What Influences User Acceptance of Ad-hoc Assistance Systems? – A Quantitative Study

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Abstract: Which factors influence user acceptance of Ambient Intelligence applications is an interesting question worth to be studied comprehensively. We describe a quantitative user study that investigates how experience, stress, and system behavior influence user acceptance of an ad-hoc assistance system. We find that stressed users perceive the assistance system as more useful than relaxed users. Furthermore, system behavior influences how useful people perceive the system, and experience influences how easy to use people find the system. Perceived usefulness also depends on how technophile a person is. Following our findings, we develop a scheme of user acceptance and performance.

1 Introduction

Imagine a meeting or conference with several scheduled talks. Each presenter only has a few minutes to configure the room for her/his talk. The presenter’s notebook needs to be configured to work with the projector, the ambient light has to be adjusted etc. It is a typical walk-up-and-use situation – the presenter usually has little or no time to get acquainted with the infrastructure in the room as the audience is waiting for the talk to begin. In a branch of computer science called Ambient Intelligence (AmI), assistance systems are developed that proactively assist users in such situations. Some of them take user goals (such as show slides) and the current world state as a starting point and compute a sequence of actions which, when executed by the devices in the environment, fulfill the user’s goals. Such assistance systems turn device-rich environments into smart environments as they relieve the user of configuring all the devices manually. Those systems must be dynamic as the environment changes frequently: New users bring in new mobile devices that become part of the existing infrastructure. We thus call them ad-hoc assistance systems. Due to their dynamicity, they tend to produce suboptimal solutions.

Thus, the AmI paradigm is quite different from traditional desktop computing: Users are typically not seated in front of a desktop or a display and control panel, but situated in “real life”, and typically the user walks into an environment and expects her/his mobile devices to integrate seamlessly with the existing infrastructure. Furthermore, user acceptance of an assistance system is likely to be influenced by various contextual factors. In this paper, we present a quantitative user study that investigates whether people accept an exemplary
proactive assistance system and how this acceptance is influenced by three factors: whether the user is stressed or relaxed, whether s/he has some experience using the system, and the behavior of the system. We first review related work and describe the assistance system used in the study. We then present the design of the user study in which 56 participants evaluate the assistance system, describe how we conducted the study and report the results. Using these results, we develop a scheme of user acceptance and performance.

2 Related Work

We cover three areas of related work. To motivate that the results of the study generalize to a particular group of applications, we review some proactive assistance systems. We then discuss prior research on technology acceptance from the field of automation science as a base for the study. Furthermore, we review work on models for evaluating AmI applications and explain our choice of model.

2.1 Proactive Assistance Systems

Several research groups have developed applications for proactive user assistance in smart environments. They leverage the concept of goal-based interaction: User goals are represented explicitly, and the applications search for ways to fulfill them at run-time. This makes the applications dynamic. Typically, planning or similar techniques are used. As planning can yield suboptimal solutions for all but the most trivial problems, these systems are inherently imperfect. The assistance system we used in the study has this property as well.

In one of the systems developed in the EMBASSI project [Hei03], goals are represented as state vectors that are to be made true in the given environment. Each device provides descriptions of its possible actions as precondition/effect rules. When the user utters a goal (e.g., “I want to see ‘Titanic’ now!”), the system gets the current context and tries to generate a plan that transforms this context into a state that fulfills the goal using partial order planning.

Another approach is that of Saif et al., called O2S [SPP+03]. Here, a goal can be viewed as a higher-level function which is to be decomposed into a set of lower-level actions. There might be several ways to fulfill a goal, and those candidates are represented in a goal tree. Choosing an action sequence corresponds to selecting a path through the goal tree. This choice is made according to values specified by the programmer. O2S’ architecture spans across a network of devices. Each device can query other devices for suitable decompositions if it cannot fulfill a goal itself. Another system that leverages goal-based interaction is Roadie [LE06].
2.2 Research on Technology Acceptance

A lot of research on technology acceptance has been carried out in automation science, in domains like flight control or manufacturing plants. Here, systems are “usually large, complex, capital-intensive, and potentially dangerous, and so it is critical they run safely and effectively” [Mui94]. Human operators are experts that monitor the system and intervene when necessary to maximize safety or productivity. This is contrary to AmI, where the human is in the focus and collaboration between the human and the machine largely takes place in “real-life situations”, not work settings. Nevertheless, it is beneficial to look at the results from automation science as a basis for our study.

