The When, Where, and How: An Adaptive Robotic Info-Terminal for Care Home Residents – A long-term Study

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ABSTRACT

Adapting to users' intentions is a key requirement for autonomous robots in general, and in care settings in particular. In this paper, a comprehensive long-term study of a mobile robot providing information services to residents, visitors, and staff of a care home is presented, with a focus on adapting to the *when* and *where* the robot should be offering its services to best accommodate the users' needs. Rather than providing a fixed schedule, the presented system takes the opportunity of long-term deployment to explore the space of possibilities of interaction while concurrently exploiting the model learned to provide better services. But in order to provide effective services to users in a care home, not only then *when* and *where* are relevant, but also the way *how* the information is provided and accessed. Hence, also the usability of the deployed system is studied specifically, in order to provide a most comprehensive overall assessment of a robotic info-terminal implementation in a care setting. Our results back our hypotheses, (i) that learning a spatio-temporal model of users' intentions improves efficiency and usefulness of the system, and (ii) that the specific information sought after is indeed dependent on the location the info-terminal is offered.

Keywords

Machine Learning (primary keyword); Older Adults; Interaction Design; User Interface Design; Field Study; Usability Study

1. INTRODUCTION

Care is considered one of the application domains that service robots will have significant positive impact in. Recent advances have seen several robotic systems being designed for care task, e.g., [19, 3]. Among the many areas of application a robot can fulfill in care homes these days is liaising with residents and visitor alike and providing them

(a) Robotic platform. (b) Subject using the developed info-terminal using touch-screen interaction.

Figure 1: Robot in the care environment.

with information. In contrast to fixed information terminals, however, it is in their nature that they can offer requested information where and when it is needed. A robot can move around an environment and be available where required. Ideally, in order to maximise its utility, an autonomous robot should anticipate what information is needed and at what time and what place it is requested. This schedule, while it can principally be designed by an expert, should adhere to the users' needs, and we suggest that it can best be learned from past experience in an autonomous manner. Hence, in the work presented in this paper, we precisely follow this aim, namely to investigate how the delivery of information to residents, staff, and visitors – in short, the users – in a care home can be optimised and improved. This question is studied by means of an autonomous system, deployed over several weeks in a real-world care home, featuring an *info-terminal* as an implementation designed to allow users to access information relevant to them at most appropriate times and locations. Fig. 1 depicts some impressions from the deployment of the robot in said residential care setting.

In particular, we are looking at two complementary key aspects towards the general aim of providing a usable info-terminal to residents, visitors, and staff alike:

a) **Interface:** *How* can information be presented and accessed by the users of a mobile robot, taking into account requirements of the environment and respecting demands and abilities of the user base? We have developed a touch-screen based interaction on a mobile

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robotic platform, displaying a carefully selected set of information from different domains (see Sec. 2). The work presented in this paper assessed usability aspects of the interface itself in a dedicated user study, and also analysed which information users request at the various places the info-terminal is provided as part of the long-term study. The outcomes of this analysis yield findings which will inform further development of the robotic system. Most importantly, the user study is required to assess if older adults with cognitive impairments are indeed able to use the info-terminal, hence forms a prerequisite for the validity of the subsequent analysis of usage patterns.

b) Adaptive Scheduling: *When* and *Where* should the robot make itself available to be used by the users? In a mobile autonomous robot like the one presented here, this is a question of scheduling, not only the time, but also deciding on the place where to make itself available. However, with the needs of the users not fully known upfront, the system should *explore* on its own where and when it is needed, and then *exploit* this knowledge to deliver a better service. This paper presents an analysis of the long-term adaptation by means of autonomously *exploring* the space of possibilities and, at the same time, *exploiting* a learned spatio-temporal model to yield a higher success and use rate in the long-term study.

The system presented in this paper is the third iteration of ongoing iterative development of a mobile robotic system in a care home developed collaboratively by 6 research groups. The overall focus is to learn about long-term changes and dynamics and exploit these to improve the service quality and usability of deployed robots [6]. The robot is autonomous and usually operated without any engineers or researchers present on site. The system developed provides a unique opportunity to study interaction with fully autonomous systems deployed for long periods of time. It serves the users through a number of different tasks. These specific tasks, including the info-terminal, implemented on the robot have been chosen from the list of tasks relevant to users in a care setting as identified in [8]. They have highlighted an info-terminal as one of the most relevant tasks for a mobile robot in a care home. Other services implemented on the robot include an application in occupational therapy [7, 5], and guiding visitors to specific rooms.

