Context-aware User Interaction for Mobile Recommender Systems

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ABSTRACT

We are witnessing more and more mobile recommender systems applied in e-tourism, utilizing contextual information in order to boost productivity and user experience by generating more tailored suggestions to them. In the meantime, the design of these applications is getting more and more user-centered. Context of use is playing an important role in the appropriateness of a user interface (UI). This motivates our study to devise a novel approach for augmenting user interaction experience on smartphones by exploiting the current context of the end user. For this purpose, we have designed and implemented a context-aware UI based on an existing mobile application for recommending tourist places. We have conducted a user study and measured the effectiveness of our method in terms of three attributes: task completion time, the perceived user ease of use and the perceived user satisfaction. The within-subject evaluation conducted with 25 participants confirms that the proposed context-aware UI can enrich user interaction experiences.

CCS Concepts

•**Human-centered computing** → *User interface design;*

Keywords

User interfaces; mobile application; recommender system; tourist guide; user study

1. INTRODUCTION

For many tourists, smartphones and other mobile devices have become indispensable as electronic personal tour guides, since they enable the access to tourist information and services anytime and anywhere. Particular emphasis has been given to benefits of exploiting contextual information in applications to provide highly accurate and relevant services to users. However, utilizing these contextual parameters to update the user interface (UI) based on the user's current contextual situation has not been given much consideration in previous studies. The fundamental motivation for our work is to investigate the influence of exploiting the traveler context in which the mobile tourism application is intended to be used in order to offer a situation-aware UI.

The primary hypothesis of the study is whether tailoring the application's UI and interaction methods to the current context of the end user enriches the end user's interaction experience. Because by considering context of use, more supportive input modalities might be offered to users to assist them for their current situation. To prove this hypothesis, in this paper, we propose and test different UI options in certain contextual situations such as moving context and still context. We also present the results of a conducted user study in which users were asked to test the adapted UI and compare it with the original, non-adapted UI. In this user study, we logged the user interaction and recorded the task completion times. Besides that, we measured the perceived user satisfaction and ease of use by means of an online questionnaire.

The contents of this article can be summarized as follows: Section 2 discusses related work and focuses on the existing applications. We will then describe the solution and high-level design and elaborate the technical set-up of the experiments in Section 4. We designed and implemented our work upon of a fully functional application that is called South Tyrol Suggests (STS) [5], which we will describe in more details in Section 3. Section 5 is dedicated to evaluation results of our experiment and a discussion of the proposed novel methodology addressing the research concerns. Finally, Section 6 draws conclusions and provides future work directions.

2. RELATED WORK

In this section, we investigate the current state of the art of: 1) the available interaction methods in existing applications, 2) and the literature and other approaches proposed for tourism recommender systems (RSs) on smartphones.

2.1 Interaction Methods on Existing Apps

Due to the lack of more flexible and personalized gestures for interaction with smartphones and the limitation of their screen sizes and other resources to access rich functionalities, new methods of input for mobile devices should be investigated and expanded. To resolve the aforementioned issue, extensive research has been conducted and a large number of interaction modalities has been proposed. Brewster et al. [6] studied pressure input method in their work. They designed a pressure-based keyboard where a soft press on the touchscreen generated a lowercase letter and a harder press an uppercase one. The results showed that text entry with pressure keyboard was effective and can outperform a standard shift-key keyboard design on a mobile touchscreen device.

In addition, as nowadays most of the tasks are being done mobile, we need more interactions that leave visual attention unoccupied, so that users can concentrate on their main activity. One of these eyes-free input modalities is auditory interfaces presented by Sodnik et al. [19], which is useful for non-concentrated situations like driving. The proposed approach proved to be very effective and safe to use, since the driver could have a low-level distraction compared to the traditional user interactions. Likewise, in our previous work [13], we investigated three different input methods in such non-concentrated scenarios. We compared three different input methods and we demonstrated free-form gestures such as tilt in our application outperformed other input modalities when the environment is distracting, and are more embraced by users in spite of higher noise rate to the cause of non- concentrated situations' nature.

Authors in [14] expanded the bandwidth of new interaction methods by proposing rotation of a handheld device around a single axis in a 90 degree range to make choice among menu items. The system is immediately learnable by novices and supports eyes-free use by experts.

Previously, Dybdal et al. [9] investigated hands-free interactions using eye movements only to control mobile devices. Two gaze-based strategies, i.e., dwell time selections and gaze gestures, were compared in their experiment to discover the optimal interaction with smartphones. The main advantage of gaze interaction is that it can be done hands-free, thus allowing to control a mobile device without touching it. They demonstrated, gaze gestures are less error prone and were faster than dwell selections by gaze but generally gaze interaction had a lower performance than touch interaction.

Another interesting technique proposed to enhance the performance of user interaction on smartphones is voice. Sakamoto et al. [18] suggested a technique called voice augmented manipulation (VAM) to augment a user's input (a finger gesture or button press) with voice input in a mobile device. There were two methods: one used a user's voice and finger gestures (scrolling, pinching, etc.), and the other used a user's voice and a button interface.

Recently, Rozado et al. [17] also carried out a study to test the feasibility of using gaze gestures to interact with a smartphone. They compared two modalities of performing the gesture: without dwell-time and with dwell-time. Based on a data set collected from 20 participants, the modality without using dwell had faster completion time, yet less accurate and more error probable than the modality using dwell time. Hence, learning effects have been studied in this project, which revealed no obvious learning effect over time in accuracy or performance.