Parasuraman and Riley review automation science papers to find out what influences people’s decision to use or not use automation [PR97]. They find that if the user does not perceive the advantage automation offers as being sufficient to overcome the overhead associated with setting it up, s/he may not use the automation. Occasional automation failures do not necessarily lead to less automation usage in the future. This depends on whether the automation is usually reliable, whether system behavior and system state are transparent to the user, the overhead involved in turning the automation on or off, or the complexity of the task.

According to Lee and See, people tend to trust a system if they understand the underlying algorithms or believe that the system can fulfill their goals [LS04]. New users base their trust on the available information about the system’s purpose, while later on users develop a feeling for the system’s reliability and predictability. If a user believes that a system functions correctly and is disappointed, s/he may choose not to use the system in the future. Self-confident users who do not trust a system very much tend to manual control. The opposite is also true: People with little self-confidence tend to rely on automation more often. People tend to rely on faulty automation if they know in advance which faults can occur. On the other hand, if information about the functionality of a system is not available or displayed improperly, trust can not develop appropriately.

Moray and Muir investigate how trust relates to human intervention in a process control simulation [MM96]. They find that trust in a machine depends strongly on how competent people perceive this machine to be, and that trust is strongly correlated with automation usage. If a system has an automatic and a manual mode, people use the automatic mode more often the more they trust the machine. The less an operator trusts a machine, the more will s/he monitor it. However, Moray and Muir also find that trust does not go down to 0 if small errors are encountered.

2.3 Models for Evaluating AmI Applications

To develop a test for user acceptance is a research project of its own. We therefore decided to opt for an existing model. Here, we review some to motivate our choice.

The Technology Acceptance Model (TAM) [Dav89] proposed by Davis has been applied in many domains and has been referenced in 450 publications. TAM consists of two con-
structs: perceived usefulness (PU) and perceived ease of use (PE). Both are measured using six-item scales. TAM is a predictor of people’s actual usage behavior, i.e. an application with a high PU and PE value is likely to be used.

Connelly developed a version of TAM for pervasive computing called PTAM [Con07]. Spiekermann proposes UC-AM, the Ubiquitous Computing Acceptance Model [Spi08]. Both are more comprehensive than TAM. However, they require to assess significantly more items than TAM. PTAM, for example, consists of 30 items. In the study, each participant was presented three scenarios and was asked to fill out a questionnaire after each scenario. Had we included a model with 30 items into the questionnaire, each participant would have rated 90 items. This would have overburdened the participants. For the same reason, we did not use UTAUT, the Unified Theory of Acceptance and Use of Technology [VMDD03], a newer and more comprehensive model than TAM. Instead, we used a slightly adapted version of the original TAM. We omitted references to jobs as AmI applications are not only present in work contexts, but in many areas of daily living. E.g., we replaced the item “Using the assistance system in my job would enable me to accomplish tasks more quickly” with “Using the assistance system enables me to accomplish tasks more quickly.” Cronbach’s $\alpha$ is 0.88 for the modified PU scale and 0.76 for the modified PE scale. Both values are above 0.7 which indicates that the scales are reliable.

3 The Assistance System Used for the Study

We now describe the assistance system we used for the study. Its purpose is to relieve users in various smart environments of cumbersome configuration tasks. The meeting room scenario introduced in Section 1 is just one example. The assistance system consists of software modules which are distributed across the devices in a smart environment. There is a separate module for every action a device is capable of. Each module includes a declarative description of its assigned action. This requires that all devices must be connected to a common network. They must also have some memory and be able to perform small computations. When the devices enter a smart environment, the assistance system is built up in a plug-and-play fashion from the modules on the devices. Hence, the assistance system is completely distributed; there is no central controlling component. In addition, hardware and software sensors in the environment provide the current world state (e.g. the user’s position in the environment) to the device ensemble.

