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MONITORING ELDERLY PEOPLE WITH THE ROBOCARE DOMESTIC ENVIRONMENT: INTERACTION SYNTHESIS AND USER EVALUATION

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This article describes aspects of a fully implemented artificial intelligence (AI) system that integrates multiple intelligent components to actively assist an elderly person at home. Specifically, we describe how constraint-based scheduling technology is used to actively monitor a pattern of activities executed by the person and how detected temporal constraint violations are used to trigger meaningful and contextualized proactive interactions. This article also presents a psychological evaluation of the system focusing on elderly people's attitudes, in which system acceptability, perceived utility, interaction modality, and emotional response are considered.

Key words: AI in eldercare, intelligent interaction, schedule monitoring, user evaluation.

1. INTRODUCTION

The research described in this article stems from a 3-year research project named ROBOCARE: "A Multi-Agent System with Intelligent Fixed and Mobile Robotic Components."[1] The motivation for this and other similar efforts which have emerged worldwide lies in the phenomenon of ageing demographics, a trend which positively integrates with the desire on behalf of aging individuals to remain independent for as long as possible. These factors motivate technological solutions to assist with human care-giving. The challenges entailed by this application area have lead to the development of the emerging field of Artifical Intelligence (AI) for Eldercare, as demonstrated by the increasing number of projects and initiatives that have fostered this new application area for artificial intelligence.

ROBOCARE has specifically focused on the development of AI-based technology for domestic assistive services. The result of our research is a prototypical intelligent home (the ROBOCARE domestic environment; RDE), in which sensors, robots, and other intelligent agents coordinate to provide support in the daily activities of an elderly person. More specifically the ROBOCARE prototypical smart home comprises a single mobile robot and an intelligent stereo-camera. These components are integrated with an activity monitoring module, the aim of which is to react to unexpected behaviors of the assisted person. The general goal of the environment is to "observe" the assisted person's actions and maintain an updated representation of the person's and the environment's state. Based on these observations, the RDE employs its automated reasoning capabilities to assess whether the person's activities fall within predefined behavioral patterns defined by caregivers on the basis of the user's medical needs. These patterns are represented in the form of flexible schedules, predefined by a caregiver as an initialization phase of the system and are reasoned upon by means of state-of-the-art scheduling technology. The system's inference capabilities allow it to project the person's activities in time and to synthesize plans to compensate anomalies in the assisted person's behavior. Examples of such plans are the speech acts through which the system warns a person of inconsistencies which can emerge as a consequence of

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[1] http://robocare.istc.cnr.it

his/her current actions. The main focus of the overall smart environment is to ensure, through daily activity monitoring, the adherence of the assisted person's behaviors to "good living" behavioral patterns.

After presenting the general architecture of the RDE, this article focuses on two aspects. First, we discuss the role of planning, scheduling, and constraint reasoning technology as an enabling tool for achieving intelligent and proactive behaviors in the RDE. In particular, we show how schedule execution monitoring is used here to produce content for speech acts that allow the intelligent environment to interact with the elderly person through a robotic mediator in a contextualized fashion. In practice we show how it is possible to support a level of mixed-initiative interaction by reasoning on the updated schedule representation. Second, we focus on the users' evaluation of the RDE services, developed through a sound methodology. In particular, we apply methods from human–computer interaction, cognitive, social, and environmental psychology to develop a psychological evaluation of the system by potential users. This class of experiments is relevant because the type of applications demonstrated through the RDE is not restricted to a set of specialized users, rather to a potentially broad range of people who differ in culture, gender, age, and personal experience.

The article is organized as follows. In Section 2, we introduce the RDE, its heterogeneous components, and the problem of their continuous coordination. Section 3 describes how the schedule management component is used to generate meaningful and unobtrusive interaction with the user. Section 4 presents the methodology for the controlled experiments and describes results aimed at underscoring how elderly people perceive the current RDE services. Some conclusions end the article.

2. THE ROBOCARE DOMESTIC ENVIRONMENT

The ROBOCARE project was aimed at investigating the use of AI techniques for enhancing the quality of elderly people's "everyday life." Similar use of intelligent technology for supporting the elderly is described in a number of surveys (LoPresti, Mihailidis, and Kirsch 2004; Pollack 2005) and addressed in other research projects. Among those that anticipated and influenced our work some are worth reminding. PEAT (Levinson 1997) is a device based on AI technology designed to increase the independence of persons with brain injury. It is a hand-held electronic calendar and address book, which uses automatic planning to generate plans for activities of daily living. PEARL (Pineau et al. 2003) is a mobile robotic assistant, developed to assist elderly individuals with mild cognitive and physical impairments, as well as to support nurses in their daily activities. Three main modules constitute the basic components for providing human-robot interaction: an automated reminder system (Pollack et al. 2003); a people-tracking and detection system; and a high-level robot controller. I.L.S.A. (Independent LifeStyle Assistant; Haigh, Kiff, and Ho 2006) is an agent-based support system that incorporates a sensing module, situation assessment capabilities, and response planning for helping elderly people to live independently in their own homes. It provides a Web interface that allows users to display reminders issued for the day, to check the medication schedule and status (taken/not taken), the user's mobility status, and to control alarm delivery. Another interesting example of use of AI techniques to assist people in daily activities is COACH (Cognitive Orthosis for Assisting with aCtivites in the Home; Mihailidis, Barbenel, and Fernie 2004), a cognitive orthosis designed to support subjects with moderate to severe dementia while they wash their hands. The system is composed of a video camera and associated software that tracks the position of a user's hand, determines the sequence of steps the user is completing, and delivers an appropriate verbal reminder in case it is needed. Experiments with potential subjects showed a significant increase in

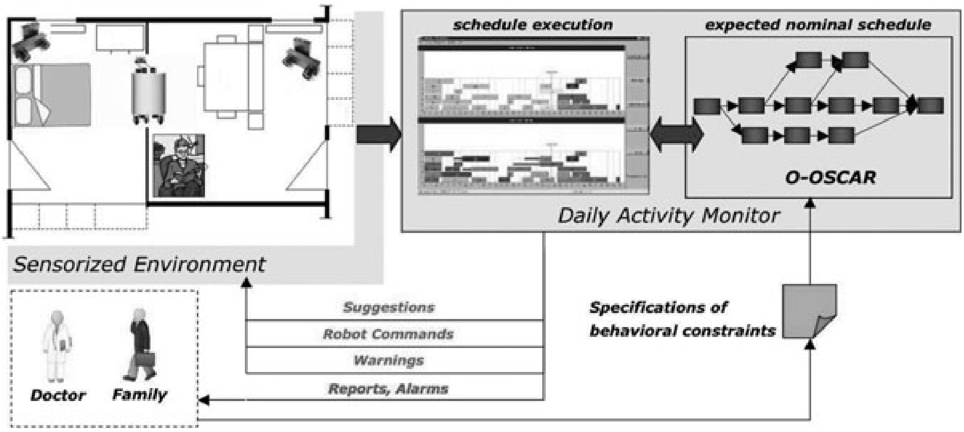

FIGURE 1. The complete service cycle in the RDE.

the number of handwashing steps that the subjects were able to complete without assistance from the caregiver.

The generic idea pursued in ROBOCARE is to integrate robotic, sensory, and software agents to create innovative services for an elderly person at home. Given the state-of-the-art of autonomous robots in terms of comprehensive support to assist human beings, in ROBOCARE we have followed the specific direction of creating an enhanced home environment dedicated to monitoring a person rather than concentrating all functionalities on a single robot. The result is a prototypical intelligent environment that integrates robotic and software components to obtain a continuous behavior that we can refer to as *Proactive Monitoring*. The goal underlying the intelligent environment concerns the ability to (a) maintain *continuity of behavior*, such as ensuring continuous monitoring of what happens in the environment (the state of the assisted elder and of his/her domestic context), (b) create a *context* at the knowledge level around the actions that the assisted elder performs (routinely, exceptionally, etc.), and (c) provide contextualized interaction services aimed at *proactive assistance* for the assisted elder.

