A Study on User Acceptance of Proactive In-Vehicle Recommender Systems

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ABSTRACT
Modern in-vehicle information systems (IVIS) are able to provide a large amount of data to the driver. If every information which might be of interest is delivered directly to the driver, information overload becomes a serious problem. Recommender systems are a promising approach to reduce information overload but they are mainly designed for desktop systems or mobile devices. In-vehicle recommender systems have to cope with interaction restrictions and limited cognitive resources of the driver. Therefore, we investigate proactive recommender systems, where recommendations are pushed automatically. The contribution of this paper is a user study in a real world setup to investigate the acceptance of a proactive recommender system while driving. The evaluation is based on the Technology Acceptance Model (TAM). As perceived ease of use is crucial for acceptance, we design an in-vehicle user interface for proactive recommendations. Our results show that our proactive recommender is perceived as helpful and assisting and is not obtrusive and distracting while driving. We also found that clear information delivery and trust is crucial for the acceptance of in-vehicle recommendations.

Categories and Subject Descriptors
H.5.2 [**Information Interfaces and Presentation**]: User Interfaces—*Evaluation/methodology*

General Terms
Design, Experimentation, Human Factors

Keywords
Proactivity, Recommender Systems, User Acceptance

1. INTRODUCTION
Modern cars have become a powerful digital device over the last couple of years. They are able to capture environmental and driver information with different kinds of sensors and access digitally available information from the Internet over broadband connections. Nevertheless, the primary task of a driver is to drive the car and maneuver through traffic situations [21]. Other tasks are even secondary including responses to the environment (e.g. a honk or a turn signal) or tertiary which is decoupled from driving and aim to provide more convenience (e.g. turning on the air conditioner). In-vehicle information systems (IVIS) exclusively comprise tertiary tasks. One kind of IVIS is searching for Point-Of-Interests (POIs) like restaurants, gas stations, etc. Nowadays a static database of POIs is used for that. With broadband Internet connection the database can be updated and additional information for POIs can be downloaded in the future which increases the amount of potentially interesting information for the driver. The usual way of selecting a POI is by querying the local database and browsing through the results.

Displaying a large amount of POIs and searching is a challenge for IVIS because of information overload. Intelligent selection of POIs by means of recommender systems [18] is a possible solution. Recommender systems became popular over the last couple of years by services like Amazon.de, Last.fm or Netflix for media or product recommendations. Due to interaction limitations, recommendations have to be provided differently in an automotive context. The driver is also not able to focus her full attention to the recommender. Therefore, we regard proactive recommender systems. They provide recommendations without explicit user request.

The goal of this paper is to investigate if user accept proactive recommendations while driving. Our application scenario is a gas station recommender. We follow the Technology Acceptance Model (TAM) [10] for evaluation. Ease of use is handled by designing an in-vehicle interface and validate it with expert interviews. An additional user study investigates the usefulness of in-vehicle recommendations. We show that our systems is perceived as useful and assistant but that trust is an important aspect.

The remainder of the paper is organized as follows. In Section 2 we discuss background information and related approaches. Next, the design of our interface is shown in detail in Section 3. Finally, we discuss the results of our user study in Section 4 and close with conclusions in Section 5.

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2. BACKGROUND AND RELATED WORK

Our system is intended to be a helpful adviser for navigation specific information, e.g. POIs and routes. The danger hereby is to distract the driver with too much information. One way to avoid distraction is to provide information in less workload intensive situations. Either we detect situations with low workload like traffic lights (e.g. in [2]) or we estimate workload directly by means of user context information (e.g. in [17]). Both methods either require additional sensors or infrastructure. Another way to cope with distraction is to reduce the amount of information generally. This is also the goal of recommender systems. The amount is reduced by means of personalization and context-adaptivity.

Our research is focused on recommender systems. In an automotive environment, input of information, e.g. for search queries, is another challenge which may cause driver distraction. Our approach applies a push instead of a pull access to the recommended items, i.e. recommendations are delivered without explicit user request. Push messages are either manually triggered by providers, e.g. news corporations push short messages to mobile user, or the system infers the need of information. For the second, we distinguish reactive systems which push recommendations based on predefined conditions, e.g. parking lots if the user is close to the destination, and proactive systems which evaluate alternatives to decide when and what to recommend. Proactive recommender systems are applied in research to provide relevant information collected in the past based on the current situation (e.g. [20]), interesting web pages based on which web page the user is watching (e.g. [7]) and interesting documents for writers based on what they are writing (e.g. [14]). However, this approaches are designed for desktop systems and mobile devices. We investigate how proactive recommender can be applied inside a car.