Conceptually, the assistance system consists of two parts: the intention analysis and the strategy synthesis. The intention analysis employs probabilistic models of user behavior to predict the most probable goals of a user given sensor data. The strategy synthesis takes these goals as an input and tries to find a sequence of actions the devices in the room must execute to fulfill the goals. Thus, the system leverages the concept of goal-based interaction: Explicit user goals form the interface between the two components. The system is akin to the proactive assistance systems described in Section 2, apart from the fact that it is fully distributed. The intention analysis is described in [BK07]. As it has not been completely implemented yet, for the user study we specified the respective user goals in advance. Thus, the assistance system contains only the strategy synthesis.
The strategy synthesis becomes active when there are open user goals: The modules on the devices communicate to select those actions that most probably fulfill the goals. The mechanism employed for this is based on an algorithm by Maes [Mae90]. The selected actions are then executed by the devices. A detailed description is beyond the scope of this paper, but can be found in [RK08].

The benefits of this approach are that due to its modular architecture, it reflects exactly the devices present in each environment. Devices can be plugged in and out anytime. All devices take part in the action selection process in equal shares, while each has only partial knowledge of the world state. Thus, no central controlling component is required, which makes the approach suitable for resource-poor environments that do not contain a device with enough power to perform planning for all the other devices. On the other hand, this benefit is also its biggest shortcoming. Due to this limited knowledge, the action sequences generated are often suboptimal. This applies in particular in complex scenarios, as will become clear.

In the action selection algorithm, ties are broken randomly. For the study, however, we needed to make sure that all participants would be presented the same action sequences. Therefore, we used a mockup system that behaved exactly like the real system. It replayed a typical action sequence generated by the algorithm.

According to Parasuraman and Riley, people tend to accept suboptimal automation if they receive adequate feedback about the system state [PR97]. We therefore created a graphical user interface that allows participants to control and monitor the assistance system. It displays the goals the system is currently trying to fulfill and descriptions of the actions that have been executed so far. According to Muir, people accept systems better if they have the possibility to override decisions of the system [Mui94]. We thus included a manual mode of operation which participants can invoke if they are not satisfied with the behavior of the automatic assistance. The manual mode is a UI where all devices in the room are represented as icons and can be controlled via point-and-click interaction. It is an easy to use version of the kind of room control panel installed in many of today’s lecture rooms. Both UIs run on the user’s notebook.

4 Conducting the User Study

4.1 The Design of the Study

The experiments were conducted in a smart environment containing the devices in Figure 1. In the study, we measured the influence of three factors on user acceptance of the assistance system: One possible determinant of user acceptance is system behavior. This applies to any kind of human-machine system and has been investigated e.g. by Muir and Moray [MM96] in automation science. We thus included system behavior as a factor. What makes AmI systems special is their context dependance: The situation the user is in may influence user acceptance. To measure the influence of the user’s current situation, we included stress as a factor, while situation in a longer-term sense is captured by the
factor experience.

4.1.1 System Behavior

Any system that assists a user can behave more or less imperfect. To be able to classify such behavior, we introduce the following four levels of imperfection:

- **Level 1** – Directly achieving the user goals: The system provides perfect assistance.
- **Level 2** – Eventually achieving the user goals: The system behaves in an unexpected way, but nevertheless fulfills the user’s goals. This may irritate a user.
- **Level 3** – Doing nothing: The system does not perform any action. The user must configure the devices manually and loses time.
- **Level 4** – Doing the wrong thing: The system behaves in an unexpected way and does not manage to fulfill the user’s goals. Thus, the system hinders the user as s/he must undo any unwanted actions and configure the devices her-/himself.

