

# Context Aware Cognitive Architecture for Adaptive Socially Assistive Robots

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**Abstract.** Socially Assistive Robots need to be aware of their context to be useful. Acceptance and usefulness come from adapting the robot’s behavior to the user and the situation. This paper aims to achieve this enhanced social awareness. It presents a cognitive architecture designed to include the whole context and to be shared by all agents in a smart environment. The architecture is provided with an ontology to facilitate the extension of the robot’s functionalities and the description of its behavior. It can adapt this behavior by toggling the execution of use cases and by modifying the execution of each use case according to the context. To test the proposed cognitive architecture, a set of use cases has been defined following a participatory design involving residents and caregivers from a retirement home. These use cases were incorporated into the architecture and analyzed in a one-month pilot study conducted in the retirement home. Results discussed in this paper show the potential of the solution to increase robot efficiency through adaptability.

**Keywords:** socially assistive robots · self-adaptation · social awareness.

## 1 Introduction

Socially Assistive Robots (SAR) [5] have received increasing attention over the last two decades. This interest in SAR is strongly linked to the demographic projections for population worldwide: by 2050, one in four people living in Europe and North America will be over 65 [21]. In this upcoming society, SAR can become a valuable tool to assist older people and caregivers in at least three application domains: communication, interaction, and monitoring. They can act autonomously but are also a proactive, mobile sensor and interface that can complement and expand the functionalities of smart assistive environments [1]. Among the contexts where SAR can be employed, retirement homes and daycare centres are some of the most interesting choices. Here, the SAR is mainly conceived as a tool for the caregiver to help in simple or repetitive tasks, allowing the human professionals more time for meaningful care [9].

While it may be possible to provide a SAR in these environments only with generic behaviours [9], its utility and acceptability, in this case, will be strongly constrained. Low robot awareness levels are currently marked as key barriers to the market in different robotic application domains [17]. Moreover, adapting the technology to the stakeholders is described as one of the main challenges of 4th generation Ambient Assisted Living environments [1]. However, to date, there are very few examples of extending robot social awareness to the complete functionalities of robots [15]. This paper updates the previously contributed CORTEX architecture [4] to address this topic. This new version of CORTEX includes a set of components that allow adaptation to the social context at two levels: (i) by selecting the appropriate use case to execute in each situation; and (ii) by modifying the execution of each particular use case. The proposed architecture has been integrated into a SAR and tested in a retirement home in a pilot study lasting for one month. The results discussed in the paper show the potential of the proposed solution in terms of increasing SAR awareness and using this awareness to increase efficiency.

This paper is structured as follows: Section 2 presents some related work, Section 3 describes the uses cases. Sections 4, 5 and 6 describes the robot, its cognitive architecture and the self-adaptation functionality. The paper concludes presenting results of the experiments and conclusions.

## 2 Related work

Social-awareness requires a SAR to be aware of its social context, and dynamically adapt its behavior to it [19]. The context here includes internal and external variables: cultural and social conventions, the agenda of the retirement home, particular user among others [3]. Moreover, social awareness faces the most demanding technical complexities in a complex research field. Traditionally, the concept has been explored only in face-to-face human-robot interactions [15], where the robot needs to share attention, extract semantic data from verbal and non-verbal cues, and keep a consistent interaction flow to be functional. More recently, social-aware navigation has received increasing attention, as robots moving in daily life environments must not only reach their navigation objectives, but also follow social conventions [22].

Context-aware autonomous robots usually rely on cognitive architectures to control their behaviour [4]. These architectures are modular systems that display complex cognitive capabilities such as perception, memory, or social learning [23]. They have recently incorporated social criteria to influence robot behaviour. Hence, the DAC-HRC (Distributed Adaptive Control - Human Robot Collaboration) cognitive architecture [6] aims at adaptive human-robot collaboration in industrial environments. It is based on the concepts of *joint intentionality* and *interdependence*, and allows a robot arm to adapt its behaviour to each human worker regarding safety distances or interaction speed. The proposal is oriented to cooperative robots that do not navigate through the environment, and do not proactively initiate interactions. Tanevska et al. [18] present a preliminary study of an adaptive cognitive architecture in the iCub robot. The robot can

adapt its behaviour to different user profiles and use internal context to engage or disengage from interactions. It is usual for these solutions to be based on the use of a certain ontology to represent semantic data, facilitate reasoning and decision making procedures, anticipate action results or ease explainability [14]. This paper follows these approaches and proposes a step towards integrating social awareness in robots deployed in unconstrained, complex daily life settings, such as a retirement home.