2.1. Apartment, Vision Sensors, and Robot

Figure 1 gives a comprehensive sketch of the RDE elements. The main context is an *apartment*, an experimental setup maintained at the ISTC-CNR in Rome which re-creates the three-room flat of an elderly person. The apartment is monitored by a number of *sensors* such as stereo cameras, whose data are used by specialized algorithms for people localization and tracking as described in Bahadori et al. (2007). A *robotic mobile platform* is located in the environment, namely a Pioneer2 equipped with Robot Development Toolkit (RDK) functional middleware (Farinelli, Grisetti, and Iocchi 2006) that integrates the capabilities of a simple path planner and a state-of-the-art Simultaneous Localization And Mapping (SLAM) algorithm (Grisetti, Stachniss, and Burgard 2005) driven by SICK Laser Scanner data. A separate subcomponent for *robot interaction skills* has been coupled with the robotic platform—see Figure 2. The interaction skills are composed of (a) a "talking head" called Lucia, an off-the-shelf software developed at ISTC,[2] which is also endowed with speech

[2] Cosi, P., Lucia, ISTC-CNR, Padova, http://www.pd.istc.cnr.it/LUCIA/

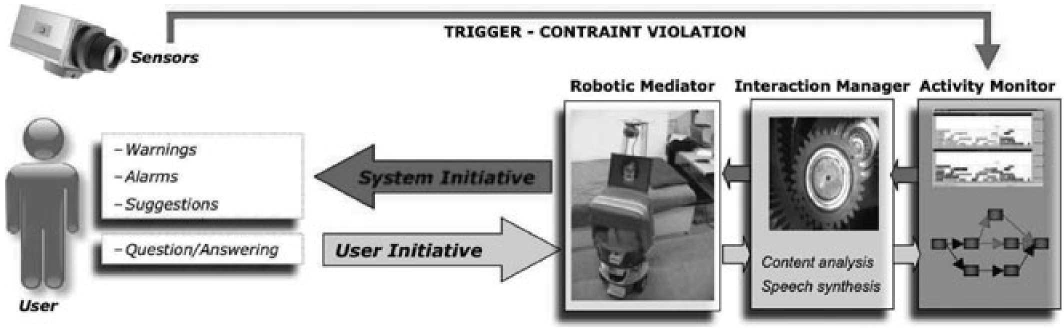

FIGURE 2. The general schema for mixed-initiative interaction generation in ROBOCARE.

synthesis functionalities based on the elaboration of specific "content files" in text format; (b) a speech recognition system called Sonic, a tool developed at the University of Colorado;[3] and (c) a simple Interaction Manager developed within the ROBOCARE project consisting of a rule-based system that fires *situation-action* rules by activating the specific submodules that are under the manager's responsibility. The Interaction Manager provides simple question answering capabilities and also participates in the remaining speech act productions as described in the following sections.

2.2. The Daily Activity Monitor

Going back to the explanation of Figure 1, an important role is played by the module for daily activity monitoring. Broadly speaking, the idea is to keep track of a number of caregiver prescribed recommendations for "healthy living" in the form of behaviors that the elderly person should follow during a period of time. Such *behavioral constraints* are specified through a specialized constraint language designed to facilitate generic users—details in (Pecora et al. 2006). Those constraints are mapped into a temporal constraint language made available by the O-OSCAR scheduling architecture (Cesta et al. 2001). To give a broad intuition, the "healthy living" behaviors are prescriptions such as "always take medicine after consuming food" or "regular timing for lunch is from 12:00 AM to 2:00 PM," etc. This set of "safe behavior specifications" is represented as a *partially ordered activity schedule* in O-OSCAR, built on top of a simple temporal problem (STP—Dechter, Meiri, and Pearl (1991)). The final link between the enhanced physical environment and the recommendations is the final module in the picture, called *schedule execution*. This is a software module described in detail later in the article which mainly simulates the execution of the recommended schedule and matches such execution with the observation from the sensors in the real environment. From the analysis of sensor data it is possible to discriminate between nominal and anomalous user behaviors. Anomalies are also classified according to level of alarm. Serious disfunctions, e.g., user not responding to interaction for too long, lead directly to alarms to the external world. Less critical anomalies, such taking medicine late, trigger verbal robot-user interaction aimed at highlighting the "healthy living" rule violation, and suggesting a proper line of action. Hence, as previously mentioned, the RDE performs *proactive monitoring* of the user. The functionalities of the daily activity monitor are addressed in detail in Section 3.

[3] See http://cslr.colorado.edu/beginweb/speech \ _recognition/sonic.html

2.3. The Multi-Agent Implementation of the Environment

A smart home is a system which is responsive to people's needs and actions, a pervasive accessory to human cognitive and physical capabilities. The simple juxtaposition of sophisticated devices or services is not sufficient to obtain a smart environment. A significant priority in ambient intelligence research today is the development of methodologies for service integration which can be reused in diverse scenarios with potentially different domestic technology. While ad hoc integration schemas have been put in place for the realization of ambient intelligence systems, the goal of building such systems by integrating off-the-shelf intelligent artifacts within a reusable framework still lies beyond the current state of the art. The ROBOCARE domain poses a challenging problem in this context. Integrating complex services is itself a problem which requires intelligent reasoning. As is the case in related fields such as Web service composition, AI problem solving can provide a key contribution to this problem. In our specific case, we have chosen to rely on distributed constraint reasoning. Specifically, we have implemented each of the specialized intelligent services (namely, the daily activity monitor, the robot interaction skills, the mobile robot platform, each of the stereo cameras and their related software for people localization and tracking) as separate agents, which expose some public variables to exchange data with other agents. A distributed constraint optimization problem (DCOP) is defined on such variables, in which valued constraints enforce preference policies for the solution of the coordination problem underlying the DCOP. The casting of the RDE as a multi-agent system is an implementation aspect that is not relevant for the purposes of this specific article. The interested reader should refer to Pecora and Cesta (2007) for a detailed description.

3. ACTIVITY MONITORING AND INTERACTION GENERATION

The availability of a domestic robot immediately creates expectations with respect to its capability to actually support the user and interact affectively with him/her. Indeed, the focus in ROBOCARE has mostly been to investigate how to use temporal plan representations to model contextual information and, when needed, use such information as "interaction content." This section highlights how the use of scheduling technology provided useful support for generating meaningful and timely dialogue with the user.