Every year, the system is deployed at the same care home for increasingly longer periods where it runs completely autonomously and offers its services. For the study presented in this paper, stemming from the third iteration of deployment, we assume that most users are generally familiar with the robot on-site and that there is only a limited novelty effect to be observed in general. The results presented in this paper originate from this deployment of the fully autonomous robot (no technicians or maintainers at site) for 63 days, covering a period from mid March to mid May 2016. Following the SiNA (Systematic Interaction Analysis) paradigm [15] for task-focused, interacting robotic systems, each annual iteration comprises a systematic analysis of user behaviour and task accomplishment, linked with detailed analysis of system logs to identify patterns of significant deviation from intended or expected interaction to derive improvements and modifications for the next implementation cycle. The work presented in this paper hence is a contribution to the most recent evaluation-implementation cycle in this model. Consequently, the paper comprises three core contributions, namely

(i) as a technical contribution it proposes a computational model to adapt to users regarding the spatio-temporal characteristics (the *when* and *where*) of the provision of info-terminal services. This contribution is presented in Sec. 3 and proven to yield improved performance over time in the long-term study in Sec. 5.2;

(ii) a dedicated user study of the usability of the implemented info-terminal and its interface with a focus on older adults (see Sec. 5.1), to verify suitability of the approach and confirm general usability as a prerequisite for the adaptation outlined above; and finally

(iii) an analysis of the information actually requested by the users during the long-term deployment in dependence of the different location the info-terminal was offered, presented in Sec. 5.3, yielding insights into the location-dependence of information and suggested further improvements of the info-terminal implementation for future deployments.

Hence, the paper specifically aims to verify the hypotheses that *(H1)* adapting to user needs over space and time in long-term deployment yields more use of the info-terminal, and *(H2)* the information requested by users is dependent on the location the info-terminal is provided.

2. THE MOBILE INFO-TERMINAL

The *info-terminal* focused on in this paper is only one of a number of different services the robot engages in during its long-term deployment. An info-terminal is a touch-screen based implementation of a mobile information point, allowing users to request information or be entertained on the screen of the mobile platform. Hence, the system is similar to static information points often available in care homes but with the added ability to provide the information at varying places in the overall environment.

2.1 Robotic Platform and System

For the development of the autonomous system a 1.76m tall SCITOS G5 mobile robotic platform is employed. The system allows autonomous, uninterrupted operation for up to 7 hours without recharge. It has a cone shaped, green hull that is mounted by a plexiglas head with two actuated blue eyes that can blink (cf. Fig. 1(a) to appraise the robot's appearance). On top of the head a Kinect camera is held in place by an aluminium frame surrounding the head for people and obstacle perception. The robot moves at a maximum speed of 0.55m/s. Safe navigation is further facilitated by a SICK s300 laser range finder used for obstacle avoidance and localisation. A touch screen on the back of the robot is the focal point for human interaction and employed for the info-terminal. A more comprehensive description of the system as a whole is presented in [6] and it is released as a whole as open source based on ROS[1].

2.2 Info-Terminal Interface and Operation

The info-terminal interface is designed with it main users (older adults) in mind. Physically, it consists of the touch-screen mounted on the back of the robot, accessible to

[1] https://github.com/strands-project-releases/strands-releases/wiki

(a) Home screen (b) Weather

Figure 2: Exemplary interface designs for the touch-screen based info-terminal.

wheelchair users and walking people alike. In particular design recommendations for such touch-based interfaces for older adults have been considered regarding button and font sizes [9] and general human factors [4, 2]. Fig. 2 shows two exemplary information screens implemented in the info-terminal interface. The information screens accessible through touch ("click") interaction from the main menu screen (Fig. 2(a)) are:

Weather Shows the local weather forecast for today and two successive days (see Fig. 2(b)).

News Shows both national and local news from the care home, automatically updated from a national TV station news feed and the institutions facebook feed, respectively.

Restaurant Menus Displays today's menus of the local cafeteria and the residents' choices for lunch. The second (residents menu) can be accessed through a further click from the local cafeteria menu in a separate tab to avoid overloading the screen with information.

Photo Album This entertainment element feature an edited collection of photographs, mostly of natural environments, but also featuring photos of the care home itself.

From each these information screen, users can navigate back to the main menu via a "back" button. The interface is implemented in HTML5 and JavaScript and served via a web browser operating in full-screen mode.

During the autonomous deployment, the robot would schedule, using a robot task scheduler [18], info-terminal tasks to be executed at chosen locations. The decision which location to offer the service at is to be taken by the approach to be presented in Sec. 3. At the scheduled time, the robot would make its way to the chosen location, position itself so its touch screen is easily accessible by users, and display the main menu of the info-terminal, ready for any user to interact with it. The default duration to wait for users to interact with he system is 10 minutes, however, to ensure the robot drives not off in the middle of an interaction, this duration is prolonged by a minute if an interaction is still ongoing at the end of the default duration.

3. SCHEDULING THE WHEN AND WHERE

The efficiency of the info-terminal service is dependent on the robot's ability to provide the service at the right locations and times. These need to be selected with respect to the behavioural habits of the people at the deployment facility and with the robot's need to recharge its batteries. For example, since the area around a cafeteria might be busy during noon, the robot should offer the info-terminal service there during the midday and visit its charging station during night-time, when the chances of meeting people are low.