Chen et al. [7] presented BlindPass, a new password entry method. They developed and evaluated four eyes-free password entry methods: (i) Number Pad, which augments the conventional input methods such as number pad with auditory feedback, tactile feedback, or both; (ii) Wheel, which mimics the spatial location of numbers in the clock face. Users can tap the numbers according to their spatial difference, or swipe along the screen to enter a password; (iii) Stroke, which allows users to enter the password using gesture, similar to a marking menu; and finally (iv) Scroll, where users input the password by swiping up or down from any position on the screen until the desired number is reached before lifting up their finger; on a smartphone in order to enhance security in secured applications such as e-banking, booking flight tickets, and etc. Their results showed that eyes-free passwords are easy to use and relatively easy to learn. Further, both Wheel and Stroke input methods were faster to perform.

Prior studies have explored a variety of input modalities, however, most of the work discussed so far is not for tourism and/or mobile domain. We focused on applying some of the user-centered, flexible gestures which could possibly improve tourists' mobile interaction satisfaction.

2.2 Tourist Recommender Systems on Smartphones

The capabilities of modern smartphones make them a primary and indispensable platform in people's everyday life. One of their most attractive services that people take advantage is mobile tourist guide applications wherein tourists increasingly spend considerable time planning their travel activities. Therefore, we review some of the research in this area that influenced our solution. New developments in network connectivity and the wide variety of available sensors in current mobile devices gave rise to the field of context-aware application and services, assisting applications to offer more personalized and tailored services to tourists in order to address some of the limitations of handheld devices such as small size and limited processing power.

Lately, Gavalas et al. [10] proposed a classification of existing mobile tourism RSs prototypes on the basis of the following aspects: (a) their chosen architecture, (b) the degree of user involvement in the delivery of recommendations, and (c) the criteria taken into account for deriving recommendations. Furthermore, they investigated the last item in more detail and classified as following: user constraints-based recommender systems, pure location-aware recommender systems, context-aware recommender systems and critique-based recommender systems. At the end the potential trends for this field in addition to its challenges have been provided.

One of the earliest works that applied context-awareness in the mobile tourist application was Setten et al. [21] in 2004. They combined context-awareness with recommender systems in a mobile tourist application named COMPASS which serves a tourist with map-based information services based on their interest and some specific context.

Another context-aware mobile recommender project, i.e., ReRex [2], has investigated the importance of exploiting a traveler's contextual situation for recommending points-of-interests (POI) on mobile recommender systems and assessed user acceptance of these recommendations by asking users to judge whether that contextual factor actually affects their rating. They took into account several important contextual factors which seem more effective in the generation of the relevant and personalized recommendation and shortly justified the recommendations. The results revealed the higher user acceptance and satisfaction for the context-aware version.

In 2013, Braunhofer et al. [5] initiated the development of South Tyrol Suggests (STS), a context-aware mobile recommender system that suggests POIs in South Tyrol in Italy. STS provides several innovative interface elements, including: (a) personality questionnaire, i.e., a brief and entertaining questionnaire used by the system to learn the user's personality; (b) active learning module that acquires context-dependent ratings for POIs that users are likely to have experienced, hence, reducing the stress and annoyance to rate (or skip rating) items that the users do not know

[4]; and (c) recommendation module that relying on matrix factorization leverages context-dependent ratings and personality information in order to generate more relevant personalized recommendations for users, even if they are new to the system (i.e., new user cold-start problem). In several live user studies and analyzing the log data produced by a larger sample of users that have freely downloaded and tried STS through Google Play Store, the authors have evaluated the system and showed that the system in general is perceived as useful and easy to use.

Biuk-Aghai et al. [3] designed and implemented content-based recommender systems for tourists. They extended their previous app "MacauMap" (a mobile tourist guide and map system) and employed a genetic algorithm for generating travel plan and a fuzzy-logic based module for calculating visit/stay times for each stop of the entire trip.

In order to offer more customized items to travelers, Kularbphettong et al. [12] introduced hybrid recommendation on smartphones including ontology, collaborative-filtering and location-based services methodologies. They designed and implemented a heritage-tourism mobile recommender system and assessed the suitability of places for users by using aforementioned methodologies.

Tumas et al. [20] implemented a personalized mobile city transport advisory system (PECITAS). Using this app users can obtain recommendations for personalised paths between two arbitrary points in the city of Bolzano, Italy by city transport means and walking which generates multiple routes. They used knowledge-based technology to recommend and rank different routes more personalized to the guests by exploiting their travel-related preferences.

Pawara et al. [16] implemented and tested a prototype which is an example of systems using collaborative-filtering. The application took advantages of collaborative user-generated content, which has a location-aware chat system. They claim that their application has easier access to information than those that used social network as it does not require process of joining and requesting associations so as to approach the valuable information of other tourists.

Page et al. [15] discovered that a communication style personality trait they called "for your information" (FYI) mostly predicts the adoption of location-sharing social networks (LSSN) and disclosure behavior. LSSN enable users to share their location with their family and friends and benefit of social advantages. They also found that the youngest interviewees are commonly FYI communicators.