3.1. Mixed-Initiative and ROBOCARE

Interactions within ROBOCARE involve the robotic mediator and the elderly person, hence the embodied robotic assistant acts as the focus of attention between the user and the entire RDE. In other words, the user does not perceive that the system performance is the combined effect of a number of intelligent subsystems, rather he/she sees the robotic front-end as the generator of all the functionalities. Although the robotic mediator has been chosen as an "attention focalizer," the interaction services are the result of a more sophisticated reasoning process which allows for *mixed-initiative interaction* (Allen, Guinn, and Horvitz 1999). All interaction services are generated through the Interaction Manager (see Figure 2). As said before, this module consists of a rule-based system that fires situation-action rules. It continuously assesses the situation and activates specific submodules as actions. Mainly, the Interaction Manager supervises the initiative of the "interactor" toward the assisted person and decides the *time* and the *content* of interaction. Additionally, it is endowed with a simple content analysis module to interpret the meaning of simple user requests and, through its connection to the speech synthesizer, it triggers the verbalization of both answers to specific queries and proactive interaction based on the knowledge repository. Indeed, it is worth highlighting here how the mixed-initiative interaction is ensured by the combination of the Interaction Manager services with the activity monitor's knowledge and reasoning capability. In fact, information coming from the environmental sensors is given as input to the activity monitor which is responsible for monitoring the actual behavioral pattern of the assisted person and comparing it with the caregiver's recommendations. Two kinds of information are fundamental for directing the mixed-initiative interaction: (a) any constraint violation represents an occasion for the system to intervene; in this light it is possible to see the constraint violation as a *trigger* for system interaction, thus determining the *timing* of the system's interventions; (b) the semantic interpretation of the violated constraints determines the *content* of the verbalization. To this purpose the Interaction Manager performs a reasoning process on the violated constraints and synthesizes contextualized verbalizations, which are presented to the user in the form of *warnings*, *suggestions*, or *alarms*.

Interaction in ROBOCARE is established in two different directions, based on *who takes the initiative* to start a dialogue. We therefore distinguish between user initiative and system initiative.

User initiative. In this case the user takes the initiative first. We categorize as *user-initiative* interaction the "Question/Answer" category of dialogues. This activity is triggered by a speech input from the assisted person. The generation of the answer is managed mostly internally by the manager that has information on activity history and/or on the current state of the environment, to answer respectively questions such as "Have I had lunch?" or "What time is it?" etc. The assisted person commences interaction, for instance, by querying the system's knowledge base: "Have I taken my pills?" or "Can I make an appointment for tomorrow at 5 PM?" In this way he/she receives support for his/her daily activity planning or for specific questions related to the environment's status.

System initiative. In this case the intelligent environment commences interaction guided by its internal reasoning. Instances of system initiative are "Danger" and "Warning" scenarios. As an example we can discriminate as a dangerous situation the case in which a person is "lying down on the kitchen floor" or "lying down in bed half an hour after usual wake up," rather than "lying down in bed within an expected period," which is recognized as a regular situation. The danger trigger is dealt with by a specific behavior of the multi-agent system that interrupts the usual flow of activities and undertakes an action: the robot is sent to the assisted person, a specific dialogue is attempted, and if no answer from the assisted person is obtained, an *Alarm* is immediately fired to the external world (call to a relative, to an emergency help desk, etc.). A warning scenario is one in which constraint violations are detected by the activity monitor which decides the values for the parameters used by the Interaction Manager to trigger a proactive dialogue with the assisted person. The content of the dialogue is synthesized on the basis of the monitor's internal knowledge.

The idea of using a mixed-initiative interaction modality is in line with current work in the literature dealing with the collaboration between intelligent technology and its potential users. Different examples include DiamondHelp (Rich et al. 2005), a new type of collaborative interface of a system that actively assists home appliance usage; an application described in Nguyen and Wobcke (2005) focusing on how user can employ different devices to interact with a collection of personal assistants each specializing in a task domain such as e-mail or calendar management, information seeking, etc.

The reminder of this section specifically focuses on describing the use of constraint-based scheduling technology to support the mixed-initiative interaction within ROBOCARE.

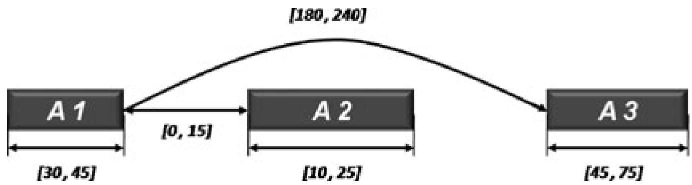

FIGURE 3. Example of prescribed behavior in form of a schedule.

3.2. Generating Interactions from Scheduler Knowledge

To provide reliable services, the RDE must maintain an internal model of the environment that is being monitored (world database), whose most significant aspects must be kept continuously updated and consistent with the environmental data received from the sensors. The precision of the alignment between the real world and the model is essential to guarantee the necessary accuracy of the monitoring task; moreover, the data contained in the world database must be properly managed to provide contextualized feedback to the user. In this section we show how the management of temporal information modeled in terms of *temporal constraints* can be effectively exploited to provide context-related system–user interaction.

3.2.1. Modeling the Desired Behavioral Patterns. As sketched in the previous section, the desired "healthy" behavior the assisted person should adhere to is initially decided by a caregiver (a doctor, or a family member) in the form of a set of behavioral constraints to be monitored. Such constraints are easily cast as activities in a *schedule*. The activities in the schedule are bound to one another through a set of temporal relationships. Should the initial plan prepared by the caregiver contain temporal inconsistencies, the system is designed to highlight such inconsistencies for correction; no inconsistent plan is ever dispatched for execution monitoring.

One example of schedule is depicted in Figure 3. The figure shows three activities that are temporally related to one another through a set of constraints (the black arrows), whose values are expressed by means of intervals $[d_{min}, d_{max}]$ that determine the minimum and maximum distance between the activities involved in each constraint. In the example, activities A_1 and A_2 are separated by a minimum and a maximum temporal constraint of value [0, 15] temporal units (e.g., minutes), while activities A_1 and A_3 are separated by a minimum and a maximum temporal constraint of value [180, 240]. Variable activity durations are also expressed in terms of minimum and maximum constraints between the start time and the end time of an activity, e.g., the duration of A_2 can vary between 10 and 25 temporal units. This representation paradigm allows to easily model and manage *temporal flexibility* through constraint management: it is in fact possible to express the occurrence of the events in terms of time windows rather than imposing rigid values to the time instants. According to this representation it is possible to describe the desired behavioral patterns, whose underlying network of temporal constraints can become very complex. Such behavioral patterns are devised to represent the set of activities that are particularly significant for the person's health. The aim of the ROBOCARE's daily activity monitor is to supervise the execution of the activities performed by the elderly user, and check its adherence to the nominal schedule, possibly reacting with warnings and/or alarms in case of failed compliance or if dangerous situations arise.

To be more concrete, let us consider the synthesis of a behavioral pattern defined by a schedule (see Figure 4) extracted from the activity graph depicted in Figure 3, where activities

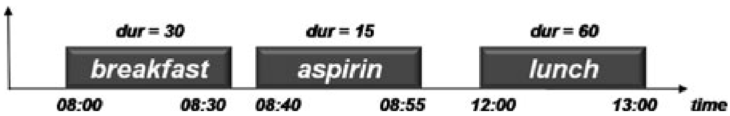

FIGURE 4. Example of schedule based on "medical" prescriptions.

A_1, A_2, and A_3 are given the meaning of *having breakfast*, *taking aspirin*, and *having lunch*, respectively. Let us also suppose that the prescription in this example directly translates into the following temporal requirements among the activities of the plan: (1) *having breakfast*: should not begin before 8:00 AM; its nominal duration should be 30 minutes; (2) *taking aspirin*: should not begin before the end of *having breakfast*; should not begin later than 15 minutes after the end of *having breakfast*; its nominal duration should be 10 minutes; and (3) *having lunch*: should not begin before at least 3 hours after the end of *having breakfast*; should not begin later than 4 hours after the end of *having breakfast*; its nominal duration should be 45 minutes. Figure 4 shows a schedule adhering to the requirements above. An important requirement for the nominal schedule representation is to avoid constraining the assisted person (and the caregiver!) with unacceptably strict, and thus unmanageable, action sequences. The expressiveness of the underlying STP representation supports this requirement by enabling the use of flexible temporal constraints that can express concepts such as maximum time lags and intervals of admissibility for activity start and end times. The ability to express such concepts is essential when dealing with models of human behavior, as it allows to define limits for activity duration and placement in time that are sufficiently flexible to accommodate strong variability.