### 3 Use cases

The cognitive architecture proposed in this paper has been tested in a retirement home, where a SAR performs a set of meaningful use cases. The selection of these use cases received the support of qualitative social scientists experienced with interdisciplinary research, applied robotics, and co-creation. User needs for residents and caregivers, in the retirement home where the robot will be used, had already been captured in previous projects [9]. However, changes in the staff routines and composition led to the performance of a new half-day focus group to update the previously collected data. Participants included two physiotherapists, a considerably fit and healthy resident, and a research assistant trained in health technology. The focus group intended to capture the day-to-day routines and interactional situations [16] of residents and care staff - a group usually neglected in digital innovation research [13]. The focus group included the phases (1) initial valorization, (2) exploration of staff-resident interaction, and (3) prioritization of ideal robot uses. After the focus group, the information collected was contrasted against previous use cases explored by the robotics team, and a set of use cases was finally specified.

- *Wandering*: The robot moves to random navigation goals in a specified area.
- *Charging*: The robot announces it has to go to the charging station and moves there.
- *Menu Selection*: The robot approaches a recognized person and asks for her menu choices for the next week. The selection is made with a touch screen.
- *Musical Therapy*: When the hour of the therapy approaches, the robot moves to the designated location, starts playing music and moves around randomly.
- *Reminder*: The robot approaches a recognized person. Then, it reminds him/her about an activity in his/her agenda that is about to start.
- *Cognitive Therapy*: When the robot recognizes a person that participates in the therapy, it offers to start an activity, through the touch screen.
- *Bring me water!*: When the robot's 'bring me' button is pushed, if the person is a valid user, it offers different options on its screen related to different requests. The user selects one of these options. The SAR then moves to a designated location and announces the petition aloud.

All these use cases adapt during their execution, according to the interacting person, her agenda, the agenda of the robot, and context parameters (e.g., hour or battery level). Some use cases may have a higher priority: e.g., if the battery is critically low, the robot should go to the charging station immediately. The *Menu Selection* and *Reminder* use cases were the main suggestions of the care staff. The

*Musical Therapy* and *Cognitive Therapy* use cases resulted from (i) identifying already ongoing activities, (ii) which could relieve time pressure for the care staff, (iii) in which residents already interact with digital technologies, and (iv) which could augment residents' wellbeing and foster interaction between them. The remaining use cases allow exploring diverse functionalities of the robot.

## 4 Materials

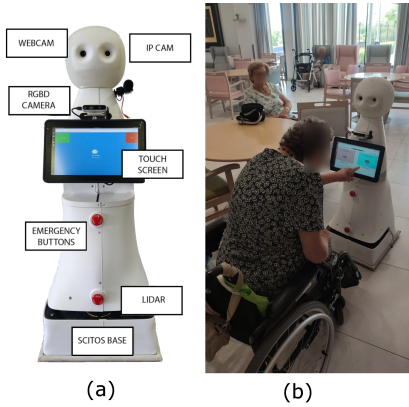
CLARA robot (Fig. 1.a) is a SAR initially developed within the framework of the CLARC EU project ECHORD++ (FP7-ICT-601116) to perform Comprehensive Geriatric Assessment (CGA) procedures [2]. It has a Metralabs SCITOS differential base, a range laser scanner SICK s300, a square safety bumper, a touch screen, speakers, and one Intel RealSense D435i RGB-D camera. This camera allows the detection within the environment of objects from the 80 classes in the COCO database using the YOLOv8 algorithm, and recognizing people using dlib's state-of-the-art face recognition algorithm built with deep learning by Adam Geitgey [8]. It also incorporates a microphone. However, after several tests at the retirement home, we discarded the voice interface for this prototype due to the frequent recognition issues caused by environmental noise. The SAR navigates autonomously using an enhanced version of the ROS 2 navigation stack 'Nav2' [11] whose main components are (i) the cost-aware Hybrid-A\* SmacPlannerHybrid and (ii) a Dynamic Window Approach algorithm to follow the path computed by the planner to the goal point. The navigation stack only requires setting the goal as (i) a desired pose for the robot, or (ii) the name of a zone, in which the robot's pose will be set randomly.

Although a SAR should be able to operate autonomously, it is currently understood that its functionality benefits greatly from being integrated into a smart environment [1]. It may also be helpful for caregivers or technicians to update system data by accessing an external computer instead of the robot. In the proposed system, the smart environment stores long-term data (e.g., user profiles). It is implemented as an embedded computer, running a MongoDB database. The computer and the SAR can exchange data using WiFi.