While the selection of the right locations and times could follow a fixed schedule created by a human expert, this kind of solution would be impractical for the following reasons: First, a good schedule requires that the expert is familiar with the behaviours and activities of the people at the deployment facility and can use this knowledge to assess the likelihood of people interacting with the robot at given areas and times. Second, even if the expert had such detailed knowledge, the behavioural patterns of the people might change over time, which would cause any fixed-schedule-based system to gradually lose efficiency. Finally, manual creation of a detailed schedule that reflects the daily and weekly patterns of human activity is a time-consuming task.

Thus, instead of using a fixed schedule, we only provide our robot with a set of candidate locations to offer the service and let it decide where and when it should provide the info-terminal by itself. This requires the robot to build and maintain a spatio-temporal model that can predict the chance of obtaining an interaction at a given location and time and use the model's predictive capabilities to construct a schedule that maximises the number of potential interactions. In other words, the robot needs not only to explore the environment to understand which areas are busy and which not, but also to exploit the obtained knowledge and provide the info-terminal service at the relevant locations during the busy times. These two contradictory requirements constitute a classic explore/exploit dilemma [22].

3.1 Spatio-temporal modelling

Given that the robot offers the info-terminal at k different locations, our spatio-temporal model consists of k functions $p_l(t)$, which represent the probability $p_l(t)$ of an interaction at a location l and time t. The spatio-temporal modelling method has to create and refine these functions from sparse and irregular data about the interaction success which are obtained during routine robot operation.

A typical spatio-temporal model used in similar scenarios is based on Gaussian Processes, which allow the robot to learn the dynamics of the environment and decide which path to take in order to refine its model efficiently [21, 16, 17]. However, the works of [13, 1, 10], which compared several types of temporal models that characterise the presence and activities of people in domestic and office environments, concluded that the Gaussian Processes were outperformed by the concept of Frequency Map Enhancement [12].

3.1.1 Frequency Map Enhancement - (FreMEn)

The FreMEn method assumes that the probabilities of the modelled phenomena are influenced by hidden processes which might be periodic. Through the use of frequency transforms, the FreMEn can efficiently identify the periodicity and influence of multiple hidden processes that affect the observed phenomena and use the extracted knowledge for long-term predictions. This reflects the fact that probabilities of interactions are subject to daily and weekly routines performed by people at the deployment area.

During out robot operation, each candidate info-terminal location is tied to a FreMEn model that maintains the number of performed interaction attempts n, mean probability μ, and two sets $\mathcal{A}$, $\mathcal{B}$ of complex numbers α_k and β_k that correspond to the set Ω of potential periodicities ω_k of the hidden processes that affect the chance of successful interaction (i.e. the chance that the info-terminal is used). To initiate an interaction, the robot positions itself at a given location, records the current time t, displays the info-terminal interface and waits for a predefined amount of time. If the info-terminal interface is used by anyone during the given time period, the robot sets the interaction flag $a(t)$ to 1, otherwise it keeps $a(t)$ equal to 0. After the time period elapses, the FreMEn model of the given location is updated as follows:

$$\begin{array}{lll} \mu & \leftarrow & \frac{1}{n+1}\,(\,n\mu + a(t)\,), \\ \alpha_k & \leftarrow & \frac{1}{n+1}\,(\,n\alpha_k + a(t)\,e^{-jt\omega_k}\,) \qquad \forall\,\omega_k \in \Omega, \\ \beta_k & \leftarrow & \frac{1}{n+1}\,(\,n\beta_k + \mu\,e^{-jt\omega_k}\,) \qquad \forall\,\omega_k \in \Omega, \\ n & \leftarrow & n+1, \end{array} \tag{1}$$

where μ represents the mean, time-independent probability of interaction, n is the number of interaction attempts performed, and α_k, β_k represent the frequency spectrum of the history of past interactions $a(t)$. While the absolute value of each α_k corresponds to the influence of a hidden process with the frequency ω_k on the probability of interaction $p(t)$, the β_k serve as corrections that prevent the model overfitting during the early stages of model construction.

To predict the probability of interaction at a given time t, we first construct a set $\mathcal{C}$ consisting of complex numbers $\gamma_k = \alpha_k - \beta_k$, which are ordered reverse to their absolute values. Then, we select the first m elements γ_j along with their corresponding frequencies ω_j. The elements γ_j and ω_j, which correspond to the influence and periodicity of the hidden processes that affect the interaction probability are then used to estimate the interaction probability at a given location and time by:

$$p(t) = \varsigma(\mu + \sum_{j=1}^{m} |\gamma_j| cos(\omega_j t + \mathtt{arg}(\gamma_j))), \tag{2}$$

where the function $\varsigma(.)$ ensures that $p(t) \in [0, 1]$. Since we assumed that the interaction probabilities will be influenced mainly by daily and weekly routines, we set the constant m to the value of 2. An overview and additional details of the FreMEn concept are provided in [11].