While experiencing Level 2 assistance, users can usually not tell whether it is Level 2 or Level 4 behavior until the goals have been fulfilled. The assistance system we used for the study exhibits behaviors belonging to Level 1, 2, and potentially even 4, depending on the complexity of the scenario. In this study, we wanted to find out how participants accept Level 1 and Level 2 behavior in an assistance system. We thus created one scenario with Level 1 behavior and two scenarios with Level 2 behavior. In all scenarios, the participants assume the role of a presenter who walks into a meeting room equipped with multiple devices and has to configure this room for a talk using her/his notebook. All three scenarios start in the automatic mode, but participants can switch to manual mode at any time.

**Scenario 1** (Level 1 behavior): The presenter’s goals are to switch on Lamp 1 and Lamp 2, lower Blind 2, and show her/his presentation, Presentation 1 (which is in pdf format), on Canvas 4. In the automatic mode, the assistance system finds the optimal (shortest) action sequence consisting of eight actions to fulfill the goals, the participant need only wait. If the subject switches to manual control, s/he has to turn on Lamp 1 and Lamp 2, lower Blind 2 and Canvas 4, turn on the steerable projector, steer it to Canvas 4, and connect the video signal from the notebook to the steerable projector via the video crossbar. All of this is to be done using the manual configuration UI. Then s/he has to open the presentation in the pdf viewer and maximize it.

![Figure 1: The room layout for the experiments.](image-url)
**Scenario 2** (Level 2 behavior): This scenario is similar to Scenario 1, but the presentation is in ppt format. The participant’s notebook has a pdf viewer, but no ppt viewer installed. However, a colleague has a ppt to pdf conversion service running on her notebook and offers to use it. In the automatic mode, the assistance system manages to send the ppt file to the colleague’s notebook automatically, converts it using the conversion service and sends back the pdf file to the participant’s notebook, which can then display it. The assistance system finds an action sequence consisting of twelve actions, where the optimum is eleven. Thus, the automatic assistance performs one unnecessary action: It opens the converted pdf document on the colleague’s notebook. If the participant switches to manual control, s/he must perform the same actions as in the first scenario. S/he must also transfer the ppt file to the colleague’s notebook using a USB stick, open the ppt file in the ppt viewer, export it to pdf and copy the pdf file to her/his notebook, once again using the USB stick. Then s/he can display the pdf presentation on her/his notebook using the pdf viewer.

**Scenario 3** (Level 2 behavior): The presenter’s initial goals are the same as in Scenario 1. When they have been fulfilled, someone from the audience (played by the experimenter) asks a question. The answer can be given by showing a diagram from a another presentation, Presentation 2, which is on the presenter’s notebook. Thus, Presentation 2 should be shown on Blind 2, while Presentation 1 should remain visible on Canvas 4. A colleague offers to use his notebook for displaying one of the two presentations. In the automatic mode, the assistance system manages to show both presentations, but performs 30 actions until all goals are fulfilled, where twelve is the optimum. If the subject switches to manual mode, s/he must perform the same actions as in the first scenario. S/he must then copy one presentation to the colleague’s notebook via the USB stick and display it in the pdf viewer. Finally, s/he must connect the video signals from the two notebooks to two projectors via the video crossbar using the manual UI.

### 4.1.2 Stress

AMl systems are designed for a variety of situations, e.g. to help people configure environments within a limited amount of time, possibly in front of other people. For example, when configuring a meeting room s/he has never used before for a talk, the user may not know the devices in the room. S/he may have secondary tasks such as configuring the headset, and may be nervous due to the upcoming talk. This can lead to stress. To assess how stress influences user acceptance, we gave half of the participants a secondary task. Next to configuring the room, they had to solve simple arithmetic tasks, a widely used method to induce stress [VV97]. To give participants a motivation to solve the tasks on the one hand and to finish configuration of the room quickly on the other hand, the amount of compensation they received depended on how they acquitted themselves. Initially, their balance was 9 Euros. For every arithmetic task they solved incorrectly or not at all, 20 Cents were deducted. For every minute the experiments took, 50 Cents were deducted. These values were chosen so that most people from the dual task group would receive between 5 and 6 Euros. Each participant from the single task group received 5 Euros.
4.1.3 Experience

Acceptance of an assistance system is not static, but evolves with the experience the user gains when using the system. To conceptualize this process, we propose the following three phases:

- **Phase 1**: First impression of the system.
- **Phase 2**: Some experience using the system.
- **Phase 3**: Long-term experience using the system.