For the investigation presented in this paper, we built a prototype system based on previous work. In [6] we describe the idea of taking into regard current, past and future situations to make a proactive decision. Our prototype system automatically monitors situation parameter, e.g. driver's route or the gas level, and performs actions to notify the user or to deliver recommendations in the right moment, i.e. if a threshold for the relevance of recommendations is exceeded. After we know when a recommendation should be given, appropriate items are selected. Classical recommender focus on the quality of items based on user preferences. For proactive recommendations, we assess items in the context of delivery. We investigate Multi-Criteria Decision Making (MCDM) methods as an approach to select items based on several criteria in [5]. To decrease computational complexity, items are prefiltered with hard constraints. E.g., items too far away from the route are cut off. Postfiltering builds a small set of items which is finally delivered to the user by incorporating properties like similarity and diversity of items. Our prototype selects gas stations by user preferences for the criteria gas price, detour, brand and remaining gas level at arrival. Preferences are set by the driver manually in advance and are adapted situation-aware, e.g. in case of an urgent appointment. Now we know when to recommend something and what to recommend. In a proactive recommender system the user does not choose the search query by herself. Therefore, proactive recommendations may lead to cognitive effort, additional interaction with the system and dissatisfaction. In [4] we show that explanations are able to convince the user of the relevance of recommended items by emphasizing its strengths. Explanations also help us to bring more transparency in the decisions of the system by explaining the reasons of delivery. Item explanations can be extracted from the recommendation process and the recommendation reason from proactive reasoning. In our prototype both items and the reason of a recommendation are explained by textual phrases.

Some related approaches also investigate POI filtering and delivery inside cars. In the work of [3] an intelligent agent for in-vehicle POI selection was proposed. Context information are used to filter POIs on the map of the central information system (CID) based on current driver load and the currently relevant POI category. Other approaches focus on POI assessment, e.g. by learning user preferences [1] or by means of hybrid recommender [22]. None of the works investigate how drivers use these kind of systems in field and if they would be accepted.

In this paper we describe our results of a qualitative investigation of user acceptance. Subjects used the system in field. To investigate user acceptance, we follow a well known model called Technology Acceptance Model (TAM) [10]. It was proposed for desktop information systems and is used in several studies. According to TAM, the two main factors for user acceptance are perceived usefulness (U) ("the degree to which a person believes that using a particular system would enhance his or her job performance" [10]) and perceived ease of use (EOU) ("the degree to which a person believes that using a particular system would be free from effort" [10]). The perception of both factors is indirectly made through application specific external variables like the design of the system. These factors influence the attitude (A) of a user to use the system which finally determines if a system is actually used. Particularly, the usefulness of a system can already be measured in an early stage of prototyping [9]. The authors in [9] argue that it has more influence on user acceptance than ease of use. However, ease of use should be considered in a study with a prototype. Otherwise it can have negative influence. Therefore, we design an interface for our prototype with focus on ease of use.

In the field of recommender systems, the work in [12] investigates user acceptance of commercial music recommender systems based on TAM. The original TAM was used because in the opinion of the authors it is general enough to be tailored to recommender systems. In their study, U corresponds to the quality of a recommendation and EOU to the effort to get recommendations. Their results show that a simple interface design, low initial effort and the accuracy of items are the main factors influencing user acceptance of recommender systems in this domain. The authors of [8] investigate how transparency influences user acceptance in content-based recommender systems. The results show that transparency lead to a higher acceptance of the recommendations, not necessarily to the system. In automotive research the work in [15] uses TAM to investigate user acceptance of different persuasive interfaces for supporting fuel efficient driving. In contrast to our work, the authors performed an online questionnaire in a pre-prototype phase.

3. AN IN-VEHICLE USER INTERFACE FOR PROACTIVE RECOMMENDATIONS

The Technology Acceptance Model (TAM) introduced in Section 2 is used as theoretical framework for our investigation. As our prototype is in an early stage, our goal is to derive perceived usefulness (U) of a proactive recommender system in a car. In TAM, perceived ease of use (EOU) is the other important factor influencing user acceptance. EOU is a crucial aspect when user interact with a prototype. Therefore, we design an in-vehicle interface in this section.

3.1 Requirements

By designing an interface for proactive recommendations for in-vehicle usage, we have to consider requirements for IVIS as well as for proactive recommendation systems. As automotive requirements are paramount, we conducted expert interviews for the design of the interface and combined the results with requirements from the field of proactive information systems.