3.2 Model exploration and exploitation

However, the spatio-temporal modelling method is not sufficient by itself. First, in order to create the model and keep it up to date, the robot must be able to provide the model with useful data. Second, one has to determine how to use the predictions to guide the robot in order to maximise the number of interactions. Both of these aims have to take into account the limitations of the robot, especially the energy-based constraint that requires the robot to recharge its batteries at least 50% of its operational time.

The first part of the problem, called life-long spatio-temporal exploration, was studied in [13, 20]. In here, the authors evaluated several spatio-temporal models and exploration strategies to be able to predict people occurrence in office and domestic environments. The paper [13, 20] concluded that the best model is based on the FreMEn concept and the best exploration strategy, i.e. a process that determines which locations to visit and when to visit them, is based on a Monte-Carlo scheme which takes into account the information gain obtainable by a visit to a given location. In the work presented in [13], the robot would establish a new schedule each midnight, ensuring that at least 50% of the time is spend on the charging station. The schedule would then be followed throughout the day, with occasional modifications imposed by unexpected events.

Unlike in [13, 20], which aim to create an accurate spatio-temporal model, but do not need to exploit the information the model provides, we need an accurate model only because its predictions are essential to create a schedule for the info-terminal service. Thus, our strategy needs to take into account both information gain that keeps the model up-to-date and the probability of obtaining an actual interaction. To construct the schedule for the next day, the robot partitions the following day to slots of identical duration and calculates the utility of visiting each location as

$$u_l(t) = \epsilon\, h(p_l(t)) + (1-\epsilon)\, p_l(t), \tag{3}$$

where ϵ represents the exploration/exploitation ratio and $h(p)$ is the information gain calculated by

$$h(p) = -p \ln_2 p - (1-p) \ln_2 (1-p). \tag{4}$$

After calculating the utility function for all possible times and locations, a schedule is generated by a Monte Carlo scheme, which prefers locations and times according to the utility function $u_l(t)$. The exploration/exploitation ratio ϵ determines how much emphasis is given to the model building compared to the model exploitation. An ϵ equal to 1 would result in a system that builds the best model possible, while not using it to obtain many interactions. Setting ϵ to 0 will cause the system to try to get many interactions, but risking that the robot will miss some good locations and times. For details on the Monte-Carlo based schedule creation, see the paper [13].

4. STUDIES DESIGN

During each year of the project the robot is deployed at the same long-term care provider. Key target groups are older adults with progressed dementia, severe multimorbidity or physical deficiencies. Furthermore the care home features units for persons with vigil coma or advanced multiple sclerosis. In total 350 beds are provided for permanent residency and there is a staff of approximately 465 employees. The robot is deployed only at the ground floor of the care facility, traversing corridors that link the administrative wing, with different offices, with a reception hall and a therapy wing with an ambulance area for acute medical aid. Hence, the potential user group is very heterogeneous, ranging from residents with cognitive decline, their visitors, to employees from different professions. Corridors are often crowded with by-passers, either on foot or with the help of different walking aids, wheelchairs or bedridden persons.

It is within this environment the robot has been deployed for a total of 63 days, providing a number of services (see Section 1) among which is the info-terminal. Two dedicated studies are presented in this context: (i) a post-hoc analysis of logged data from the 63 days duration of the long-term deployment of the info-terminal robot, called "Long-term

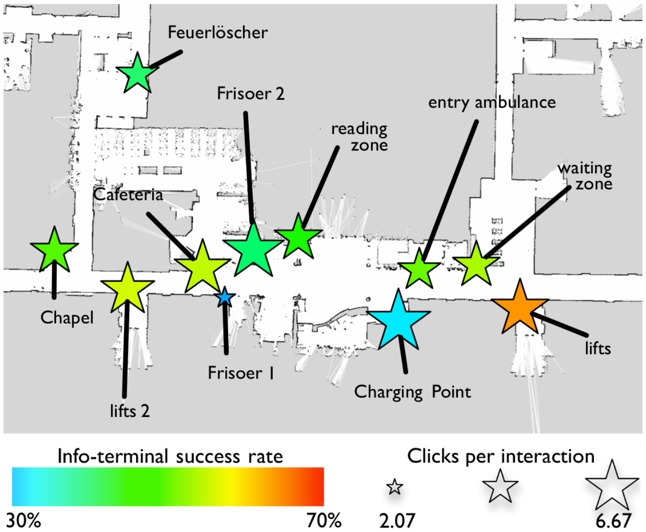

Figure 3: Partial map of info-terminal locations indicating overall success rates for specific locations and how many clicks per task were recorded. The locations "Kindergarten", "Infoboard", and "Lift 3" are off this map for readability.