3.2.2. The Execution Monitoring Algorithm. Once the behavioral constraints are specified by the caregiver in terms of a consistent set of actions, monitoring of the assisted person's behavior in the environment is initiated. As the activity monitor starts, the sensors are periodically queried and the nominal schedule is adjusted in accordance with the patient's detected behavior. At each detection cycle, the execution status of each activity is checked: among the possible cases, some activities may be reported as under execution before their nominal start time, the execution of other activities may be reported as delayed, the duration of some activities may exceed the nominal value, and so on; each deviation from the nominal schedule is an *event* that may entail a conflict which has to be acted upon.

Algorithm 1 shows the execution monitoring algorithm employed in ROBOCARE. As shown in the algorithm, an "environment sensing" action is periodically performed (line 1). At each iteration, the set $Events_t$ of the occurred events is acquired by accessing the symbolic representation S_t of the current situation at any instant t (line 2); the latter is computed through the cooperative multi-agent deduction process mentioned in Subsection 2.3.

If events are detected (line 3), the first action the activity monitor performs is to remove all the *active constraints* present in the internal schedule representation (`removeActive-Constraints()` function). An active constraint is a constraint such that it involves at least one activity that has not completed execution; obviously, not active constraints do not take part in the temporal analysis because they will not play any role in the evolution of the future states of the world. At each iteration, all the constraints that are active at time t are stored in the set $C_{r,t}$ (line 4).

The next step of the algorithm consists of the insertion in the plan of all the detected contingencies (i.e., events), properly modeled as further constraints, through the `insertContingencies()` function (line 5). This is the step where the system

ALGORITHM 1 The Execution Monitoring Algorithm.

1. **while** true **do**
2. $Events_t \leftarrow S_t$
3. **if** $Events_t \neq \emptyset$ **then**
4. $C_{r,t} \leftarrow$ removeActiveConstraints()
5. insertContingencies($Events_t$)
6. $K_t \leftarrow \emptyset$
7. **while** $C_{r,t} \neq \emptyset$ **do**
8. $c_j \leftarrow$ chooseConstraint($C_{r,t}$)
9. **if** $\neg$ reinsertConstraint(c_j) **then**
10. $K_t \leftarrow K_t \cup c_j$
11. **end if**
12. **end while**
13. **end if**
14. **end while**

updates the internal representation of the schedule to preserve the alignment with the world's sensed state. At this point of the algorithm, the internal representation of the current schedule contains only the constraints that model the contingencies; the nested cycle (*while* loop at line 7) must therefore implement a constraint reinsertion cycle, where the algorithm tries to restore as many original constraints as possible, as they model the caregiver's requirements. The `chooseConstraint()` function (line 8) is responsible for the implementation of the reinsertion policy of the constraints, while the `reinsertConstraint()` procedure (line 9) is in charge of launching the temporal constraint propagation algorithms. It should be remarked that in general, a number of original constraints will fail the reinsertion, and will therefore be rejected. In fact, the occurrence of the contingencies might have changed the temporal network *constrainedness*, so as to make impossible the complete reinsertion of all the temporal constraints removed at the previous step. All the rejected constraints at each cycle are stored in the set K_t (line 10).

Constraints insertion (and rejection) is an issue worth some attention for these reasons:

- The significance of system reaction strongly depends on the contents of the set K_t; therefore, the analysis of the rejected constraints quantitatively and qualitatively determines the system's response. Quantitatively, because the content of K_t determines the number of detected violations, in a utilization context where no violation should possibly go undetected; moreover, K_t also determines the quality of response, as the more information is contained in K_t, the more "contextualized" is system−user interaction. In other words, given a temporal network *TN* underlying the current schedule, the set $K_t = \{k_{t,1}, k_{t,2}, \ldots, k_{t,r}\}$ must satisfy the following conditions: (1) attempting the insertion of each $k_{t,j}$ in *TN* causes a propagation failure and (2) the cardinality of K_t is maximum. Condition (1) ensures that every constraint in K_t plays a meaningful role in determining system's reaction, ruling out false-positive situations; condition (2) ensures that no contingency escapes the system's attention.
- The acceptance of each constraint c_j (and complementarily, the contents of K_t), usually depends on the particular policy chosen for reinsertion. More specifically, different reinsertion orders can be implemented in the `chooseConstraint()` method, each leading to different results. To clarify this issue, let us consider a temporal network *TN* and

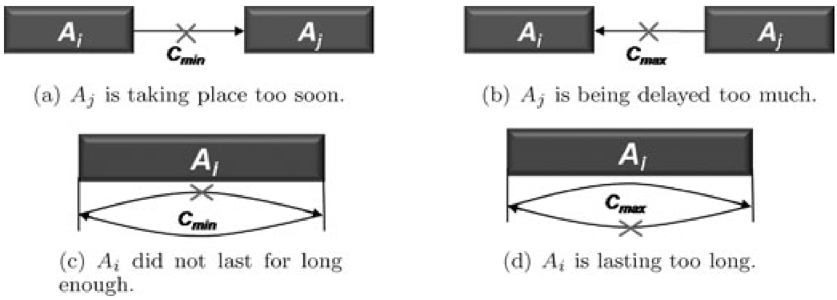

FIGURE 5. The building blocks for speech act generation based on constraint violations.

two constraints c_1 and c_2 such that the attempt of posting both of them in *TN* determines an inconsistency: trivially, depending on the specific order chosen for reinsertion, either c_1 or c_2 will be rejected. Because in the ROBOCARE context it is essential that the reaction be related to the closest contingency with respect to execution time t_E, the particular heuristic employed for reinsertion is backward-chronological; the result of this choice is that the rejected constraints will be the ones that are temporally closer to the actual instant of execution, therefore meeting the condition of reaction immediacy. In other terms, the ROBOCARE monitoring system is oriented toward synthesizing a suggestion regarding the closest cause of violation with regard to the current time, rather than synthesizing automatic explanations based on temporally distant effects of the assisted person's behavior.

3.3. Constraint Violations as Content of Verbal Interactions

The main problem tackled in this section is how to translate constraint violation information into semantically meaningful speech acts that the user may immediately understand. We start by presenting the building blocks this semantic analysis is based upon. At this level, all semantic inferences will have to be derived exclusively from the analysis of information of a temporal nature; later on, we will show how temporal data can be integrated with different types of environmental information. As we have seen in the description of Algorithm 1, each element in the violated constraints set K_t is either a *minimum* or a *maximum* constraint. At a basic level, the violation of each constraint can immediately be given a semantic interpretation, depicted in Figure 5: the violation of the minimum constraint c^{ij}_{min} between activities A_i and A_j (where A_i can be the *SOURCE* activity, i.e., a particular activity with zero duration whose start time coincides with the origin of the temporal axis), directly entails the following semantics: "*A_j is taking place too soon.*" (Figure 5(a)); the violation of the maximum constraint c^{ji}_{max} between activities A_j and A_i (where A_i can be the *SOURCE* activity), entails the semantics: "*A_j is being delayed too much.*" (Figure 5(b)).

Duration constraints undergo a slightly different analysis: in fact, a violation of a duration constraint on activity A_i might either involve the violation of the minimum or of the maximum constraints involved: the violation of the minimum duration constraint entails the semantics: "*A_i did not last long enough*" (Figure 5(c)); the violation of the maximum duration constraint entails the semantics: "*A_i is lasting too long*" (Figure 5(d)).