3.1.1 In-Vehicle Information Systems (IVIS)

We carried out expert interviews with BMW engineers to design the interface as close to the current BMW interface for information systems as possible. This shortens the initial learning phase. We showed the experts an early version of our prototype and asked them about their opinion. They were selected based on their expertise. One is a specialist for HMI aspects in cars, the other for POIs in the navigation system of the car, the next for driver assistance systems and the last for customer marketing. Some example statements are listed in Table 1. They are grouped according to common guidelines for IVIS found in [11].

3.1.2 Proactive Information systems

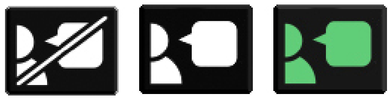
Additionally, requirements for proactive information systems are considered. We found the main requirements in [7] and [19]. In [19] the concept of a ramping interface is introduced. It starts with little information in the first phase, provides more and more information in further phases by user request and always gives the user the chance to exit the system. A ramping interface aims to provide an interface which is *unobtrusive* and *accessible* at the same time. Besides, the authors in [7] emphasize that a proactive recommender should be *transparent* to the user to give her the chance to quickly recognize if a recommendation is relevant.

3.2 Design of an In-Vehicle User Interface for Proactive Recommendations

Our recommender is integrated in the Central Information Display (CID) which is located in the central console of the car. It can be controlled by the iDrive controller which is also in the central console. More advanced interfaces like the control display or the head-up display are out of scope of this work. Same applies to other channels of output like audio or haptic. The iDrive controller can be pressed, turned and pushed to the right, left, top or bottom. The recommender is mainly designed according to the three main requirements for proactive information systems and takes into account requirements of IVIS.

3.2.1 Unobstrusiveness

If a recommendation system has information for the driver, she should notice this while driving. On the other hand, distraction from the primary task of driving with information overload should be avoided. For this reason we chose a two-stage proactivity approach (comparable to the ramping interface of [19]). The recommender is represented by a small icon in the right lower corner of the screen (Figure 2). It can either be inactive (Figure 1a) or active without (Figure 1b) or with recommendations (Figure 1c).



(a) inactive (b) idle (c) notify

Figure 1: Recommender icon with different states

In the first stage the driver is notified about available recommendations by change of color (Figure 1c). This gives the driver the chance to look up the recommendations in advance. A less workload intensive situation like a traffic jam or standing at a traffic light can be used by the driver to review available recommendations. For the second stage, the recommender pops up by itself at the right time or is invoked by the driver manually (Figure 2).

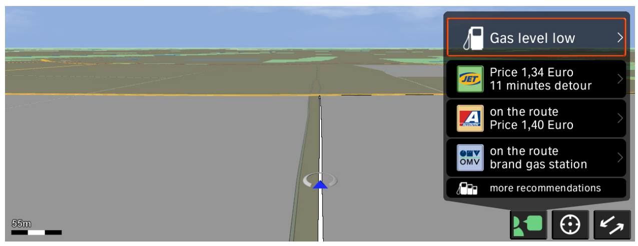


Figure 2: Pop up view of the proactive recommender on top of the navigation map

The pop up captures one third of the map view, which leaves enough space in the viewing area to navigate or to orientate oneself on the map. It is placed on the right side to cover the area which is farer away from the driver. This is less distracting as on the left side which is closer to the driver. After the pop up appears, the map stays in the same mode as it was before (navigation mode). No interaction of the driver is required at this moment. After a certain amount of time (e.g. 30 seconds) the pop up starts to fade out and finally disappears, if the driver is not interested. Any kind of interaction, except the closing action, changes the map to exploration mode, where the location of items and the current position is shown (Figure 4).

3.2.2 Accessibility

Proactive recommendations appear without user request. For efficient decision making, all relevant information should easily be accessible. To shorten the learning phase, we used interaction patterns from the current BMW Human Machine Interface (HMI) derived from expert interviews. The pop up in Figure 2 is designed as list to map its usage to the turn movement of the iDrive controller. Pushing and pressing of

ID	Guideline	Description	Examples of expert statements
G1	Minimal Information	Too much information as well as complex information should be avoided	The display of a detour route provides no information while driving
G2	Scannability	The information should be comprehensible by as few glances as possible	Long-term action sequences on the map like animated zooming should be avoided
G3	Consistency	The effect of actions, icons and colors should be consistent over the interaction	A push to the left should lead to more details; Unfamiliar information presentation, e.g. gas level in liter, and icons known in other context should be avoided
G4	Expectation	The system should be controllable and structured the way a driver expect it to be or is familiar with	Pressing the controller is always coupled with an action
G5	Metaphors	Information delivery and interaction should be mapped to known metaphors	A checkered flag should indicate that the item can be integrated in the current route
G6	Controllability	The driver should have all the time the full control over the system	Every action should deliver feedback, e.g. a conformation for a selected item
G7	Input	As less input from the driver as possible should be required while driving	The pop up should easily be escapable
G8	Understand-ability	Text and graphics should be understandable by laymen	Usage of colors for assessment should be transparent; Icons should be easy to understand or familiar; The current position should always be displayed