Study" (Sec. 4.1), and (ii) a focused evaluation of the perceived usability of the info-terminal with a sample of older residents ("Usability Evaluation", Sec. 4.2).

4.1 Long-term Study of Info-Terminal

The info-terminal is embedded into the general 63 days of robot deployment. During this deployment, the adaptive scheduling outlined in Sec. 3 has been employed in order to determine where the robot would go at a specific moment in time. As described earlier, the info-terminal is just one of a number of tasks implemented on the robot. However, the info-terminal constitutes the task that is running the most by far, roughly being active more than 90% of the active operational time of the robot. In this paper, we focus the analysis solely on this info-terminal task.

While the other tasks are either pre-scheduled for specific time slots or requested by staff on-site spontaneously, the info-terminal has been set up to work opportunistically, i.e., it will schedule info-terminal tasks as long as it is not requested to engage in any of the other tasks. Hence, the robot, if not engaged in any other task, every ten minutes went to one of the 14 designated info-terminal locations (see Fig. 3 for a partial map of most of the locations, one location is off the map, omitted for readability), chosen according to the Monte-Carlo sampling outlined in Sec. 3. It shall be noted that the specific location to offer the info-terminal service is chosen entirely autonomously at any given time, based on the successively refined spatio-temporal models. To achieve this adaptation, the robot learned which of the designated 14 locations and times are the most suitable ones to offer the info-terminal service. As mentioned in Sec. 3, each of these locations l was associated to a temporal model $p_l(t)$, which represents the probability of successful interaction at time t. During the deployment, the robot had to establish temporal models that can predict the probability of interaction for any time t despite the fact, that it can operate only during working hours on weekdays.

The robot operated every weekday between mid March and mid May from 9am until 6pm for a total span of 63 days. A total of 20 days were excluded from the study because these were either public holidays or weekends for which no permission to run the robot had been given, or they were due to technical problems (e.g. two days were excluded because a power board had to be replaced). As a result, 43 days have been subjected to further analysis.

During the entire deployment, the system captured for each attempted info-terminal task the following information:

1. location where the info-terminal is run,
2. date and time when it was started,
3. information screens users chose to look at (either "weather", "news", "restaurant menu", or "photos"),
4. number of clicks ("interactions") on the touch screen.

This information was both used to adapt the spatio-temporal model in Sec. 3, as well as to analyse the system performance in relation to hypotheses *H1* and *H2*, which were specified in the last paragraph of Section 1. Overall, an info-terminal task was assumed as successful if at least some user interacted with the system during the 10 minute period of the individual task, i.e., the user chose to request at least one of the information screens.

4.2 Usability Evaluation

In order to complement the long-term study in a more controlled setting and to specifically assess the implementation of the info-terminal itself, a complementing usability evaluation study has been conducted in the course of the third deployment of the robot in 2016. Its main purpose was to gain further insights into perceived usability of this task in general and the design of the screen in particular. This study was embedded in the overall context of the long-term study, but with explicitly selected participants in a set location. This allowed to eradicate any location-specific effects. In the context of the overall deployment, these specific appointments of subjects with a facilitator were scheduled in the system as special info-terminal tasks with a priority overriding the usual info-terminal routines.

4.2.1 Sample

13 older adults, all residents of the care home participated in the study. They were all recruited by members of care staff. The criteria for inclusion of participants were: age 65 or older; living in the care home for more than three months; able to autonomously move in the care home; no diagnosis of severe dementia (this was important to gain valid feedback for using the info-terminal). Furthermore we tried to balance for gender. The participants were aged between 66 and 94 years ($M = 80.77$). Seven participants were male and six participants were female. None of them had a diagnosis of severe dementia. Eight persons stated that they had never used the robot before. Of the five participants using the robot, one used it once a week, three used it once a day and one person made use of the robot several times per day. Regarding technical experience only two participants told us that they possessed a laptop and a smartphone. 11 participants said they had no experience with computers. One participant possesses a laptop, two a smartphone, eight own a key-operated phone.

4.2.2 *Procedure*

We arranged fixed single appointments with each participant. At the set times the participant was invited into the reception area, where the robot was positioned in its docking station, presenting the screen towards the open space. A facilitator introduced the participant to the project, the aim of the evaluation study, and to the robots touch-screen (an initial demo-task – accessing the news menu – was conducted by the participant together with the facilitator). After signing an informed consent, socio-demographic data were collected and subjects were asked if they already had used the robot. Thereafter the facilitator asked the participant to complete a series of pre-defined tasks that increased in difficulty, as they required the user to enter the info-terminal menu by an additional layer. These tasks were:

1. **Time**: Participants first were asked to find out what time it is on the robots screen (clock is situated directly on the overall screen, cf. Fig. 2(a)).
2. **Weather**: Participants were asked to tell the interviewer the weather forecast for the next day. The task consisted of only one step: clicking on the weather icon and reading the forecast for the next day (user had to enter one layer of the menu, cf. Fig. 2(b)).
3. **Resident-Menu of the day**: Participants were asked to tell the interviewer the menu of the day for residents. This task consisted of three steps: Return to the main menu of the robot's interface by first clicking on the return arrow on the left lower corner of the weather screen. Second, access the "menu of the day"-screen, by clicking on the button "menu of the day" and third access the "residents menu of the day"-screen, by clicking on the button "to the residents menu" (two layers of the menu structure had to be entered).