Given the previous basic interpretations, the integration of other kind of information can be exploited to improve semantic precision.

(a) Delay of linked activities. (b) Another complex pattern.

FIGURE 6. Exploiting causal information for meaningful semantics deduction.

3.3.1. Status of Execution of the Activities. In general, the meaning of the violation of a constraint may vary depending on the execution status of the involved activities. For example, in case A_i has not yet been executed, it is easy to see that the violation of c^{ij}_{min} directly implies that activities A_i and A_j have been temporally swapped, against the caregiver's prescriptions. Therefore, a general speech act consistent with the situation would certainly be: "*Should not A_i be performed first?*" Obviously, in case A_i has been executed, a more realistic verbalization might be: "*Should not you wait a while longer before performing A_j?*"

3.3.2. Activity Type Analysis. In general, in assessing the meaning of the violation of a constraint regarding the maximum constraints c^{ji}_{max}, a different interpretation might be given depending on whether the activity A_i is the *SOURCE* or not. When $A_i = SOURCE$, we are describing an *absolute* time limit that involves the start time of A_j; in the opposite case, the time constraint is *relative* to the end time of A_i. This difference might influence the speech act synthesis associated to the c^{ji}_{max} violation: in the first case, "*Expedite the execution of A_j*" might suffice; in the second case, "*It is taking too long between A_i* and A_j" would probably be more appropriate.

3.3.3. Causal Domain Theory. Another source of information that can be used to enhance the meaningfulness of the produced speech acts is related to the causal domain theory. In other words, information about casual links between direct neighbors of the activities involved in a constraint violations can be exploited to deliver explanations. An example is given in Figure 6(a): in the depicted situation, the delay on A_2 involves also a delay on A_3, as both activities are causally linked; as shown, two maximum constraints might be simultaneously violated, and causal link analysis might interpret the situation according to the following semantics: "*Commence* A_2, as it cannot be executed too late with respect to A_1, and A_3 *cannot begin later than a certain time*." Figure 6(b) shows another example: A_1 is currently under execution and the causal link between A_1 and A_2 pushes A_2 forward until the maximum constraint between A_2 and A_3 is violated. Again, the deduced speech act might be: "*Stop* A_1, as A_2 must be immediately executed because it cannot be performed too late with respect to A_3."

3.4. Remarks on the Use of Temporal Knowledge

In the last section we have described our approach to exploit the information contained in the temporal relations among activities to synthesize meaningful feedback to the user. In the ROBOCARE system, the use of scheduling technology and the underlying temporal propagation techniques constantly maintains the highest possible amount of original information against the inherently unpredictable behavior of the assisted person. The capability to *add and retract* temporal constraints to/from the ongoing plan, as explained in Section 3, allows to continuously retain only the original information that is consistent with the current world status, disregarding the temporal information that conflicts with the detected environmental situation (which is exploited to trigger warnings and alarms). The fact that the health-related informational content initially provided by the caregiver is maximally retained in the schedule as time progresses is used to provide to the assisted person a reliable and high-quality monitoring service, also in terms of delivered explanations.

It is worth mentioning that in this kind of application it makes little sense to assess system performance in terms of number of activities that can be accommodated in the behavioral pattern and/or the related reaction times; in fact, the scheduling technology used for implementing the monitoring functionalities can normally solve schedules in the order of thousands of activities, which makes the management of plans that model the activities of a single person trivial. As will be presented in the following sections, the real problem we have tackled in the ROBOCARE experience is the assessment of *how profitably* state-of-the-art scheduling technology might be employed in the context of human assistive systems.

A second comment concerns how the services described in this section resemble those described in the Autominder system (Pollack et al. 2003), the closest related work to ours. Both Autominder and the ROBOCARE activity monitor are used together with a robotic application, both offer similar services, and both use temporal constraint technology. As in our project, Autominder was conceived to be deployed on a mobile robot, namely Pearl (Pineau et al. 2003). The main focus in Pearl is on autonomous robotics, whereby the entire system is conceived as an independent platform able to operate in a domestic context. On the contrary, as described in Section 2, the attention in ROBOCARE is on creating an enhanced home environment that includes a robotic mediator and several active services to be combined together, among which the activity monitor described in this section. The general goal of Autominder is on the same line of our Daily activity monitor with the notable addition of a service of plan adaptation, called PCO for Personal Cognitive Orthotic (McCarthy and Pollack 2002) that allows modifying the current plan according to heterogeneous knowledge sources (not only commonsense knowledge, but also from the user's current context) to adaptively propose different things to the user. This type of innovative service is not included in ROBOCARE. The services of the ROBOCARE activity monitor are provided in Autominder by its two other building blocks, namely the plan manager (PM) and the client modeler (CM). The PM provides plan representation functionality and is based on the use of disjunctive temporal problems (DTP—Stergiou and Koubarakis (2000)), a more expressive temporal representation whose services are computationally rather expensive. The CM reasons on how current activities contribute to belief states for alternative scenarios. For this task a particular formalism is proposed called the quantitative temporal Bayesian network (QTBN—Colbry, Peintner, and Pollack (2002)). Autominder has indeed set the path for employing temporal reasoning in the context of domestic activity monitoring and contextual service provision. In following this path, we have taken a different direction, where instead of using very expressive formalisms such as DTPs and QTBNs our goal has been to investigated which types of services could be obtained starting from a computationally inexpensive temporal representation such as the STP. The advantage of the STP lies in its polynomial propagation algorithms and in a consolidated bulk of knowledge on its efficient use—e.g., Cesta and Oddi (1996). Through the use of temporal constraints alone we model services provided by Autominder's PM and CM modules, i.e., behavioral requirements, when interaction should occur as well as the content of interaction. Within ROBOCARE, we have also dealt with the problem of facilitating the process of modeling such knowledge by external users.[4] It is also worth underscoring how since the beginning our attention has been toward using the activity

[4] This issue is outside the scope of this article, see (Pecora et al. 2006).

monitor to generate content for interaction, an aspect described as secondary in Pollack et al. (2003). To sum up, though the ideas presented in Autominder have been a source of inspiration, in the ROBOCARE context we have focused on different objectives. Furthermore, the cooperation of all the ROBOCARE agents allows to promptly recognize and respond to dangerous situations that might arise in the everyday life of an elderly person, an important step ahead toward automated services for personal safety.

In pursuing our goal of using computationally inexpensive temporal formalisms we have connected our work with current trends in explanation generation. The problem of generating automatic explanation is an open challenge as well as a hot research issue that has been recently addressed in the context of temporal representation. For example, Bresina and Morris (2006) present a similar attempt to extract meaningful information from constraint-inconsistency detection in the context of planning for space. In their work, all temporal constraints in the plan are analyzed, and the possible temporal inconsistencies (no-goods) are detected and categorized. Eventually, the cause of the failure is returned, together with a simple explanation. In Smith et al. (2005) a simple algorithm to compute "user-oriented explanation" is described which employs a filtering step to reduce the constraints in the no-good. The remaining constraints are then "interpreted semantically" to enable the user to understand the reason of temporal conflicts. The problem tackled in ROBOCARE presents a similar challenge but in the context of human–machine direct interaction and cooperation. In our system, it is essential that feedback is produced as soon as possible, and moreover, its explanation must be related as much as possible to the current time of execution, to provide the *primary* cause of the inconsistency in terms of reaction immediacy.