Table 1: Design guidelines derived from expert interviews

the controller follows expectations of user already familiar with the BMW HMI. A push to the left indicates a step down in detail or closing the recommender if on the lowest detail level. A push to the right reveals more details if available. For novice user, allowed directions of pushing are depicted by a small arrow (e.g. in Figure 3 or Figure 4). The user is able to escape the pop up whenever she wants with an extra button. Pressing the controller on a list entry leads to a change of view. E.g., pressing the list entry of an item in Figure 4 adds the item to the route and automatically plans a route via the item location. Important details of an item (Figure 3b) and a list of more recommendations can easily be accessed (Figure 5b). The driver may also dislike the items because she is interested in recommendations for another task. Other tasks can be accessed by a left push on the header of the pop up (Figure 3a).

(a) task view (b) item (c) situation

Figure 3: Levels of detail: Lowest level with all tasks to which recommendations exist (a) and highest level with detailed information about items (b) and the current situation (c).

3.2.3 *Transparency*

An IVIS should be understandable to the user in general. This even stronger accounts for proactive recommendations, as information is delivered without user request. System decisions are made transparent by means of explanations for the reason of a recommendation and the strength of each recommended item. In our interface, the most influencing reason of a recommendation is explained in the header of the pop up (Figure 2). If more detailed information about the situation is needed (Figure 3c), it can be accessed with a push to the right on the header. Furthermore, the recommended items are explained with facts, like in Figure 2, or interpreted information, like ”low priced”. Again, further details like facilities can be accessed by a right push (Figure 3b). We only use short sentences like ”gas level low” and avoid additional explanations like ”This items were recommended to you because ...” to reduce information overload during driving with minimal information. The type of recommendation is indicated by an icon in the header.

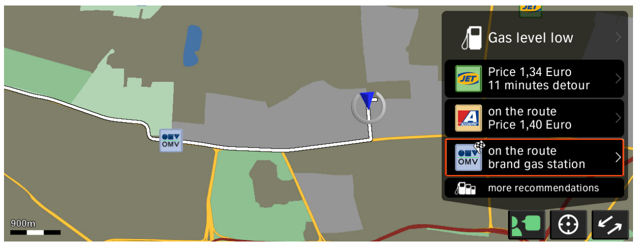
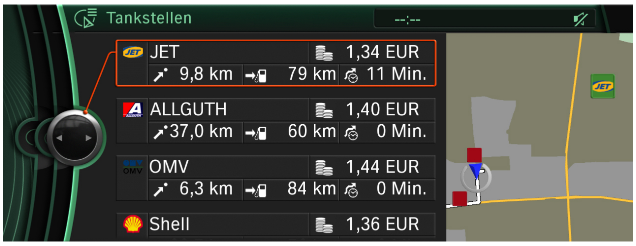


Figure 4: Map view of item location and current position

As the map view provides a rich information source for quick orientation, the items in the list of the pop up can be matched to the POIs on the map by the brand of the item and a unique color. For better orientation in exploration mode, the zoom level of the map is adjusted automatically if an item is selected and shows the current position of the car and the location of the item (Figure 4). This makes it easier for the user to estimate the location of the item relative to her route.

(a) small icons on the map



(b) list view

Figure 5: More recommendations shown on the map with small icons (a) and as list view (b)

Every further item is displayed by a colored icon on the map like in Figure 5a. If further information is needed, a list of all items (Figure 5b) can be accessed by pressing the controller on the last entry of the list.

4. USER STUDY

The previous section addressed ease of use (EOU) of the prototype based on expert interviews and requirements from the literature. We carried out a second study with potential user to investigate perceived usefulness (U) in more detail.

4.1 Evaluation method

Our prototype is deployed in a BMW 550i GT. The CID of the car is connected with our prototype which is installed on a regular PC located in the trunk. Drivers control the prototype with the iDrive Controller. A common street map is used with around 15.000 gas stations. We updated the gas prices in advance of the study by means of an online service. All routes are calculated by a common route planer. As we neither use artificial data nor mock-up functionality, the setup was close to a real commercial system. The study involved 15 subjects, 5 female and 10 male: 5 are between 20 and 39 years old, 6 between 40 and 49 and 4 over 50. All of them own a car and 12 even a BMW, so they are familiar with BMW interaction logic. 6 of the subjects have much driving experience (25.000 to 50.000 kilometer a year) and 9 have average experience (5.000 to 15.000 kilometer a year). Only one subject has no experience with navigational systems. The others use it daily (6), several times a week (4), once a week (2) or less than once a week (2). They usually use it for guidance to a destination or for orientation on the road map. 5 of the subjects already used POI selection and guidance to a selected POI.