Cut-off times for completing those tasks were also defined. For task 1 the time out was 30 seconds, for task 2 it was 60 seconds and for task 3 90 seconds were chosen. This should help to compare performances between participants and also prevent them to become too frustrated if not able to complete the task. An observer was present to document the performance of the participants on an observation form. He noted down if the user was able to solve the task within the cut off time, the number of errors and what kind of errors occurred (pressing the icons too long or too short, pressing a wrong icon, person did not find the correct icon to press) and number and form of hints (help to press the icon, verbal hints, both) needed to complete the task. After the three usability-tests, participants took part in a short semi-structured interview to gain further insight into usability issues and their perception of and attitude toward the robot. They were asked about their technical pre-experience and their experience with the robot (frequency of use prior to study), their opinion about the optical design and comprehensibility of the menu, the readability of the readability of the contents on the screen, how difficult it was to click on the screen, if they had to think a lot when using the screen (the last five questions were to be answered on a 5-point Likert scale (not at all, rather not, don't know, rather, very much). The whole procedure took approximately 30 minutes per participant. The robot was not moving at any time during this interaction.

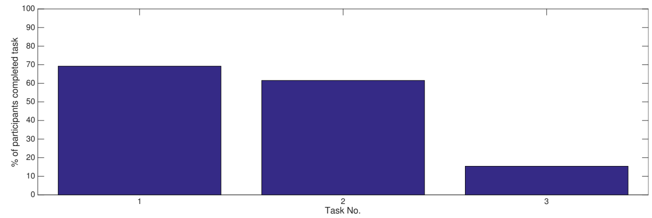

Figure 4: Rates of accomplishment of the three tasks in usability study.

5. RESULTS

In the following, we shall present our key results, addressing the two main hypotheses *H1* and *H2* in Sec. 5.2 and 5.3, respectively. Before this analysis of the long-term interaction, findings originating from the focused usability study are presented in the following Sec. 5.1.

5.1 Usability Evaluation

The focused usability evaluation was to assess the perceived Usability by older adults and to identify the key issues of the current interface implementation. Chi-square analysis of the quantitative data and non-parametric tests did not yield any significant results. Thus we will report descriptive findings of our info-terminal evaluation.

5.1.1 *Task performance*

The three tasks were increasingly difficult for the participants, reflected in differing accomplishment rates shown in Fig. 4. While task 1 was solved by 69.2% (one person needed verbal hints to solve task 1), and task 2 by 61.5% (no help required), only 15.4% (2 persons) of the sample could complete the 3^{rd} task within pre-defined cut-off times for each task, one needing verbal help and another solved task 3 independently. Frequently noted problems in using the touch screen were: pressing icons too long (11 times) and not finding or noticing icons (8 times), clicking the wrong icon (7 times) or clicking icons to short (2 times) - error rates are given over all three task for all 13 participants.

5.1.2 *Observation*

As the majority of participants never used a computer before they did not have a concept of a typical menu structure. Furthermore the meaning of some interface icons was not clear for the residents of the care home. E.g. the icon leading to the photo gallery was misinterpreted as access to a photo camera. Due to the photos-icon, some thought that they could take pictures with the robot. Furthermore the info-icon and its label were not clear to some. 4 out of 13 participants had difficulties to access the time via the clock on the screen. The clock was too small, misinterpreted as an icon or not readable. Some participants missed feedback when using the robot, e.g. when the loading of contents took longer, they did not know if the touch screen had registered their action.

5.1.3 *Questionnaire*

Descriptive statistics showed that the optical design was liked by most participants (38.5% very much, 38.5% rather). 7.7% stated to not like the design at all. Most participants also rated the interface as understandable (69.2% very much, 23.1% rather; 7.7% not at all). 69.2% of participants stated that the texts were very much readably, 15.4% stated that they rather were and 15.3% stated that it was (rather) not readable. In terms of ease of use 61.6% of the older adults stated that they had rather or no difficulties at all. 38.5% found it rather or very much difficult to use the screen. In terms of cognitive effort of using the screen 46.2% mentioned that it was no effort at all and 38.5% mentioned that it was rather no effort. No participant stated that it was very much an effort to use the screen, 15.4% meant that it rather was an effort.

