的依據。
- 在天氣不好的時候，我會以餐廳的評分作為我選擇餐廳的依據。

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Appendix B – Onboarding survey

English version.

Instruction: Onboarding survey can be divided into two parts, cuisine preference and recommender system usage habits.
Cuisine preference **Q1** Please select your preferred cuisine to be used as parameters for the recommendation algorithm in the app. You can select as many options as you want. • Taiwanese • Chinese • Korean • Hong Kong style • Thai • Vietnamese • Italian • French • American • German • European • Southeast Asia • Japanese • Indian • Mexican • Russian • Middle Eastern • Hawaiian

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• drinks • coffee • Bar/Bistro
Recommender system usage habits **Q1** How often do you usually use your cell phone to check information? • Never. • Once a day. • Several times a day. • Once a week. • Several times a week. **Q2** Have you ever used a recommender system? (e.g., Netflix movie recommendations, Spotify music recommendations...) • Yes, I have. • No, I haven't. **Q3** How often do you usually use the mobile recommender system to check information? • Never. • Once a day. • Several times a day. • Once a week. • Several times a week.

Mandarin version.

介紹：onboarding survey 可以分成兩個部分，分別是菜系偏好和推薦系統使用狀況。
菜系偏好 **Q1** 請選擇您偏好的菜系，作為 APP 中推薦演算法參數使用。

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- 台式
- 中式
- 韓式
- 港式
- 泰式
- 越式
- 義式
- 法式
- 美式
- 德式
- 歐式
- 東南亞
- 日式
- 印式
- 墨式
- 俄式
- 中東式
- 夏威夷式
- 飲料
- 咖啡
- 酒吧／餐酒館

推薦系統使用狀況

Q1 請問您平常使用手機查詢資訊的頻率為何？

- 從來不會。
- 一天一次。

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- 一天多次。
- 一週一次。
- 一週多次。

Q2 請問您是否使用過推薦系統？（例如 Netflix 影劇推薦、Spotify 音樂推薦...）

- 是。.
- 否。

Q3 請問您平常使用手機推薦系統來查詢資訊的頻率為何？

- 從來不會。
- 一天一次。
- 一天多次。
- 一週一次。
- 一週多次。

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Appendix C – Post survey

English version.

Instruction: Please answer the following questions. Q1.1 to Q1.6 are about perceived active control. Q2.1 to Q2.3 are about MMRS anticipation. Q2.4 to Q2.9 are about effort.

Q1 To what degree do you agree with the following statements regarding your control over the intention factor set when you use the restaurant recommendation app to select a restaurant?

1. When I use the app, I can freely choose which intention factors I want to see.
2. When using the app, I can freely save the adjusted intention factor sets.
3. When using the app, I can always tell which intention factor set I'm currently using.
4. When using the app, I can always tell which intention factor set I'm about to switch into.
5. When using the app, I can only use the intention factor sets provided by the system.
6. Throughout my experience with the app, I felt that I had a lot of control over the intention factor sets.

Q2 To what degree do you agree with the following statements regarding your overall experience when using the restaurant recommendation app to select a restaurant.?

1. When I use the app, I want to see information that is only relevant to me.
2. When I use the app, I want to decide my own process.
3. When using the app, I would expect the app to be designed to meet individual differences.
4. Overall, I am satisfied with the simplicity of the restaurant recommendation app.
5. I think it is easy to use the intention factor set in the restaurant recommendation app.
6. I can effectively use the intention factor set in the restaurant recommendation App to complete tasks.

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7. I can use the intention factor set in the restaurant recommendation App to complete tasks quickly. 8. I can use the intention factor set in the restaurant recommendation App to complete tasks efficiently. **9.** I think it is easy to learn how to use the intention factor set in the restaurant recommendation App.
All the questions are measured on 7-point Likert scales: 1 = Strongly disagree. 2 = Disagree. 3 = Somewhat disagree. 4 = Neither agree nor disagree. 5 = Somewhat agree. 6 = Agree. 7 = Strongly agree.

Mandarin version.

介紹：請回答下列問題。Q1 是關於控制程度的感受。Q2-1 到 Q2-3 是關於客製化的動機。Q2-4 到 Q2-9 是關於花費的心力。
Q1 請針對您在使用餐廳推薦 APP 去進行選擇餐廳的任務時，對傾向因素組合的控制，回答以下問題。 1. 在使用 APP 時，我可以自由選擇我想看到哪些傾向因素。 2. 在使用 APP 時，我可以自由儲存我調整過的傾向因素組合。 3. 在使用 APP 時，我永遠可以知道我目前正在使用哪個傾向因素組合。 4. 在使用 APP 時，我永遠可以知道我正要調整成哪個傾向因素組合。 5. 在使用 APP 時，我只能使用系統提供的傾向因素組合。

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6. 在使用 APP 的整個經驗中，我覺得我對傾向因素組合有很大的控制權。
Q2 請針對您在使用餐廳推薦 APP 去進行選擇餐廳的任務時，對整體使用體驗的感受，回答下列問題。 10. 在使用 APP 時，我會想看到只與我個人有關的資訊內容。 11. 在使用 APP 時，我會想自己決定自己的操作流程。 12. 在使用 APP 時，我會期待這個 APP 有滿足個體差異的設計。 13. 整體來說，我對餐廳推薦 APP 的簡單程度感到滿意。 14. 我覺得使用餐廳推薦 APP 中的傾向因素組合很簡單。 15. 我可以有效的使用餐廳推薦 APP 中的傾向因素組合完成任務。 16. 我可以使用餐廳推薦 APP 中的傾向因素組合快速的完成任務。 17. 我可以使用餐廳推薦 APP 中的傾向因素組合有效率的完成任務。 **18.** 我覺得要學習如何使用餐廳推薦 APP 中的傾向因素組合是容易的。
所有問題都以 7 分的李克特量表來衡量。 1 = 非常不同意。 2 = 不同意。 3 = 部分不同意。 4 = 普通。 5 = 部分同意。 6 = 同意。 7 = 非常同意。

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