## 5 Cognitive architecture

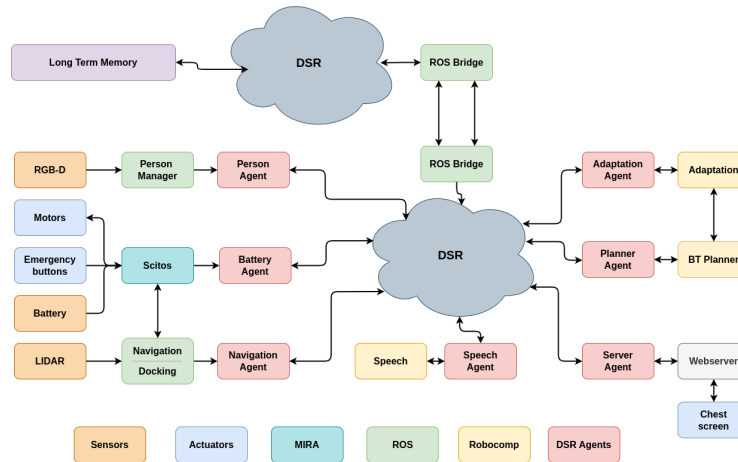
The cognitive architecture used in this paper is an updated version of the CORTEX architecture [4]. The core of this architecture is the Deep State Representation (DSR), an oriented graph that stores the immediate context. Long-term data, such as user profiles or agendas, are stored in long-term memory. These elements represent a self-centered world corresponding to the *Umwelt* concept [20]: the world understood from the robot's point of view. The components of the cognitive architecture connect to the DSR as Fig. 2 shows. They only exchange data with the DSR, which acts as a shared blackboard.

Fig. 3 shows an example of the content of the DSR during the execution of a use case. More precisely, the figure represents the typical configuration for the *Menu Selection* use case, when the menu has been collected for a particular user. As depicted, the DSR contains nodes that store the physical agents (e.g.,



**Fig. 1.** (a) Socially Assistive Robot CLARA; (b) A resident selecting the menu.

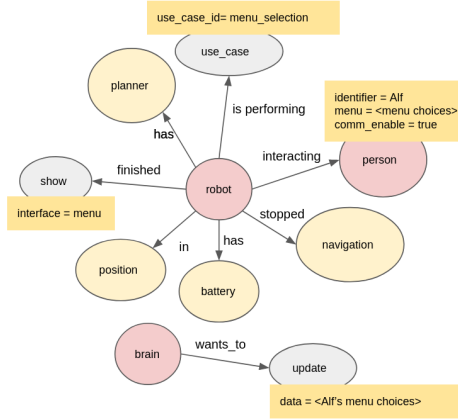
people), actions (e.g. *move*, *update*, *say*), executed use cases, and agent subsystems (e.g. *navigation*). The edges are relations set and updated according to the ontology described below. Nodes and edges can incorporate attributes that provide additional information, such as the user profile for a recognized person.



**Fig. 2.** Cognitive architecture for CLARA robot.

Two main changes have been made to the architecture compared to previous proposals. The first is the inclusion of a long-term memory and software components in charge of adapting the behavior of the robot. On the other hand, this paper proposes to distribute the software components between different physical agents. Some components are deployed in the embedded computer (referred to as *brain* in this paper), which is the core of the smart environment, and is always

connected. Some other components run in the SAR. Each physical agent runs its components autonomously.



**Fig. 3.** DSR during the execution of the *Menu selection* use case.

All agents work with a copy of the same DSR and the same long-term memory. To keep the context representations of different agents synchronized, a bridge component (Fig. 2) is responsible for sending and receiving DSR updates. Nodes and edges have a generic attribute detailing the physical agent that made the last change. Action-level synchronization is achieved following an event-driven approach, in which all updates have an associated timestamp and are only considered if the updated timestamp is later than the current one.

Updates of the long-term memory are also performed through the DSR: these updates are encoded in the DSR itself as specific *update* actions to be performed by an agent. Fig. 3 shows an example of this process, where the robot has collected the menu options for a particular user (Alf) and these options need to be stored in the long-term memory of the smart environment (the *brain* agent). As depicted, the bridge component of the robot has created an *update* action for the *brain* node. When the robot connects to the rest of the smart environment, the DSR of the *brain* agent receives this update, and the CORTEX components in that agent perform the long-term memory update action as detailed below.