One of the recent works which utilizes contextual information for recommendation is Pythia, a privacy-enhanced personalized contextual suggestion system for tourism. An innovative user-centric architecture has been proposed in this work which combines the following features: the (sensitive) personal data (e.g., location data) are stored at the user-side as well as the profile of user interest which will be created based on these data. The contextual suggestions are also generated at the user-side. This combination offers strong privacy since the personal data is not disclosed to any party, including the recommender service provider [8].

The state of the art stated in this section reveals that mobile tourism RSs are one of the most popular strand of research for mobile RSs. Particular emphasis has been given to benefits of exploiting contextual information to deliver highly accurate and relevant recommendations. Despite these significant efforts, not much work has been done with respect to exploit these contextual parameters to update the UI based on user current situations. This highlights our study motivation that takes into account traveler current context to offer situation-aware UI.

3. APPLICATION SCENARIO

We designed and implemented our work upon South Tyrol Suggests (STS) [5]. STS is an Android-based mobile recommender system aimed at offering context-aware recommendations for touristic items (i.e., accommodations, restaurants, sport, cultural attractions and events) for the South Tyrol region of Italy. Its main functionality is to suggest context-aware and tailored recommendations of touristic items to tourists and they can search for POIs.

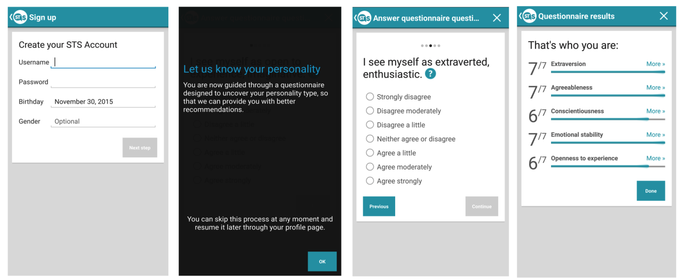


Figure 1: Personality questionnaire

This application uses a repository of approximately 27,000 POIs/tourist items data, as it is connected to the most comprehensive databases offered by the Regional Association of South Tyrol's Tourism Organizations (LTS[1]), the Autonomous Province of Bolzano[2], the Municipality of Bolzano[3] and SASA[4].

The system computes rating predictions for items by considering their contextual information with the aim of providing more accurate and personalized recommendations for tourists. Moreover, user personality and active learning are exploited in order to tackle the cold-start problem. Then, the items with the highest predicted ratings are recommended for that specific context.

As depicted in Figure 1, the first phase of the active learning procedure in STS starts by entering some basic information by the user through registration stage such as her birthdate and gender, in addition to the Five-Item Personality Inventory (FIPI) [11].

Another source of information to predict the most relevant items for the user can be obtained from the context settings, which are accessible from the user profile page, as illustrated in 2. They allow the user to fine-tune the current contextual situation by enabling and setting the values of those factors that can not be automatically acquired, such as the duration of the current stay, the user knowledge of the travel area, the current budget, the actual companion and feelings.

By exploiting the evaluated personality (as mentioned previously), the user's age and gender (if available), in addition to the value of the considered contextual factors, the system

[1]LTS: www.lts.it
[2]Autonomous Province of Bolzano: www.provinz.bz.it
[3]Municipality of Bolzano: www.gemeinde.bozen.it
[4]SASA: www.sasa.bz.it