4.1.1 Metrics for perceived usefulness

We determined 4 external variables to measure perceived usefulness (U) based on findings in literature. *Expectation* is one important variable because the prototype is an early stage where subjects do not know the functionality in advance. The more a system meets user's expectations the more valuable it is perceived (derived from expectation confirmation theory [16]). In case of proactive recommendations, *transparency* also influences U. The better the system explains its reasoning the stronger relevance and utility are perceived. It was already shown by [8] that transparency has a positive effect on how user perceive the competence of a system. *Relevance* of items is in general an important factor for recommender systems. In case of proactive recommender systems, relevance comprises context-awareness as well as accuracy. Additionally to the relevance of information, [19] suggests to measure the *utility* in case of proactive information systems.

ID	Statements
Q1a	The recommendation fits my given profile
Q1b	The recommendation fits my current situation
Q2	The number of items is enough
Q3	I can make a decision for a gas station based on the given information
Q4	I understand why I got this items
Q5	I am satisfied with the recommendation

Table 2: statements for measuring usefulness (U)

4.1.2 Scenarios

The first scenario is only for familiarization. For the second scenario, we chose a route from the north of Munich to Herrsching with a gas level of 6 out of 80 liter where refilling the tank is necessary. In the third scenario, the gas level was set to 13 liter, where refilling is not necessary but may be performed by chance. For every subject, the chance was a very low priced gas station on the route. Only this item was recommended. In the third scenario, the gas level was set back to 6 liter and time pressure due to an appointment was added. In this scenario user preferences were adapted proactively, e.g. if price is preferred, it became less important in the assessment.

4.1.3 Study Design

Each subject was interviewed individually within our test vehicle in a standing situation and while driving. After a socio-demographic questionnaire, we asked the subjects about their expectations of a proactive recommender in general and a gas station recommender in special. They also had to put in their preferences for gas price, detour, brand and remaining gas level. Then, we successively gave them descriptions of the scenarios. The method of thinking aloud was used while selecting a gas station to analyze the decision making process. For each of the scenarios the gas level of the car was adjusted accordingly. In the first scenario the car was in a parking position to make the subjects familiar with the prototype. In all other scenarios the subjects drove the car, following a guidance to a specific destination. To shorten each run, the scenarios were interrupted after item selection.

ID	Statements	
S1	It is simple to use this system	EOU
S2	The information is presented clearly	U
S3	It is not difficult to learn to use the system	EOU
S4	The system helped me to find a suitable gas station	U
S5	The system does not bother me while driving	EOU
S6	The system has all functions and capabilities I expected	U
S7	Overall, I am satisfied with this system	U
S8	I trust the information the system presented	T
S9	I do not feel restricted by the system in my agency	EOU
S10	The recommendations match my user profile	U
S11	I would use this system in my car	A

Table 3: statements for ease of use (EOU) and overall usefulness (U) and Attitude to use (A) and Trust (T)

To measure the usefulness of the recommendations, the subjects had to assess 5 statements (Table 2) on a 5-point Likert scale after the pop up view appeared and before they were allowed to interact with the system. The scale ranged from "strong disagreement" (-2) to "strong agreement" (2). The preferences in the second scenario were less situation dependent, therefore we used Q1a here. The study was completed by a final survey. The subjects assessed statements (Table 3) for how easy it was to use the system and if it is useful in general. Additionally, a semantic differential was established. Finally, we asked for the best combination of wordings for item explanations with paper prototypes of the variants. We used two kinds of wordings in the study. Fuzzy wording maps a subjective assessment of crisp values to vague statements like "low price" and crisp wording shows the facts. After the first five subjects it was clear that the system provides too few recommendations and all subjects prefer crisp wording instead of fuzzy wording. Therefore, we slightly adjusted our settings after the fifth subject to address this observation. The resulting assessments of the subjects are shown in Figures 6, 7 and 8. We discuss them in detail in the following sections.

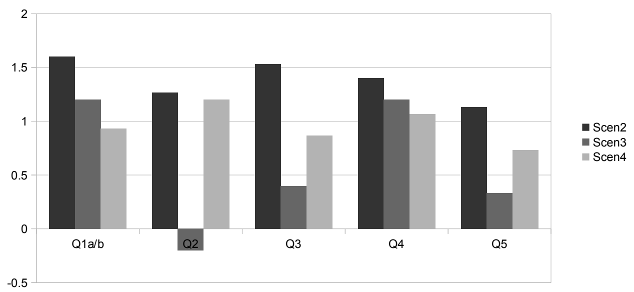


Figure 6: Subject assessments for scenarios 2 to 4 for the statements in Figure 2

4.2 Perceived Usefulness (U)

Figure 7 shows that subjects perceive the system as useful in general because their assessment of satisfaction is between agreement and strong agreement (S7). In the following we discuss our established external variables for U: relevance of items, utility, transparency and expectations.