5.2 Adaptive Scheduling

The main goal of the adaptive scheduling described in Sec. 3 is to learn about the best locations and times to offer the info-terminal service, and to verify our hypothesis *H1* which stated that adapting to user needs over space and time in long-term deployment yields more use of the info-terminal. Over the 43 days where the info-terminal was run, the robot offered its service to its users a total of 1770 times. In 760 of these occasions (42.9%), the users actually used the info-terminal, indicated by clicking on the screen. Fig. 3 presents the locations at which the info-terminal was offered, the respective success rates of the provision of the info-terminal, and the number of clicks recorded for each task at a location. As described in 3, each of these locations l was associated with a temporal model $p_l(t)$, which represents the probability of successful interaction at time t. Thus, one of the results obtained are the temporal models for the individual locations. Examples of five temporal models learned during the actual deployment are shown in Figure 5, which indicates that despite of the fact that the temporal modelling method could not obtain data from nights (operations times were restricted to 9am-6pm), it predicted that during night, the probability of interaction is very low.

This result was obtained trough interpolation from the observation that early morning and late evening interactions are less probable than interactions during mid-day. These models also exhibit both daily and weekly periodicities: one can see that in some areas, obtaining an interaction on Friday afternoon is slightly less probable than during the other days. In the case of the Cafeteria temporal model, the interpolation into the night time is actually misleading – here, the robot observed that the info-terminal at the Cafeteria is mainly used during four peak times that might correspond to breakfast, lunch, afternoon tea and dinner. Thus, having no data from night, the robot simply assumed that the Cafeteria is busy every 2-3 hours.

However, the temporal model serves only as a means to construct a meaningful schedule that improves the chances that the visitors and staff of the facility use the info-terminal service. During the initial stages of the deployment, the robot visited all locations with the same frequency, because initially, all $p_l(t)$ were equal to 0.5. As the robot learned the model, it started to prefer visiting certain locations at certain times, which resulted in increased chances of obtaining an interaction. Figure 6 shows the success rates of interactions over time along with a linear regression model. The p value of the linear model F-statistics versus a constant model is $6.74 \, .10^{-4}$, which indicates that the increase of the interaction success rate is statistically significant with $p < 0.001$. Thus, we can say with certainty that during the deployment, the robot gradually increased the chance of the info-terminal usage by the visitors and clients of the facility.

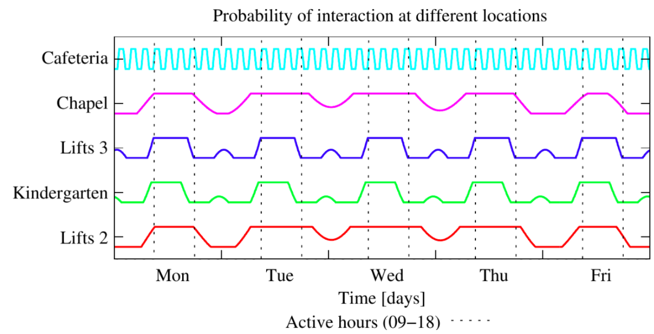

Figure 5: Examples of temporal models of selected locations.

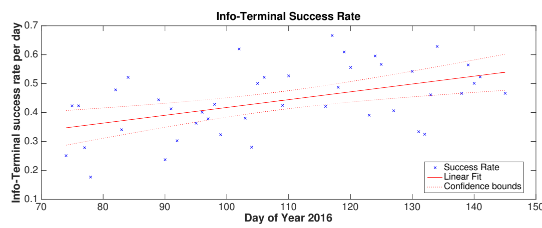

Figure 6: Interaction success rate over time.

5.3 Where information is requested

In order to analyse which information user chose to look at at the various location the info-terminal was offered, a contingency table of the frequencies of specific information screen being requested has been computed from the logs of interactions, shown in table 1. In this table, all locations but the "ChargingPoint" that offered info-terminal tasks are included. "ChargingPoint" has been omitted, as it is a special case where info-terminal was offered all the time when charging and not specifically scheduled for in most cases. Here, we counted all interactions (clicks on the screen) that led to the display of the specific information screen, as described in Sec. 2.2. Over all the 760 instances users interacted with the info-terminal, they displayed clicked to see different information screens a total of 2513 times (just above 3.3 interactions per successful task on average). Multiple clicks per task execution can be a result of several users interacting during the 10 minute window or one user looking at different information screens in one session. The data does not allow to discriminate between these two conditions. However, for the analysis at hand, this discrimination is irrelevant anyway, as we are interested to identify only if the information requested by users is dependent on the location (*H2*).

Overall, the χ^2 statistics for this contingency table indicate a very significant rejection of the null hypothesis ($df = 33, p < 0.001$, overall $\chi^2 = 107.8$) that the information requested is independent of the location the robot is offering the info-terminal service. Consequently, we can assume that indeed the kind of information requested is depending on the location where it is requested, confirming hypothesis *H2*. Likewise does table 1 highlight once again the variance in usage of the info-terminal at the different locations, exploited in the adaptation of the info-terminal scheduling.