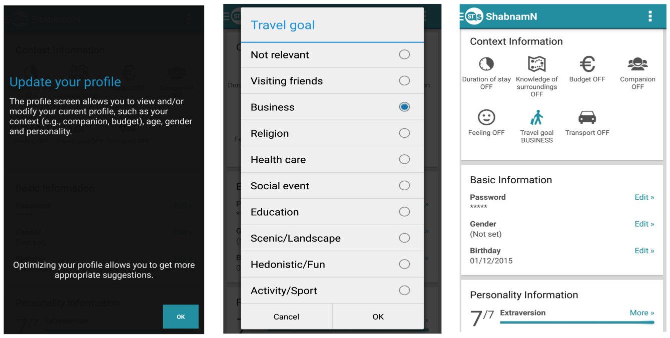


Figure 2: User profile and context settings

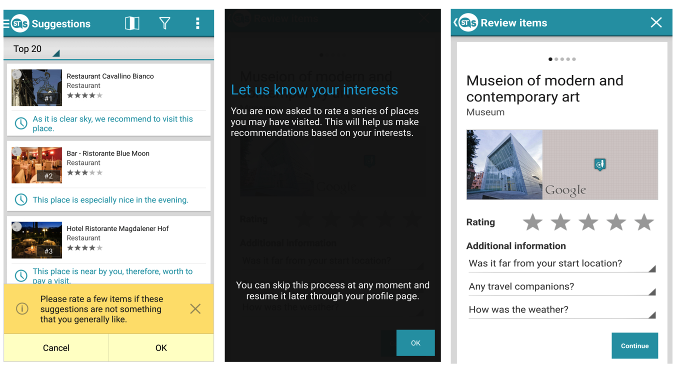


Figure 3: Ratings-in-context for POIs

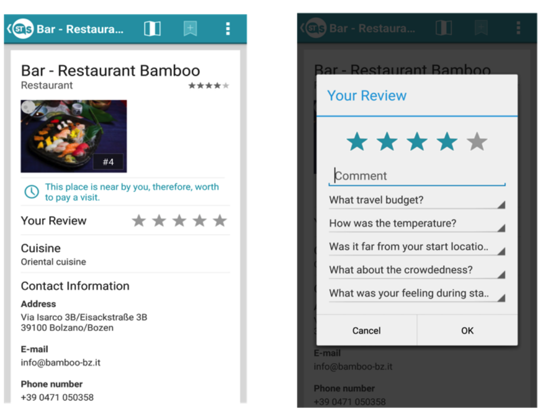


Figure 4: Item details

identifies and shows 20 highly relevant POIs to the tourist. The user can see for each item on the list information such as a photo, its name, as well as an explanation of the reason why that recommendation has been offered which estimated most influential contextual condition by the system. Another feature of the POI suggestions screen is that it provides users with a pop-up window that request the user to provide more ratings-in-context for POIs, as can be seen in Figure 3.

As illustrated in Figure 4 (left), by clicking on any preferred item, the user is redirected to the item details page where she can access more data of the selected POI such as its photo, name, description, user reviews, its category as well as an explanation of why this item was offered to the user or request a route suggestion to reach there. Tagging and bookmarking the POI in order to easy get back to it later is also possible in this page. Furthermore, there are options to rate the item as well as write a review for it, which is depicted in the right image.

Our work enriches the app by considering context such as tourists' current activity like walking or still in order to tailor the UI.

4. DESIGN AND IMPLEMENTATION

This section provides a description of the research approach used in this project in addition to other possible solutions that might be useful. At first, the initial ideas are explored, and then we elaborate on the technical setup of the described experiments in this section.

4.1 Research Methodology

The main idea is tailoring and adopting input modalities to interact with handheld devices based on tourist's current contexts. In our previous work [13], we investigated the influence of interaction methods on the user's rating behavior as one possible source of noise in ratings. In the next stage, we would like to address the following issues:

- Automatic context detection
- Introduce new interaction methods
- Set an appropriate modality for the detected context

Afterwards, we implemented the solution into STS for the experimentation. Finally, the perceived user satisfaction was evaluated to measure the usefulness of our proposed approach.

4.2 Contextualizing Input Methods

It is important to identify meaningful contextual factors, e.g., ambient conditions, display brightness level, display size, noise level, user activity, experience of user (experienced or new). Also it is crucial to identify possible interaction consequences (e.g., interface will change from colour to black and white, font or picture size increases, certain functionality like voice input / output is omitted, certain functionality asks for confirmation (e.g., "5 stars? Are you sure?"). Users could then be asked to perform a specific user task under various contextual conditions (can be simulated) using a specific interaction method (e.g., search for a POI recommendation, provide a review for a POI) and provide their subjective feedback, which together with some implicit feedback (time to completion, success rate, ...) will be used

Table 1: Context and Interaction Consequence(s)

Context	Interaction consequence
Low brightness level	Interface changes to large font text, increase the brightness level of the screen while the environment is dark [22]
User is stressed by high noise levels	Ask for confirmation after entering a rating, e.g., "1 star? Are you sure?"
User is new to the application	Show on-screen tutorials/ context-sensitive help
User is driving a car	Switch to car mode (eyes-free interaction) [19]
User is walking	Interface changes to bigger icons/buttons
User is sitting	Shows more detail to user
High noise level	Voice gesture is omitted
Cold weather	Switch from touch-screen gestures or button press to hands-free gestures like voice or gaze
The user hands are busy	Switch to hands-free interaction method like "gaze" to send commands [17]
The mobile phone is in a Wi-Fi environment	Playing item-list video and animations [22]
The mobile phone is not in a Wi-Fi environment and using its internet connection (e.g., 3G)	Only allows images displayed at the current network environment [22]

to evaluate the right interaction method for each context.

Table 1 has been obtained by analyzing some other scientific methods in addition to suggesting some new context and interaction consequence(s) pairs to examine. Zheng et al. [22] have proposed a rule-based approach in order to design the context-sensitive mobile UI. The rules consisted of conditions and actions. In order to personalize their proposed context-sensitive UI, they have considered the context information that comes from various sensors built in the mobile device as well as from the user's profile. Suppose, for instance, a user wants to check the latest recommendations and order an item in a dark and noisy environment. Then, the UI can display the result in large font text, increase the brightness level of the screen; accept the order given by the user by tapping, rather than typed on the keyboard, or by voice in order to adapt to the context. In this scenario, the rule was: change to large text output while the environment is dark and noisy. Besides, there were three options to accept the order given by the user including tapping, typing on the keyboard, or by voice. Each action would be activated based on the match context value. Therefore, tapping would be activated in her current situation.

Our research differs in that we have been able to implement a context-adaptive UI and conduct a user study to investigate whether it enriches the end user interaction experience on smartphones.

In the following, we are describing the suggested context and UI consequence(s) pairs:

To improve the accuracy of the user rating we propose to ask her for confirmation after entering a rating, while she is stressed by high noise levels. For example, "1 star? Are you sure?"

On-screen tutorials/context-sensitive help can quickly show new users what's important on the Application in use. Hence, gestures used for the interaction and the UI controls can also be explained.