In this study, we are interested how Phase 1 and Phase 2 influence user acceptance of an ad-hoc assistance system because these are the typical usage situations for this kind of application. Phase 1 corresponds to a situation where the user walks into a smart environment and is confronted with a completely new situation, e.g. s/he has never been to this meeting room before and has to configure it using the assistance system. Phase 2 corresponds to a situation where the user has some time to get acquainted with the assistance system, e.g. s/he is the first speaker in a conference session, the audience has not yet arrived and the user has some time to try out the infrastructure in the room. It would also be interesting to investigate how Phase 3 influences user acceptance, but we refrain from it for two reasons: First, a longitudinal study would have to be carried out, which would require considerably more time and resources, especially with the number of participants we were aiming at. Second and most important, systems like ours are walk-up-and-use systems. In practice, the device configuration in the environment and thus the assistance system itself will most likely have changed before Phase 3 is reached.

To assess how experience influences user acceptance, half of the participants were allowed to familiarize themselves with the system in a training phase (Phase 2), the other half were not (Phase 1). To keep the training phase short, the experimenter would first demonstrate the automatic and the manual mode before allowing the participant to try out the system her-/himself. The training phase usually took five to seven minutes.

Thus, we have three factors: system behavior (three levels), stress (two levels), and experience (two levels) in a fully crossed 3x2x2 design with twelve cells. System behavior is a within-subjects factor, stress and experience are between-subjects factors.

4.2 Experimental Procedure

The user study was conducted in eight days and consisted of 56 sessions – one for each participant. Each session took about 30 minutes and consisted of three experiments corresponding to the three scenarios. Thus, we conducted 168 individual experiments. As each participant was presented all three scenarios, we conducted 56 experiments for each scenario. As half of the participants were trained, we conducted 84 experiments with training and 84 without. As half of the participants had a secondary task, we conducted 84 dual task and 84 single task experiments.

In the beginning of the session, each subject completed a questionnaire that assessed the control variables: demographic data and the TA-MEGA scale for measuring technophilia.
This scale consists of 19 items such as “I enjoy trying out new technical devices” to be rated on a five-point Likert scale, where 4 corresponds to “I totally agree” and 0 to “I do not agree at all”. The technophilia value of a person was calculated by summing up the participants’ ratings for each item and normalizing this sum to a range of 0 (technophobic) to 4 (technophile).

The demographic characteristics of the sample are the following: All 56 participants are students at the University of Rostock (undergraduate or postgraduate/PhD). We classified the subjects they study according to four groups. 14.3 % study Arts and Humanities, 51.8 % Science and Technology, 5.4 % Health and Life Sciences and 28.6 % Social Sciences. 54.6 % are male, 46.4 % are female. Technophilia values ranged from 2 to 4 among participants: 14.3 % had a value of 2, 46.4 % had 3, and 39.3 % had 4.

After filling out the first questionnaire, each subject took part in the three experiments. The sequence of the experiments was varied among subjects to avoid order effects. If the subject was in the training group, s/he was trained prior to the first experiment. During the experiments, each click in the UI of the assistance system and each action of the automatic assistance was logged.

Before each experiment, the subject read the scenario description. If the subject was in the dual task group s/he was given the arithmetic tasks. S/he would then carry out the experiment. Each experiment was followed by a questionnaire to assess perceived usefulness (PU) and perceived ease of use (PE) using five-point Likert scales (0 to 4). The PU and PE values were calculated by summing up the six items of each scale. Thus, the range of both PU and PE was 0 to 24. If people switched to manual control during the experiment, they were asked for their reasons.

In the end, subjects filled out another questionnaire that asked them to rank order the three scenarios according to their perceived satisfaction with the assistance system. In addition, the questionnaire included the open question, “Do you have any more comments?”