4. EVALUATING ROBOCARE SERVICES

Users acceptance is a key factor in determining the uptake potential of intelligent systems. Extensive evidence of this is reported in literature describing the development of systems for supporting specialized real-world tasks, such as MAPGEN (Ai-Chang et al. 2004) and MEXAR2 (Cesta et al. 2007a) in the space domain, and AMC BARREL ALLOCATOR (Becker and Smith 2000) and PASSAT (Myers et al. 2003) in military domains. A common feature of these very different systems is their being dedicated to specialized users in restricted work environments. In such domains, users are generally aware of the role of an intelligent system and its ability to provide precious assistance for their decision making. Yet even in these cases, aspects related to interaction have proved to be a key issue for acceptability. Other intelligent systems driven by planning and/or scheduling techniques have been developed for less expert users, such as applications of everyday life management (e.g., McCarthy and Pollack (2002); Refanidis (2007)) and cognitive human assistance services (e.g., Levinson (1997)). In these and other contexts, the acceptance of advanced services by users is paramount. Questions that remain very often unaddressed are: How to guarantee that the partial/complete automation and the flexibility provided by advanced automated reasoning will be accepted by end users? How do we cast this technology so that it becomes usable for nonspecialized users, who are potentially not even familiar with information and communication technology? A user-centered approach needs a psychological analysis of people's response to AI applications as a guide for technology development in eldercare.

Our previous experience in evaluating user response to mixed-initiative systems relied on a comprehensive approach and experimental techniques imported from human–computer interaction and social, environmental, and cognitive psychology (Cortellessa and Cesta 2006). This work has been particularly useful to establish a consistent theoretical and methodological approach for our planning/scheduling technology and the related interaction with potential users, based on the analysis of their attitudes toward AI technology. In the ROBOCARE project we have applied a similar approach to evaluate the acceptability of the overall system. After spending 3 years developing different advanced functionalities in the RDE and reaching a fixed point in the technology development, we asked ourselves the question "We have understood what we are able to do, but what exactly do potential users think of the system we have obtained?"

To answer this question, our study focused on understanding the psychological response of elderly people to the RDE. We thus set up a rather complex experimental procedure for the analysis of users' attitudes toward the RDE, its perceived usefulness, and its acceptability. We also analyzed the role of some psychological variables potentially influencing the response of users.

4.1. Experiments with Elderly Users

Eight different scenarios, each representing a daily situation in an elderly person's experience, were developed. The situations were based on preliminary research within ROBOCARE (Giuliani, Scopelliti, and Fornara 2005) aiming at understanding users' expectations toward a robotic assistant, as well as on a certain amount of realism with respect to the services that robust versions of the RDE could offer. Such scenarios range from the most emotionally involving to less critical and emotionally neutral, with the aim of exploring elderly people's evaluations of the supportive role of a domestic assistant in a variety of everyday activities. The study focuses on three aspects.

First, we aimed at understanding how useful state-of-the-art assistive technology can be in solving real needs. Therefore, we performed an evaluation of the likelihood of each scenario in the everyday life of respondents. We also evaluated the perceived utility (*usefulness*) of system support and the users' willingness to accept a similar device at home in the presented situations (*acceptability*).

Second, to gauge the preferred level of autonomy of the assistive device and provide some hints on users' evaluation of mixed-initiative interaction, we arranged scenarios according to the distinction between *user-initiative* and *system-initiative* categories presented in Subsection 3.1. User-initiative scenarios imply an explicit request for the system activity by the user; in system-initiative scenarios, the robot autonomously intervenes in the domestic environment, for both emergencies and simple suggestions.

Third, we aimed at highlighting some positive and negative qualities of the overall system, as well as the emotional response of elderly people to this kind of support technology. Thus, we focused on respondents' attitudes toward our robotic mediator. The analysis addressed the physical aspect of the robot, its interaction capabilities, and its suitability in the domestic context (e.g., size, mobility, integration with the environment).

4.1.1. Evaluation Method. A video-based methodology has been used as opposed to bringing the users to a specific laboratory for user testing. Video-based trials can constitute a valid means to overcome some of the drawbacks of live evaluation (e.g., reliability and replicability of complex robot behaviors). Relevant research in the literature (e.g., Kidd (2003)) shows evidence of no significant differences between video-based and live trials.

Materials. Eight short movies (ranging from about 30 seconds to slightly more than 1 minute) were developed showing potential interaction scenarios between an elderly person and the RDE's robotic agent in a real domestic environment (see Figure 7).[5]

[5] Samples of the videos used in the evaluation can be found at the project's Web page: http://robocare.istc.cnr.it/

FIGURE 7. Sample frames from the videos depicting the eight scenarios.

The scenarios present critical everyday life situations in which the robot provides cognitive support to the elderly person, and pertain to the categorization put forth earlier on the modality of interaction with the human user (*user initiative* versus *system initiative*). This second category has been subdivided into two subcategories: *system initiative—safety* and *system initiative—suggestion* (see Table 1).

Tools. A questionnaire was developed for data collection consisting of three sections, plus a final part for sociodemographics. The sections were arranged as follows: Section 1 contained eight fill-in papers referring to each scenario, with questions about the *likelihood* of the situation, the *usefulness* and *acceptability* of the system; Section 2 presented an attitude scale, consisting of 45 Likert-type items, aimed at measuring the general evaluation of the robot; Section 3 presented an affective scale, consisting of 16 adjectives for the evaluation of the emotional response to the RDE at home. In the Likert-type items, agreement/disagreement was expressed on a scale ranging from 0 to 4.

Participants and Procedure. We recruited 100 people (40 males, 60 females) living in Rome, aged 56–90 years ($M = 70.4$, $SD = 7.38$). As regards the educational level, 12.2% attended primary school, 30.6% attended middle school, 36.8% have a high school diploma, and 20.4% have a degree. Most of them (83.3%) are retired. Before retirement, 20.2% were office workers, 17% were teachers; among females, 24.5% were housewives. The videos were either projected on a notebook monitor, in a face-to-face administration, or on a larger screen, in a small-group administration. Two different sequences of scenarios were used, to avoid an order effect of episodes on results. After the vision of each scenario, participants were asked to fill in the paper referring to it (Section 1 of the questionnaire). At the end of the whole presentation, subjects were asked to give general evaluations of the robot (Sections 2–3 of the questionnaire), and to fill the final part of the questionnaire, referring to sociodemographic (gender, age, etc.), experience (familiarity with new technologies) and psychological (perceived health, worry about future cognitive impairment) variables.

4.1.2. Results. We performed different analyses, namely analysis of variance, factor analyses, chi-square, and Pearson's correlation, to understand the users' response to the RDE.

Likelihood, Usefulness, and Acceptability. The analysis of scenarios showed that our selection was effective in identifying likely everyday situations; in addition, both usefulness and acceptability of the robot was quite high. Means of the usefulness are presented in Figure 9. Likelihood and acceptability means show a similar pattern. In particular, the robot emerged as a very useful device for Personal ($M = 2.92$, $SD = .95$) and Environmental safety ($M = 2.60$, $SD = 1.02$), Reminding medications, ($M = 2.65$, $SD = 1.04$), and Finding objects; ($M = 2.56$, $SD = 1.02$); conversely, it was not evaluated as particularly useful for providing suggestions ($M = 1.82$, $SD = 1.19$) (see Figure 8).

TABLE 1. Description of Scenarios Used in the ROBOCARE Evaluation

	Scenarios description
USER INITIATIVE	*The user asks for the system help*
Finding objects	The person asks for the robots' help to find objects within the environment.
Activity planning	The system supports the activity planning of the assisted person (e.g., planning his/her weekly appointments).
Reminding medication	The assisted person does not remember whether or not he/she took his/her medicine after lunch, and asks the robot.
SYSTEM INITIATIVE—SAFETY	*The system takes the initiative for safety related situations*
Environmental safety	The robot warns the assisted person of a potentially dangerous situation (e.g., the kettle was forgotten on the stove).
Personal safety	The system detects a medical emergency and alarms the assisted person's family.
SYSTEM INITIATIVE—SUGGESTION	*The system takes the initiative for suggestions or warnings*
Reminding analyses	The robotic assistant reminds the user of a medical appointment he/she has forgotten.
Suggestions	The system suggests to go for a walk as the user has been watching television all day (noncritical situation).
Reminding events	The system reminds the assisted person of the birthday of the user's acquaintance (noncritical situation).