For some situations like driving it is very important employing interactions to not draw the user's visual attention away from their main activity. Sodnik et al. [19] proposed exploiting auditory interfaces, which are eyes-free gestures and proved they have a low-level distraction compare to the traditional user interactions. Therefore, these interfaces are very effective and safe to use.

When a user is in distracting situations such as walking, it is hard to focus on the mobile screen. Thus, bigger icons/buttons and large font size was proposed to keep the user focused on her main activity. In contrast, in a sitting situation she can further concentrate on her mobile screen so representing more details might be preferred.

Table 2: Context and interaction consequence(s) for various functions of RS

Context variation	RS function	Interaction consequences
User is moving	Searching among suggested items	Bigger icons/buttons with less detail information appears
	Bookmark	Long press anywhere on the screen of the selected item page
	Rating	The review question page before rating is omitted and switch to tilt interaction to rate
User is sitting		Switch to one-finger-hold-pinch

In high noise level conditions, detecting the correct command via voice is very challenging. So, omitting the voice gesture is recommended in these situations.

Another case is when the weather is cold; touchscreen gestures would be very annoying. Since users do not like to be enforced taking their gloves off and freezing their fingers off to use the smartphones. Hands-free gestures like voice or gaze have no such problem.

Rozado et al. [17] indicated the benefits of using gaze gestures in situations where one or both of our hands are busy with other tasks. For example, when using public transportation and holding the smartphone with one hand while using the other hand to hold a handle, it would be very useful to send commands to the phone by means of gaze gestures.

In addition, downloading videos are only suggested if the mobile phone is using Wi-Fi signals. In other Internet connections (e.g., 3G) the application only displays images [22].

Meanwhile, in our previous study [13], we illustrated that different users might prefer different interaction methods in various contexts. As a result, a dynamic adaptation of the UI based on individual users is preferred. The appropriate UI for the detected context and the user type must be learned by the system, not simply enforced by the system designer. Thus, there is the need to implement learning techniques that detect what input modality or UI element qualifies that specific situation as well as the user type. This could be done as a classification task where its input comprises the user personality type and the corresponding context, and the category/class is one of the available input modalities/UI features.

We are in the phase of proposing and testing the several options in the certain contextual situations, which can be the foundation of a dynamic adaptation. In other words, this information can be utilized as example inputs for personalization.

We created Table 1 as a starting point with options in principle. However, we opted to implement only some of them which will be represented in the Table 2. A user study will allow to determine which interaction consequence(s) are truly relevant for the various contexts.

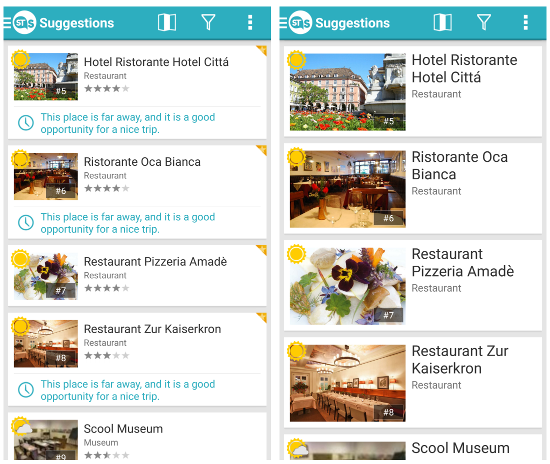
4.3 Implementation Details

Table 2 specifies the augmented functionalities for the STS app in this study.

One of the most important contexts for the study purpose is the user's current activity. To this objective, we used Google's Android Activity Recognition API [1] to recognize a user's current activity, such as walking, driving, or standing still.

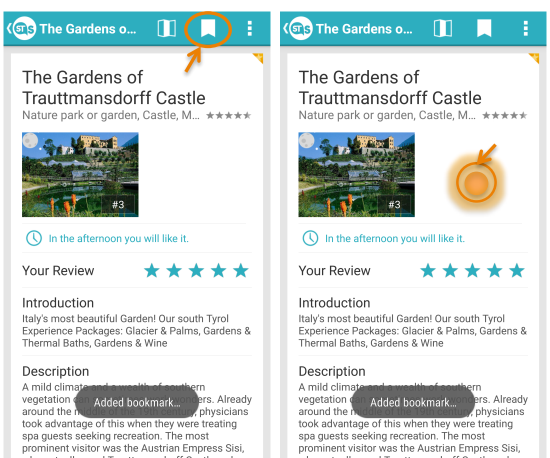
4.4 User Interface

Figure 5 depicts the comparison between the suggestion list in the non context-aware and context-aware UI both in moving context. The improved UI with the context-aware adaptations is called "context-aware" UI. Figure 5a shows the original app in moving context, while Figure 5b represents the bigger icon/text in context-aware app when the user is in moving state.



(a) (b)

Figure 5: **Suggestion list in the Original UI vs. our proposed Context-aware UI**
(a) Original UI, Smaller icon/text with more details (b) Context-aware UI, Bigger icon/text with less details



(a) (b)

Figure 6: **Bookmarking items in the Original UI vs. our proposed Context-aware UI**
(a) Original UI, Press bookmark button (b) Context-aware UI, Long press anywhere on the item detail page

The screen where users are asked to bookmark an item is illustrated in Figure 6. We proposed long press anywhere on the item detail page as a bookmark interaction method in moving context which is shown in Figure 6b. Figure 6a shows how to bookmark an item in original UI before applying context-awareness.