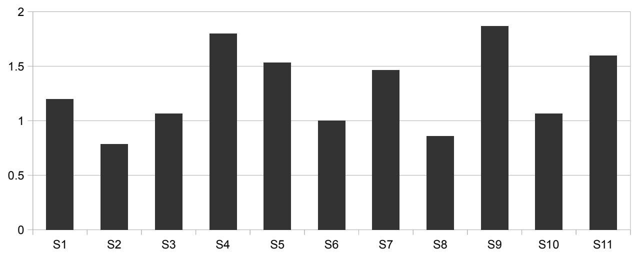


Figure 7: Subject assessments of statements in the follow-up survey in Figure 3

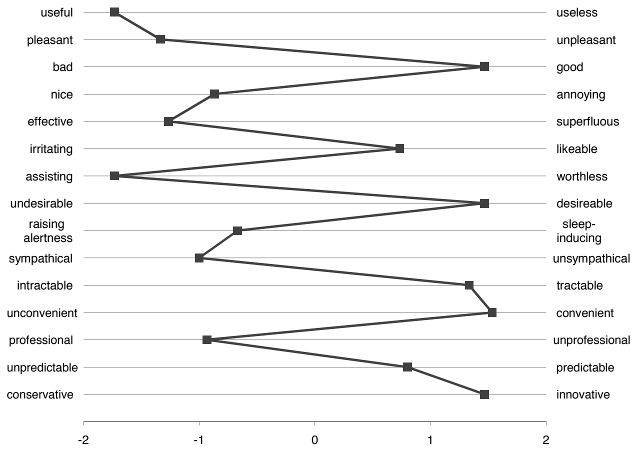


Figure 8: Semantic differential

4.2.1 Expectations

The initial question in our study was about expectations of a proactive in-vehicle recommender system. The most frequent expectations are the quality of data (completeness, correctness, up-to-dateness) (7 out of 15) and easy interaction (5 out of 15). Also personalization, situation-awareness and clarity of information delivery are expected by more than 3 subjects. In the second question, we asked about expectations of a gas station recommender. Subjects mention the incorporation of several data sources as the most expected property. This includes static (location, brand, facilities, type of gas) as well as dynamic sources (gas price, detour, opening times). Price and detour is mentioned by more than two thirds of the subjects. A proactive gas station recommender should also be sensitive to situations (primarily gas level and current route) and make intelligent calculations, like an economic optimum of gas price and detour. Subjects agree that the system altogether met their expectations (S6 in Figure 7).

4.2.2 Transparency

Transparency comprises the quality of item and situation explanations and their comprehensibility based on the wording. At the end of the study, we showed the subjects paper prototypes of the pop up view (Figure 2) with 4 different variants of wordings (fuzzy price and detour (A), fuzzy price and crisp detour (B), crisp price and fuzzy detour (C), crisp price and detour (D)). 10 subjects prefer D and 8 say that A is worst. Less amount of information and ambiguous understanding of fuzzy interpretations are the most serious complaints about fuzzy wording. Most subjects add that just in case of same amount of information, e.g. "on the route", they prefer fuzzy wording. The quality of explanations was investigated with statements Q4 and Q3 (Figure 6) in every scenario. Subjects agree that they understand why items were recommended to them (Q4). On the other hand, they less agree with the overall clarity of information delivery (S2 in Figure 7). Subjects mention that they prefer a fixed order of arguments in general to quickly scan the attributes of an item. Overall, transparency was highest in scenario 2. Subjects strongly agree in that scenario, that they can make a decision with the provided information (Q3) and agree less to that in the more advanced scenario 4. Although subjects were dissatisfied with the recommendation (Q5) in scenario 3, they understand why that item was recommended (Q4). The second aspect which accounts for transparency is whether subjects understand why they got a recommendation at all. The reason of the recommendation delivery was obvious in all scenarios except the third. Here, all subjects saw the explanation "Inexpensive gas stations along the route". The assessment of Q1b (Figure 6) for that scenario shows that the short explanation helps to understand the reason, although the subjects are not satisfied with the recommendation (Q5).