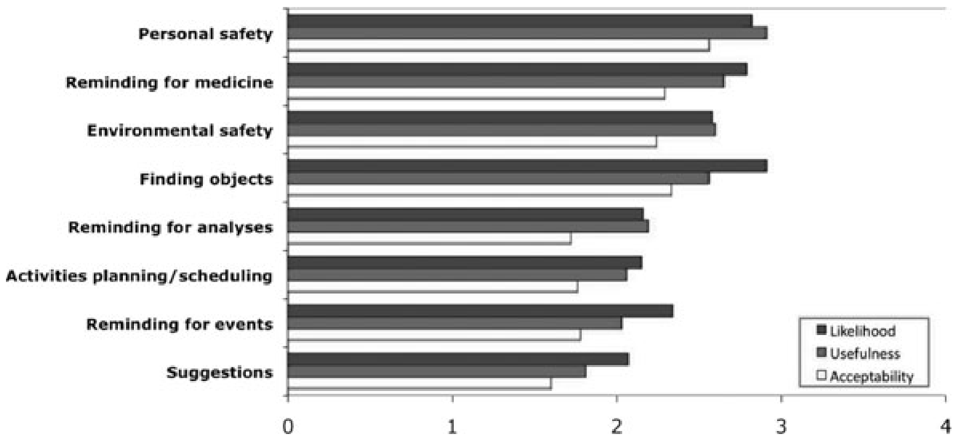

FIGURE 8. Likelihood, usefulness, and acceptability of the domestic robot in everyday situations.

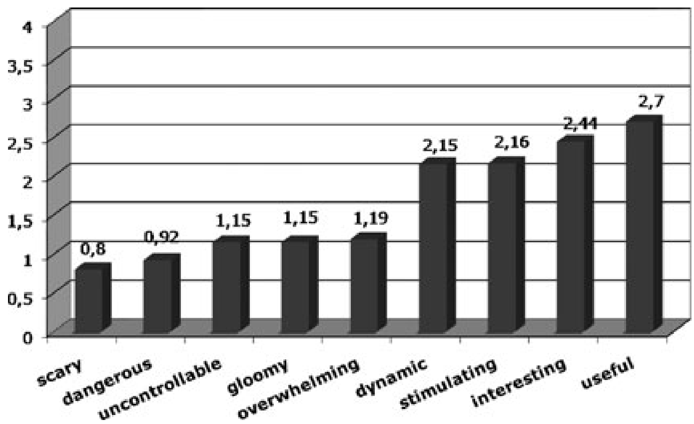

FIGURE 9. Emotional reaction of elderly people to the robot (means).

The evaluation of the scenarios, in terms of likelihood of the situation, utility, and acceptability of the robot, was not influenced by sociodemographic (gender, age), experience (familiarity with technology), and psychological (perceived health) variables. A significant effect of worry about future cognitive impairment emerged, with reference to likelihood of the situation ($F(2, 194) = 4.46, p < .05, \eta^2 = .05$), usefulness ($F(2, 194) = 13.38, p < .001, \eta^2 = .13$) and acceptability ($F(2, 194) = 7.37, p < .01, \eta^2 = .07$) of the robot: the higher the worry about future cognitive impairment, the higher the scores of the three variables.

In addition to usefulness, the robot was also indicated as a solution users would accept when difficulties arise, again with specific reference to Personal ($M = 2.95$, $SD = 1.06$) and Environmental safety ($M = 2.55$, $SD = 1.01$). In general, a significant correlation emerged (Pearson's r) between likelihood of a specific scenario, usefulness, and acceptability of the system in that scenario (i.e., the higher the likelihood of the scenario, the higher the users' perceived usefulness and the probability they would accept such a device at home).

User-Initiative versus System-Initiative Scenarios. Both user-initiative and system-initiative situations involving emergency and healthcare (safety) were evaluated as

TABLE 2. Evaluation of the System-Initiative versus User-Initiative Interaction (Scale 0–4)

	Likelihood		Usefulness		Acceptability	
Type of situation	Mean[A]	St. dev.	Mean[A]	St. dev.	Mean[A]	St. dev.
System in. (safety)	2.52^{a}	.63	2.57^{a}	.75	2.17^{a}	.98
User initiative	2.62^{a}	.71	2.42^{a}	.88	2.13^{a}	1.03
System in. (suggestions)	2.20^{b}	.90	1.92^{b}	.98	1.69^{b}	1.11

[A]The letters (a,b) indicate significant differences between typologies of situations.

significantly more likely than system-initiative situations referring to suggestions ($F(2, 194) = 18.09$, $p < .001$, $\eta^2 = .16$); in system-initiative situations involving emergency and healthcare and in user-initiative situations the robot was evaluated as significantly more useful than in system-initiative situations referring to suggestions ($F(2, 194) = 42.95$, $p < .001$, $\eta^2 = .31$); finally, the acceptability of the robot's support was significantly higher in system-initiative situations involving emergency and healthcare than in user-initiative and system-initiative situations referring to suggestions ($F(2, 194) = 26.13$, $p < .001$, $\eta^2 = .21$) (see Table 2).

The likelihood of the domestic situation depicted in each scenario emerged to be higher than the utility of the robot in that situation in five out of eight scenarios, while in system-initiative scenarios referring to emergency, utility and likelihood did not show a significant difference. Scores of acceptability were always lower.

General Evaluation of the Robot. We first performed a factor analysis on attitude items to identify significant dimensions of evaluation from the users' perspective. The analysis yielded a five-factor solution, with Oblimin rotation, explaining 47.4% of the variance. The attitude factors were labeled *Intrusion* (10 items, $\alpha = .81$), which refers to the perception of the robot as an imposed presence, observing personal affairs and operating even when it is not required; *advantages and capabilities of the RDE* (12 items, $\alpha = .88$), which focuses on the possibility for the system to perform tasks at home, support the users' activities and reduce age-related impairments; *management difficulties* (6 items, $\alpha = .76$), which implies potential difficulties in using, repairing and interacting with the robot; *positive communication modalities* (5 items, $\alpha = .62$), which refers to the appreciation of speech as interaction modality used by the robot; and *psychological distance* (8 items, $\alpha = .74$), which alludes to the dissimilarity from human beings and a slight mistrust.

The general evaluation of the RDE showed to be rather positive: Elderly people mainly appreciate the advantages and capabilities of the RDE, and do not recognize a high level of intrusion in the domestic environment; conversely, some management difficulties are expected. As to both positive communication modalities and psychological distance (e.g., mistrust, no similarity to human beings), users gave a midpoint evaluation (see Table 3).