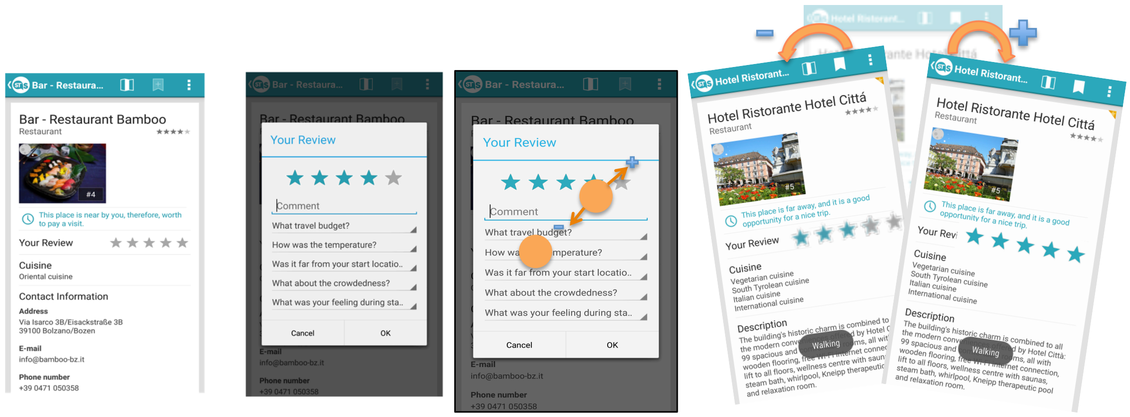
As shown in Figure 7 there are three options for rating. For moving context, we suggested removing pop-up review page and tilt gesture for rating in the main item detail page (Figure 7c). In addition, one-finger-hold-pinch was proposed for sitting context on the pop-up review page (Figure 7b). This gesture is a two-finger gesture. One finger is kept on the screen, while the second finger goes farther or closer on the screen to increase or decrease the rating stars [13]. Figure 7a also shows the original UI for rating which works by touching the star on the review pop-up page.

5. USER STUDY AND EVALUATION RESULTS

To evaluate the usability and effectiveness of our proposed method, we did an experiment to examine how the quality of user interaction in a mobile recommender system environment is influenced by the context-adaptive, multimodal UI based on the user's current context. Another objective of this study was to study the learning curve, i.e., to see whether task completion time or other metrics are lower/better (changes) after n iterations (trials) with the same interaction method. At the end we evaluated the usefulness of our proposed approach and the efficiency of the opted interaction method for each context condition by assessing the objective criteria (e.g., task completion time) as well as subjective measures (i.e., perceived user satisfaction etc.). The tests that were performed include a main comparison: STS original UI (non-context-aware UI) versus context-aware UI.

Side hypotheses of the research are defined as follows:

- H1 Bigger icons in moving context reduce the task completion time;
- H2 Bigger icons in moving context have a direct positive effect on perceived user satisfaction;
- H3 Long press anywhere on the item details page in order to bookmark that item in moving context reduces the task completion time;
- H4 Long press anywhere on the item details page in order to bookmark that item in moving context has a direct positive effect on perceived user satisfaction;
- H5 The review question page before rating is omitted and switch to tilt interaction to rate in moving context reduces the task completion time;
- H6 The review question page before rating is omitted and switch to tilt interaction to rate in moving context has a direct positive effect on perceived user satisfaction;
- H7 One-finger-hold-pinch gesture for rating function in still context reduces the task completion time;
- H8 One-finger-hold-pinch gesture for rating function in still context has a direct positive effect on perceived user satisfaction;
- H9 There is a learning curve in every interaction method; especially in complex input modalities the learning curve has a higher value, e.g., task completion time or other metrics are lower/better after n iterations (trials) with the same interaction method;



(a) (b) (c)

Figure 7: **Rating items in the Original UI vs. our proposed Context-aware UI** in Sitting/Moving context
(a) Original UI, Pop-up review page and touch the stars (b) Context-aware UI, One-finger-hold-pinch (c) Context-aware UI, Removing pop-up review page/apply tilt gesture (X-axis)

5.1 Procedure

The study consisted of one experiment with two conditions. One condition was performed with the proposed contextualized UI version, whereas the other condition was performed with the original STS before applying context-awareness to the UI.

Participants were first introduced to the application and scenario in addition to the determined tasks to accomplish. Afterwards, respondents were asked to search among suggested items while walking. Since the detected context by the application is walking, the UI switched to bigger icon/buttons. Then they were asked to select an item, bookmark it and rate the item. Long press on the screen is applied to bookmark an item. As regards to the rating, the review question page before the rating page is omitted and the input method switched to tilt gesture. All rules for walking context have been applied in this step for all aforementioned functions. Then they were asked to rate items in still context while one-finger-hold-pinch is activated. In addition, we asked participants to do aforesaid steps 10 times in order to measure the learning effects while performing the tasks. Their task completion time has been logged for each function separately.

In order to evaluate our hypothesis, we used the same study design and questionnaire with both app versions. To avoid bias due to possible learning effects, we used a counterbalanced experiment. One group first tested the context-aware UI, then the original UI; another group did it vice-versa.