4.2.3 Relevance

Relevance is measured by regarding subjective assessments towards the perceived quality of items and selection behavior of the subjects. First, we look at the position of items which were selected in case of more than one item in a recommendation. Only in 52% of the cases the first item is selected. The second item is selected in 35% and the third in 13%. Most of the subjects associate with the list of recommendations a ranked order with the first item as the most recommended one. In 95% of this cases an item out of the recommendation is selected. Additionally, subjects agree that the items match their user profile in scenario 2 (Q1a) and that they fit to their situation in scenario 3 and 4 (Q1b). Overall, the system is considered as effective in the semantic differential (Figure 8) and subjects agree that recommendations match their user profile (S10 in Figure 7) in general.

4.2.4 Utility

Besides relevance, we also want to know if the recommendations are useful for the subjects in their situations. In the semantic differential (Figure 8) subjects strongly agree that the system is useful and assisting. It also helped them to find a suitable gas station (S4 in Figure 7).

4.3 Other Results

4.3.1 Trust

During the study we observed that the recommendation of only one item confused subjects. When asked about the reason, most of them mentioned missing trust in the functionality of the system in this early stage of usage. The assessments of the statements in Figure 9 underlines the observation. It shows that in case of one item the satisfaction with the system (Q5) is much lower than for two or three and subjects think that one item is not enough (Q2). Thus, decision making becomes harder (Q3) even though subjects understand why they got the recommendation (Q4). In 70% of the cases, it also leaded to the usage of the list view (see Figure 5b). On the other hand, subjects rather trust the data source (S8 in Figure 7) or at least they do not distrust it.

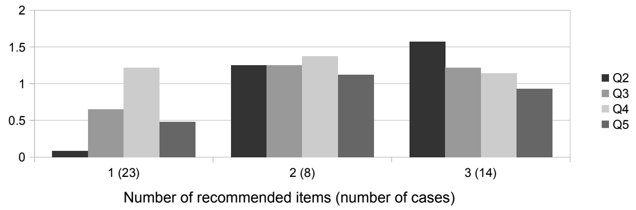


Figure 9: User assessment relative to the amount of items recommended

4.3.2 Perceived ease of use

Ease of use (EOU) is not explicitly part of the study but we should check if subjects also perceived the interaction the way we attempted to. Overall, subjects do not seem to have trouble with the usability of the system (Figure 7). It is easy to learn system functionality (S3) and to use it (S1). Also, they have not been distracted from driving (S5). Similar results can be found in the semantic differential (Figure 8). Strong agreement exists for tractability, pleasantness and convenience.

4.3.3 Attitude to use

Subjects seem to have the attitude to use our recommender in their own cars (strong agreement of S11 in 7). In the semantic differential (Figure 8), subjects also strongly agree to adjectives like good, desirable and innovative. It reflects a positive attitude towards the system. They also rather agree that the implementation is professional.

4.4 Discussion

We derive from the results of our study that a positive attitude towards using proactive in-vehicle recommendations is available. All indicator (relevance, utility, transparency and expectation) for U are rated mostly positively and EOU was confirmed by the subjects. We think that trust is an important indicator for long-term usage of the system which confirms results from the area of mobile services [13]. Our proactive recommender can be improved by a clearer and more precise information delivery, which may also accounts for more trust. The system is overall less seen as a feature which is raising alertness but as useful and assisting. The short explanations for the reason of a recommendation seem to be enough, as the detail view for situation explanations (Figure 3c) was never used and the subjects mostly understand why they received the recommendation. The information in this view may become useful in long-term usage, where subjects are on their own. Finally, the position of the selected item in the recommendation list shows that it makes sense to recommend more than one item. Only half of the selected items are the first one in the list and most subjects mention that they associate a ranking with the list.

5. CONCLUSIONS AND FUTURE WORK

We investigated user acceptance of an in-vehicle proactive recommender system in an early phase of prototyping. Subjects perceive our system as useful and easy to use. If trust issues are solved, we assume that such a system would be accepted. Long term usage studies with hands on experience in real situations are needed to confirm our assumption. Trust issues may be addressed by a clearer and more precise information delivery. As quality of data plays an important role, indicator for quality may increase trust as well. We think that such a system may change user behavior towards physical item consumption like gas stations and parking lots. Today, mostly the next available item is taken. In future, these items may be selected based on recommendations, which can be enhanced by advertisement. Further research in behavior change would be interesting. Another challenge is to cope with many kinds of item categories at the same time.

6. REFERENCES

[1] Markus Ablassmeier, Tony Poitschke, Stefan Reifinger, and Gerhard Rigoll. Context-Aware Information Agents for the Automotive Domain Using Bayesian Networks. In *Conference on Human Computer Interface*, pages 561–570, Beijing, China, 2007.