No significant *gender* and *age* difference emerged in the attitude toward the RDE. Conversely, with reference to the educational level, a significant difference emerged in the evaluation of management difficulties ($F(2, 95) = 2.99$, $p < .05$): people with a lower educational level expected higher difficulties than people with a degree. *Perceived health* was not found to influence any of the attitude dimensions emerging from factor analysis. Familiarity with new technologies showed a significant effect on the evaluation of Intrusion ($F(1, 96) = 4.20$, $p < .05$): less familiar people expressed a higher level of perceived Intrusion. Finally, worry about future cognitive impairment showed a significant influence

TABLE 3. General Evaluation of the Robot

Dimensions of evaluation	Mean	St. dev.
Advantages and capabilities	2.55	.75
Intrusion	1.85	.83
Management difficulties	2.32	.77
Positive communication modalities	2.03	.83
Psychological distance	1.95	.74

on the evaluation of advantages and capabilities of the RDE ($F(1, 94) = 6.21, p < .05$): people reporting a higher level of worry expressed a better evaluation of advantages and capabilities of the RDE. In this respect, elderly people also showed a positive attitude toward a training interaction with the robot, aimed at the reduction of the loss in cognitive functioning ($M = 2.50$, $SD = 1.14$).

Finally, the emotional reaction of elderly people to the robot was very good, scoring high on the positive adjectives *useful*, *interesting*, *stimulating*, and *dynamic*, and very low on the negative adjectives *scary*, *overwhelming*, *gloomy*, *dangerous*, and *uncontrollable* (see Figure 9).

A significant gender difference emerged in positive adjectives ($F(1, 95) = 9.10$, $p < .01$), which were higher for males than females. In addition, worry about future cognitive impairment showed a significant influence on positive adjectives ($F(1, 93) = 6.92$, $p < .01$): People expressing a higher level of worry reported stronger positive emotions than less worried people.

4.2. Discussion

This study proposes some observations on the interaction of elderly people with assistive technology, identifying relevant issues about the acceptability of intelligent systems on behalf of elderly users in the domestic environment. The psychological perspective and the experimental methodology we adopted showed potential for application.

4.3. Likelihood, Usefulness, Acceptability

The proposed scenarios emerged as representative situations in everyday life. The central concern of health and safety in elderly people emerged also when analyzing the relationship between perceived likelihood of scenarios and usefulness of the system in that situation. In fact, in the situation involving an emergency, the acceptability of the robotic support is higher than the perceived likelihood of the situation itself, and the perception of usefulness scores the highest. Conversely, with respect to activities which are not considered to be essential in everyday life, elderly people show a tendency to assign a low score on likelihood of occurrence, and even lower scores on usefulness and acceptability. Overall, even if emergencies are not likely to occur, their central role in elderly people's experience makes both the perceived usefulness and the expressed acceptance of a proactive robot higher. This picture is in line with the model of successful ageing put forward by Baltes and Baltes (1990), which stresses the role of selection and optimization of activities with increasing age, and the importance of compensation strategies to manage the loss of personal resources.

4.4. User Initiative versus System Initiative

The distinction between user-initiative versus system-initiative situations showed to be meaningful as well, because elderly people's evaluations of the RDE are influenced by the specific type of the activity in which assistance is given. Elderly people perceive a clear distinction between important and unimportant activities to be performed at home. For those activities that are perceived as of greatest relevance, mainly concerning personal and environmental safety, the autonomy of the robot in the management of the home environment and in taking decisions proved to be a very useful resource. The robot is also appreciated for its capability to respond to a specific need expressed by the user, especially when referring to a cognitive difficulty associated with ageing, and involving activities related to healthcare (e.g., remembering things to do or what has been already done, with particular reference to medications and analyses). Conversely a robot making suggestions regarding unimportant activities is perceived both as less useful and less acceptable.

4.5. General Evaluation of the Robot

The general attitude toward the artificial assistant showed to be rather positive, although multifaceted. In the evaluation of the robot along the different dimensions, elderly people seem to recognize especially the practical advantages provided by an intelligent assistant, which can help the users in the management of everyday activities and age-related difficulties, makes them feel safer, and is a source of intellectual stimulation. In this respect, the system is perceived also as a means to maintain competence and self-efficacy (Bandura 1977), key factors for successful ageing (McAvay, Seeman, and Rodin 1996): in fact, the elderly appreciate the possibility to interact with the robot not only passively relying on its capabilities, but also through active training to enhance their cognitive functioning. Intrusion does not seem to be a relevant problem; however, some difficulties are expected with the management of the robot: What if it breaks down? What if an accident should happen? In addition, a moderate ambivalence seems to emerge between pros and cons in communication modalities and psychological closeness/distance: on the one hand, physical closeness is not perceived as a problem and users tend to trust the robot; on the other, they feel somewhat uncomfortable when speaking to a nonhuman agent but nonetheless they give a positive evaluation of its nonhuman aspect. Yet, speech is clearly recognized as a suitable communication modality.

Also the emotional response emerged to be positive, being feelings of danger, fear and loss of control definitely out of place, and positive emotions much more prevalent. Both the cognitive and the affective components of attitude showed to be influenced by socio-demographic, experiential and psychological variables. Gender seems to affect only the positive emotions toward the robot, where males show a more positive response.

Familiarity with new technologies also emerged as an important variable in the evaluation of such an innovative device, because it significantly decreases the level of perceived intrusion in everyday routines. Finally, personal concern about cognitive impairment plays a role on both cognitive and affective components of attitude: in fact, the higher the concern about personal health conditions, the better the evaluation of the capabilities of the system and the emotional response. This seems to be the consequence of a wishful thinking, according to which positive characteristics are recognized as a consequence of a perception of personal needs.

5. CONCLUSIONS

The ROBOCARE project has addressed research issues arising from the increasing interest in intelligent assistive technology for elderly people (LoPresti et al. 2004; Pollack 2005; Broekens, Heerink, and Rosendal 2009). ROBOCARE focused on a selected array of topics within this wide research area, and specifically emphasized the issue of integrating state of the art AI technology toward the aim of obtaining a comprehensive, service providing system. Specifically, attention was given to (a) the issue of combining heterogeneous intelligent systems to create an overall multi-agent system for proactive assistance, (b) the use of temporal planning knowledge, and (c) the synthesis of a robust robotic platform for domestic use. Less attention has been devoted to the use of sensors and the algorithms for elaborating their readings. For instance, strong assumptions were made on activity recognition (which is a research direction in its own right). In general the final RDE is to be considered as an important proof of concept rather than a solution ready to be deployed in a real context. A wealth of ideas regarding the implementation of AI techniques for elder care have emerged from ROBOCARE, several of which can directly enable the development of industrial strength solutions and marketable products through further investments in ambient assisted living[6].

This article has focused on two aspects of our system. The first aspect described here is an activity monitor entirely based on the knowledge representation of a scheduling system. It is worth highlighting how this module is based on a particular use of constraint-based temporal knowledge to manage changes in the environment. Specifically, we have shown how constraint violations determine *when* the system has to interact (i.e., violations that correspond to dangerous situations for the assisted person entail the need for synthesizing suggestions or alarms). The analysis and interpretation of the violation contribute to determine *how* to interact with the user (i.e., the content of the speech act).

A second important aspect we have addressed in this article is related to the issue of technology acceptability. In fact, it is worth highlighting the extreme difficulty that is connected to developing intelligent P&S technology for the mass market. This challenge becomes particularly relevant in light of the failures of AI in the 1970–1980s, and the proven complexity of deploying such systems in both specialized and market-oriented contexts. We have presented here an evaluation of our intelligent assistant based on a sound methodology. On one hand, these experiments can either reinforce or contradict common beliefs on the utility of general features of these systems. On the other, they require a great amount of work due to the involvement of real people. Despite the large effort required to apply this approach to evaluation, it is extremely precise and useful. In this light some work still remains to be done to better understand how to speed up and facilitate the application of a psychological perspective in the specific context of mixed-initiative system evaluation, and to further understand the generality of the outcomes.

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[6] See: http://www.aal-europe.eu/ or http://cordis.europa.eu/fp7/ict/programme/challenge7_en.html

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