	Kinderg.	**Ambul.**	**Feuerl.**	**Wait. Z.**	**Lifts 1**	**Cafet.**	**Read. Z.**	**Chapel**	**Lifts 2**	**Lifts 3**	**Infob.**	**Frisoer 1**	**Frisoer 2**	**SUM**
Menu	25	61	23	34	43	48	34	36	69	49	23	37	7	489
Weather	29	37	28	34	35	44	36	28	45	33	10	20	7	386
News	21	33	24	34	31	29	14	22	36	29	13	41	3	330
Photo	165	127	96	128	79	110	111	110	170	62	71	69	10	1308
SUM	240	258	171	230	188	231	195	196	320	173	117	167	27	2513

Table 1: Contingency Table of information screens requested in dependency of the 13 locations chosen for this analysis. The names of the locations (in columns) correspond to the ones in Fig. 3. "ChargingPoint" has been omitted from this study.

6. DISCUSSION

Info-terminal scheduling. While *H1* is confirmed and the robot gradually learned the spatio-temporal dynamics of people's usage patterns and adjusted its schedule to improve the usage of the info-terminal, the schedule building strategy was rather simple. First, the strategy ignored travelling times between the individual locations, so the schedule sometimes produced sequences of location visits, where the robot spend more time navigating than offering the info-terminal service. Second, the exploration/exploitation dilemma was addressed not by using two different strategies, but simply by combining the exploration and exploitation utility in a single function (3) with an arbitrarily chosen exploration/exploitation ratio ϵ. Since there are multiple options how to address the service scheduling problem and verification of each option would take at least 4 weeks, we already used the temporal models learned by the robot in the deployment to create a dynamic simulation of the deployment environment. Using this simulator, we tested over 50 different scheduling strategies, service utility functions and path planning policies and we found out that a more complex utility function in combination with distance-aware path planning can double the number of potential interactions [14]. Thus, for the next deployment of the robot, implemented these improvements and we will compare them to the original scheduling method.

Usage Patterns. As can also be seen in Fig. 3 there is not only a dynamic model, but also a static trend indicating that some locations are more popular than others. Of course, this static trend is also represented in the spatio-temporal model as μ for each location (see eq. 1), but looking at it a bit closer can give us some indication of the general use of the info-terminal. The most successful location (in terms of number of info-terminal provisions that lead to actual interactions with users) is "lifts" with 68.2% successful tasks. One can hypothesise that this is due to people regularly waiting close to that location and therefore opportunistically using the robot. The most clicks per task were recorded for location "Kindergarten", which indeed is a close to an on-site Kindergarten, probably explained by children being particularly engaged with the robot. It is subject to future research to look at particular user groups, an aspect currently not possible to investigate to due ethical guidelines prohibiting the recording of individual interactions. The confirmation of hypothesis *H2* in Sec. 5.3 leads to another suggested improvement for the next iteration of the system. As it is clear that users are preferring certain types of information at certain places (and possibly even at certain times), a redesigned interface with an always visible menu-bar will allow to start an info-terminal task with the most likely sought after information screen already visible.

Usability. The usability study showed that while users are capable of interacting successfully with the system, also indicated by the number of successful info-terminal tasks identified in the long-term deployment logs, there is also strong evidence that the interface needs to undergo further improvement as part of the evaluation-implementation cycle. Admittedly, these findings are rather specific to the presented system and mostly hint suggested improvements from users and the facilitator: For instance, there ought to be an appropriate form of feedback that the click of the user was registered and the new page is already loading. And due to the generally low complexity of the info-terminal GUI, its interface should be redesigned in a way that makes it possible to provide support for GUI navigation. Environmental support in form of an additional menu bar reduces demands on working memory and facilitates recognition (instead of recall) [2]. These insights will inform the next iteration of the system development.

7. CONCLUSION

This paper presented a spatio-temporal model in order to model the *when* and *where* of interactions in order to improve the service provisioning of a mobile robotic info-terminal. The info-terminal system has been assess as usable by older adults, however, additional insights into how users use the system and what they struggle with in the current implementation have been presented in a focused usability study. We concluded that while the system is sufficiently usable to render the long-term findings valid, the interface itself indeed needs to more even more simplified, reducing memorisation requirements of the users. The presented longer-term study of 63 day autonomous robot deployment in a real-world care environment itself has statistically confirmed the two hypotheses that (i) modelling the spatio-temporal dynamics in usage pattern of the info-terminal yields are more efficient use over time, and that (ii) the specific information sought after is indeed dependent on the location the info-terminal is offered. Furthermore, insights into how users use the system and what they struggle with in the current implementation have been presented in a focused usability study,

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