[2] Florian Alt, Dagmar Kern, Fabian Schulte, Bastian Pfleging, Alireza Sahami Shirazi, and Albrecht Schmidt. Enabling Micro-Entertainment in Vehicles Based on Context Information. In *Conference on AutomotiveUI*, Pittsburgh, KS, 2010.

[3] Katharina Bachfischer, Thorsten Bohnenberger, Martin Hofmann, Christoph Waeller, and Yongmei Wu. Kontext-adaptive Fahrerinformationssysteme am Beispiel eines Navigationssystems. *KI*, 21(3):57–63, 2007.

[4] Roland Bader, Andreas Karitnig, Wolfgang Woerndl, and Gerhard Leitner. Explanations in Proactive Recommender Systems in Automotive Scenarios. In *Workshop on Decision Making and Recommendation Acceptance Issues in Recommender Systems*, Girona, Spain, 2011.

[5] Roland Bader, Eugen Neufeld, Wolfgang Woerndl, and Vivian Prinz. Context-aware POI recommendations in an automotive scenario using multi-criteria decision making methods. In *Workshop on Context-awareness in Retrieval and Recommendation*, pages 23–30, Palo Alto, CA, 2011.

[6] Roland Bader, Wolfgang Woerndl, and Vivian Prinz. Situation Awareness for Proactive In-Car Recommendations of Points-Of-Interest (POI). In *Workshop on Context Aware Intelligent Assistance*, Karlsruhe, Germany, 2010.

[7] Daniel Billsus, David M. Hilbert, and Dan Maynes-Aminzade. Improving proactive information systems. In *Conference on Intelligent User Interfaces*, pages 159–166, New York, NY, 2005.

[8] Henriette Cramer, Vanessa Evers, Satyan Ramlal, Maarten Someren, Lloyd Rutledge, Natalia Stash, Lora Aroyo, and Bob Wielinga. The effects of transparency on trust in and acceptance of a content-based art recommender. *User Modeling and User-Adapted Interaction*, 18(5):455–496, 2008.

[9] F.D. Davis and V. Venkatesh. Toward Preprototype User Acceptance Testing of New Information Systems: Implications for Software Project Management. *IEEE Transactions on Engineering Management*, 51(1):31–46, 2004.

[10] Fred D. Davis. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3):319–340, 1989.

[11] Paul Green, William Levison, Gretchen Paelke, and Colleen Serafin. Preliminary Human Factors Design Guidelines for Driver Information Systems. Technical report, University of Michigan, 1995.

[12] Nicolas Jones and Pearl Pu. User Acceptance Issues in Music Recommender Systems. Technical report, EPFL, 2008.

[13] Eija Kaasinen. *User acceptance of mobile services*. Phd thesis, Tampere University of Technology, 2005.

[14] Mari Carmen Puerta Melguizo, Toine Bogers, Anita Deshpande, Lou Boves, and Antal van den Bosch. What a Proactive Recommendation System Needs: Relevance, Non-Intrusiveness, and a New Long-Term Memory. In *Conference on Enterprise Information Systems*, pages 86–91, Madeira, Portugal, 2007.

[15] Alexander Meschtscherjakov, David Wilfinger, Thomas Scherndl, and Manfred Tscheligi. Acceptance of future persuasive in-car interfaces towards a more economic driving behaviour. In *Conference on AutomotiveUI*, number AutomotiveUI, page 81, New York, NY, 2009.

[16] Richard L Oliver. A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. *Journal of Marketing Research*, 17(4):460–469, 1980.

[17] Walter Piechulla, Christoph Mayser, Helmar Gehrke, and Winfried König. Reducing drivers mental workload by means of an adaptive man machine interface. *Transportation Research Part F: Traffic Psychology and Behaviour*, 6(4):233–248, 2003.

[18] Paul Resnick and Hal R. Varian. Recommender systems. *Communications of the ACM*, 40(3):56–58, 1997.

[19] Bradley J Rhodes. *Just-In-Time Information Retrieval*. Phd thesis, MIT Media Lab, 2000.

[20] Bradley J Rhodes. Using physical context for just-in-time information retrieval. *IEEE Transactions on Computers*, 52(8):1011–1014, August 2003.

[21] M. Tonnis, V. Broy, and G. Klinker. A Survey of Challenges Related to the Design of 3D User Interfaces for Car Drivers. In *IEEE Symposium on 3D User Interfaces*, pages 127–134, 2006.

[22] Wolfgang Woerndl, Michele Brocco, and Robert Eigner. A Context-Aware Gas Station Recommender System for Vehicular Ad-Hoc Networks. In *Conference on Wireless Applications and Computing Conference*, Amsterdam, Netherlands, 2008.