After performing all determined tasks, users were asked to fill out an online questionnaire. The questionnaire aimed at evaluating the proposed context-aware UI from the end user point of view as well as how users perform on realistic tasks. The questionnaire consisted of four main categories: prior knowledge, context-adaptive UI perceived user satisfaction, original UI before applying context-awareness perceived user satisfaction, improvement of interaction experience from end user point of view. In each part we inquired the ease of use as well as the user satisfaction for each method. At the end the interviewer asked participants if the user interface and interaction methods tailored to their current context improved their interaction experience, and if they have further suggestions or ideas on the proposed idea.

5.2 Participants and Apparatus

We conducted a within-subjects user study in order to test the hypotheses. The experiment followed a within-subjects design which means every single participant is subjected to every experimental treatment, thus allowing also a small sample of respondents. It involved 25 participants (selected from the computer science and mathematics student population at the Technical University of Munich) aged between 22-35. The experiment was performed using a Samsung Galaxy S6 mini smartphone running Android 5.1.

5.3 Evaluation Results

As mentioned in the procedure of the experiment in Section 5.1, after the users tested the UIs, they answered the set of questions related to the perceived user ease of use and satisfaction. The questions were evaluated using a Likert scale with five options ranging from "Very dissatisfied" with the value of 1 to "Very satisfied" with the value of 5 (0 means the user did not rate that UI).

5.3.1 Perceived Ease of Use

Figure 8 provides information about how satisfied users were with the ease of use of the four mentioned functions in the context-aware and original UIs. The data represented are the mean value of the user responses for the ease of use, in addition to the error bars, which indicate the standard deviation of these data.

As can be seen from the data, the context-aware UI for searching among the items and rating the items in moving context performs noticeably better than the original UI. There is slightly less difference of perceived user ease of use for rating items in sitting context between context-aware UI and original UI. For the item bookmarking function in moving context, the pattern is repeated. Furthermore, the bookmarking function of the original UI has the highest value of standard deviation.

In general, users are more satisfied with the ease of use in the context-aware UI compared with the original UI in the determined functions in moving and sitting context. The

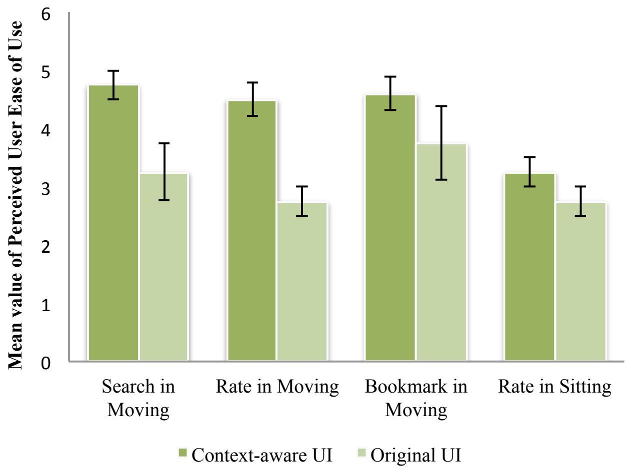


Figure 8: Perceived user ease of use results

one-tailed t-test shows that the difference in ease of use between the context-aware UI and the original UI is statistically significant (p-value = 0.05). The difference in rate in sitting is marginally statistically significant (p-value = 0.10). Rate in moving is very statistically significant (p-value = 0.003). Besides, bookmark in moving is also likely to become statistically significant if the sample size is increased.

5.3.2 Perceived Satisfaction

Figure 9 shows the mean value of perceived user satisfaction for the different functions in both context-aware and original (non-context-aware) UIs. The questions are evaluated using a Likert scale with five options ranging from "Strongly disagree" to "Strongly agree". Analogously to the previous chart, the error bars indicate the standard deviation of these data.

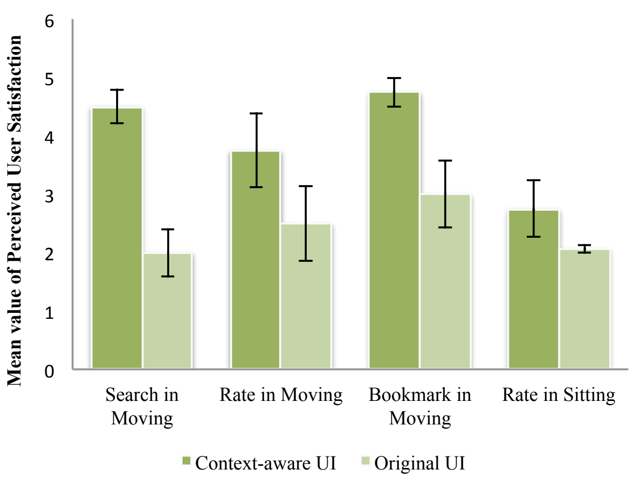


Figure 9: Perceived user satisfaction results

We conjecture that the context-aware UI has a direct positive effect on perceived user satisfaction compared with the original UI. We are interested in this hypothesis as we think context-aware UI can lead to a better interaction between users and smartphones because interaction methods are tailored to the users' current context.