### 5 Results of the User Study

In the following subsections, the results of the user study are presented in text and tables. To check for statistical significance, we used t-tests (or Welch tests if the equal variances assumption was violated), analyses of variance (ANOVAs) and \( \chi^2 \)-tests. We used an \( \alpha \) level of .05 for all statistical tests. However, statistical significance alone does not say whether the relationship between two variables is strong enough to be practically relevant. We therefore consider the effect size in addition to statistical significance. Different effect size measures exist for different statistical tests. We used Cohen’s d for the t-tests, Cramer’s \( \phi \) for the \( \chi^2 \)-tests and Cohen’s f for the ANOVAs [BD06]. Table 1 lists which values correspond to a small, medium, and large effect for those three measures.
5.1 Quantitative Findings of the User Study

A two-tailed t-test showed that experience influences PE: People that were trained perceived the system as significantly easier to use than those that were not (see Table 2). Apparently, people developed some routine after training. This indicates they proceeded from Phase 1 to Phase 2.

PU depends on a number of factors. A two-tailed t-test showed that stress had a significant effect on PU: Subjects from the dual task group rated the assistance system higher in terms of PU than subjects from the single task group (see Table 3). We can conclude that people that are stressed due to some secondary task value automatic assistance more than people that are relaxed. One explanation is that the assistance system relieves people of cognitive load, giving them more time to attend to their secondary task.

A two-tailed t-test showed that switching from automatic to manual configuration is correlated with a lower PU value (see Table 4). As both are dependent variables, it is not clear whether people switch because they perceive the system as not useful enough or vice versa. However, PU is notably high even among subjects that switched ($\mu = 17.93$). Comments given by participants explain this finding: Several people said they preferred a system that occasionally fails to pure manual control because in most cases the automatic assistance system works fine and then it relieves them of work and saves time. This result is consistent with the findings of Parasuraman and Riley [PR97] and Muir and Moray [MM96] that occasional system failures do not deter people from using the system in the future. Apparently, people accept assistance systems even if they are imperfect (i.e. exhibit Level 2 behavior).

An analysis of variance showed that PU depends on system behavior. PU is lower for Scenario 3 than for Scenarios 1 and 2 (see Table 5). Furthermore, a $\chi^2$-test confirmed that there is a relation between system behavior and switching to manual mode: People

<table>
<thead>
<tr>
<th>classification of effect sizes</th>
<th>PE</th>
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<tr>
<td>effect size</td>
<td>training</td>
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<tr>
<td></td>
<td>without</td>
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<td></td>
<td>with</td>
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<tr>
<td></td>
<td>overall</td>
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<tr>
<td>Cohen's $d$</td>
<td>0.20</td>
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<tr>
<td>Cramer's $\phi$</td>
<td>0.10</td>
</tr>
<tr>
<td>Cohen's $f$</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Table 1: Classification of effect sizes.

Table 2: Influence of training on PE.

<table>
<thead>
<tr>
<th>task</th>
<th>PU</th>
<th>switched</th>
<th>PU</th>
</tr>
</thead>
<tbody>
<tr>
<td>single</td>
<td>84</td>
<td>19.00</td>
<td>3.96</td>
</tr>
<tr>
<td>dual</td>
<td>84</td>
<td>20.80</td>
<td>3.63</td>
</tr>
<tr>
<td>overall</td>
<td>168</td>
<td>19.90</td>
<td>3.89</td>
</tr>
</tbody>
</table>

Table 3: Perceived usefulness depends on the number of tasks.

Table 4: Perceived usefulness is correlated with switching to manual configuration.
switched more often in Scenario 3 than in Scenarios 1 and 2 where the action sequence produced by the assistance system was more optimal (see Table 6). Furthermore, this finding corresponds with another result: One question in the final questionnaire asked people to rank the scenarios according to satisfaction (ties were not allowed). A $\chi^2$-test showed that the results are significant (see Table 7). It surprised us a little that Scenario 2 was ranked higher than Scenario 1, although the system took longer to find a solution and produced one useless action. Comments given by users after the experiments suggest two reasons: First, several people did not perceive the useless action as a useless action. Thus, they thought it was Level 1 behavior when it was actually Level 2 behavior. Second, people felt that the benefit was higher in Scenario 2 because the automatic assistance saved more configuration work than in Scenario 1.