Regarding the bar chart, the highest user satisfaction was obtained by the function bookmarking the items in the context-aware UI, closely followed by searching among items in the same UI. These results are in accordance with hypotheses H4 and H2. By contrast, satisfaction result for searching among items in the original UI is considerably lower. Also, perceived user satisfaction of rating items in the context-aware UI in both moving and sitting contexts is higher than in the original UI which indicates hypotheses H6 and H8.

To sum up, users have demonstrated higher satisfaction of the context-aware UI in comparison with the original UI. Based on one-tailed t-tests for the perceived satisfaction of the context-aware UI and the original UI for both search and bookmark in moving context, the results are considered to be statistically significant (p-value = 0.01) for both of them. On the other hand, rate in sitting and moving context are marginally statistically significant. It might be remedied by testing among more participants.

5.3.3 Task Completion Time

The graphs in Figure 10 show in seconds (s) terms the changing patterns of task completion time for the aforementioned functions for both context-aware and original UIs over the 10 measurements.

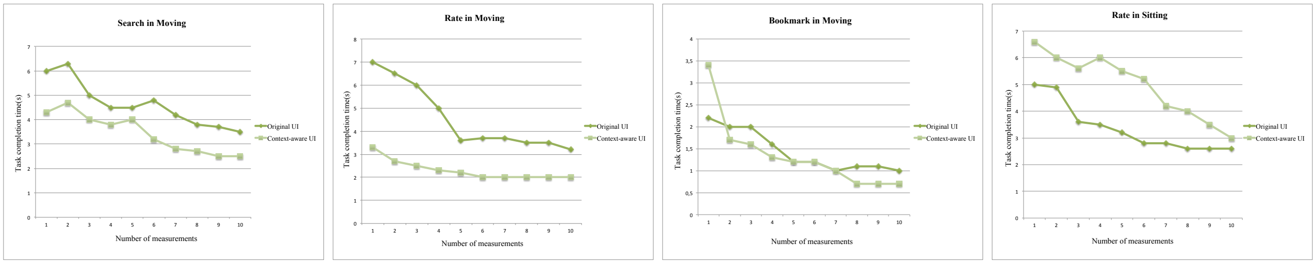
As can be seen in Figures 10a and 10b, the task completion time for the context-aware UI is lower than for the original UI which supports hypotheses H1 and H3, respectively. By contrast, in Figure 10d, the pattern is reversed which is in contradiction with the hypothesis H7. We think improving the implementation or altering the selected input modality might solve this. Furthermore, Figure 10c shows higher task completion time for context-aware UI in first measurement whereas it is equal or lower for the next measurements similar to the hypothesis H5.

It is interesting to note that regarding the four graphs, there is one basic general trend over the measurements: downward and then leveled off. It shows that there is a learning curve in every interaction method; specially in complex input modalities the learning curve has higher value, i.e., mean task completion times are lower after n iterations (trials) with the same interaction method which is according to our hypothesis H9.

6. CONCLUSION AND FUTURE WORK

In this study we built a context-aware UI to help users to boost their interaction experience for the South Tyrol Suggests (STS) mobile tourism RS. We have investigated how adapting the UI to the tourist context of use can improve her satisfaction. To this end, we used the Google's Android Activity Recognition API to recognize the user's current activity whether she is in still or moving context. We developed an appropriate UI depending on that specific context. Users then were asked to perform tasks in a study under those contextual conditions and provide their subjective feedback (i.e., perceived user satisfaction), which together with some implicit measures (task completion time) have been used to evaluate the research hypothesis.

We showed that the context-aware UI outperforms the original UI in terms of both perceived user ease of use and perceived user satisfaction. Besides, the statistical signifi-



(a) (b) (c) (d)

Figure 10: Mean value of logged time for every user in each determined interaction (a) Task completion time for searching among items in moving context (b) Task completion time for rating items in moving context (c) Task completion time for bookmarking items in moving context (d) Task completion time for rating items in sitting context

cant test showed the outperformance for the rating function in walking state in terms of the perceived ease of use. In addition, searching and bookmarking functions in moving context in terms of the perceived satisfaction showed significant differences. We conjecture the perceived satisfaction may be improved by involving further participants.

In addition, the context-aware UI decreased the task completion time in search, rate and bookmark functions in moving context. We believe, a more sophisticated implementation of both interaction methods and tourist context detection could help to further reduce task completion time. Another possible extension might be implementing and evaluating other input modalities for each aforementioned functions to decrease task completion time.

It is noticeable that regarding the task completion time graphs, a learning curve was observed during the experiment. This means after repeating the same task in a series of trials the learning will be increased; consequently task completion time can be reduced.

We can conclude that the proposed context-adaptive UI outperformed the original UI of STS that did not utilize the current context in which the application is intended to be used. Since context of use is playing a critical role in the appropriateness of a UI, further investigation of this approach is strongly recommended.

Future work can be done in a number of different directions. In a practical sense, the current quality of our context detection should be improved and some more contexts such as light, noise, weather and Internet connection of the environment should be considered.

Future research could include improvements to the system personalization, i.e., UI adaptation to context should not be same for all users. So the system must learn the type of user, in terms of adaptation preferences. In other words, as we discussed different users might prefer different interaction methods in different contexts. Therefore, our future work lies on using learning techniques for personalization. This could be done as a classification task where its input comprises the user personality type and the corresponding context, and the category/class is one of the available input modalities.

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