An analysis of variance also showed that PU depends on one of the control variables – how technophile a person is. Surprisingly, participants with a technophilia value of 2 or 4 rated the assistance system more useful than those with 3 (see Table 8). A possible reason is that less technology-savvy people are glad because the automatic assistance system relieves them of cumbersome configuration tasks and very technophile people like it because of a certain “coolness” factor, while averagely technophile people are happy with automatic or manual configuration, so it does not make such a big difference to them.

Table 9 shows how much time participants took for their tasks averaged over all three scenarios. A t-test revealed that people that switched to manual control took significantly more time (120 seconds more on average) than those that did not switch. Table 10 shows that they also had significantly more interactions with the assistance system (13 more on average). This is an interesting result. Several people commented they switched to manual control because they felt the automatic assistance was slow and they could configure the room quicker when doing it manually. The figures show that this was not the case. How-
Table 9: Switching to manual control had a strong influence on the time taken to configure the room.

Table 10: Switching to manual control influenced the number of interactions with the assistance system.

ever, some participants’ comments indicate that it gave them greater satisfaction to switch to manual control than to wait for the automatic assistance to finish.

6 Scheme of User Acceptance and Performance

Using the results of the user study, we develop a scheme of user acceptance and performance for AmI assistance systems based on Davis’ Technology Acceptance Model [Dav89] (see Figure 2). The scheme shows which factors directly or indirectly influence PU and PE (determinants of user acceptance) as well as the number of user interactions with the assistance system and the time taken to fulfill the user’s goals (determinants of user performance). All arrows in the scheme correspond to influences identified in the study. This scheme is incomplete as it comprises only those factors found to be relevant in this study. However, we believe that it can help to understand what influences user acceptance not only of this system, but of other proactive assistance systems (e.g., those introduced in Section 2) as well. Furthermore, it can serve as a basis for discussion among researchers wishing to further investigate the notion of user acceptance of AmI applications.

7 Limitations of the Study

Four limitations of our study need to be acknowledged. First, we used the original version of TAM as a model for user acceptance. TAM was developed for desktop applications and has its shortcomings when applied to AmI. For example, it includes neither social
acceptability nor trust, concepts deemed important in AmI [Con07]. However, it allows to measure perceived usefulness and perceived ease of use with a small number of items. Second, our results do not apply to all AmI systems. We only measured people’s acceptance of one exemplary system. Nevertheless, we believe that our results generalize to systems that proactively assist the user and tend to produce suboptimal solutions due to their dynamic nature. We introduced some examples in Section 2. Third, the characteristics of the sample were not optimal. All subjects were university students that were moderately to very technophile. Thus, we cannot say whether our findings generalize to other demographic groups. Fourth, we did not perform a longitudinal study and can thus not give any indication how acceptance develops over a longer period of use (Phase 3).

8 Conclusion

In this paper, we have described a user study that investigates whether people accept imperfect AmI assistance systems and how experience, stress, and system behavior influence user acceptance. In summary, one can say that user acceptance was high across all experimental conditions, but was significantly influenced by:

- stress: Under stress, people perceived the automatic assistance as more useful than when relaxed, probably because it relieved them of workload.
- experience: People that had some experience with the assistance system (Phase 2) found the assistance system easier to use than those with no experience (Phase 1).
- the behavior of the automatic assistance: When experiencing Level 2 behavior, people perceived the system as less useful and were more likely to switch to manual control than for Level 1 behavior. On the other hand, the more benefit the automatic assistance offered over pure manual control, the more useful it was perceived and the more likely would people stick to the automatic assistance even if it exhibited Level 2 behavior.
- technophilia: Moderately and very technophile people perceived the assistance system as more useful than averagely technophile people.

We furthermore observed that people who switched to manual control took more time and had more system interactions than those that used the automatic assistance. Based on these results, we developed a scheme of user acceptance and performance for AmI assistance systems.

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