### 5.1 Ontology

The proposed system uses a precise ontology to define the contents and relationships in the DSR. This ontology is designed to facilitate the scaling of the robot’s functionalities and the description of the causal effects within the execution of the use cases. So far, it includes the following set of categories:

**Node types.** Nodes in the DSR are included in one of these categories:

- *Agents*. These nodes represent a physical agent in the environment, such as a robot, a person, or a smart device. Agents can have subsystems and can execute

use cases composed of sets of actions. Their attributes can encode their profiles and agendas.

- *Actions*. These nodes represent an action being performed by an agent. Their attributes include action parameters (e.g., the phrase to say for a *say* action).

- *Use cases*. These nodes represent use cases being executed. They are similar to the action nodes, but while it is possible for a single agent to perform multiple actions in parallel, it can only perform one use case at a time.

- *Subsystems*. Some agents may have additional nodes linked to them, that are in charge of encoding the functionality of a particular subsystem (e.g., the navigation system of a robot).

**Edge types.** Nodes can be connected using edges. While the subsystem nodes can use *ad-hoc* edges, links between agents, or that relate agents with use cases or actions, are constrained to a generic set. Thus, agents can only link to each other using *is with* or *interacting* edges, and can link to actions or use cases only using *wants to*, *is performing*, *finished*, *abort*, *failure* or *cancel* edges. The last three edges have a generic *result code* attribute, which contains the result of the action.

**Action execution sequences.** The execution of a use case mainly involves executing a set of actions, encoded into Behavioral Trees (BT). All actions follow the same steps: first, the agent is linked to the action with a *wants to* edge. Then, once the agent starts executing the action, the edge changes to *is performing*. Once the execution finishes, the edge changes to *finished*, and a *result code* attribute appears in the edge. After executing these steps, any planner component can delete the action node. The execution of use cases follows the same steps.

It is possible for a planner component to interrupt the execution of an action or to cancel it before its execution starts. Interrupted actions are linked to the agent node with an *abort* edge before they can be deleted. Canceled actions are linked with a *cancel* edge. If an action fails, a *failure* edge is generated along with the corresponding result code indicating the reason for the failure.

**User profiles.** Agent nodes can have attributes that encode their profile. These profiles are stored in the long-term memory and loaded into the DSR on demand. These profiles are particularly relevant to person nodes. Thus, when a person near the SAR is recognized, the node representing her will be loaded with items. These items have been discussed with the professional caregivers of the retirement home where the SAR will be deployed, and are closely related to the data used by these professionals. User profile items are encoded as Likert scale scores related to physical and cognitive abilities and attitudes towards the robot. Communication preferences determine interface-related parameters (e.g., subtitles or voice volume).

**Agendas.** Agendas store the daily activities for a particular agent. They are loaded from the long-term memory into the agent node attributes. User profiles and agendas can be updated manually in the long-term memory and from the DSR attributes. Therefore, it is possible to implement autonomous learning mechanisms in the cognitive architecture.

## 6 Smart use case switching

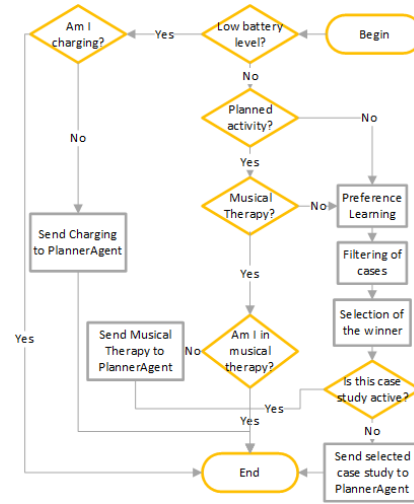
Use cases are encoded into Behavioral Trees (BT). The *Planner Agent* (Fig. 2) implements a BT engine that allows BT nodes to take data from the DSR and modify the execution of the use case according to the context. Moreover, the robot can switch the use case in execution. One of the challenges here is selecting the appropriate use case, taking into account the number of possible context configurations, which is very high. While there are situations in which the use case selection for execution is evident, for example, those involving the battery or the retirement home agenda, others require careful consideration of the person in front of the robot and the surrounding context. To select the best course of action for these last cases, we apply an approach based on preference learning [7]. Preference learning is a subfield of machine learning that focuses on classification based on preference information, usually provided by experts. We gather preferences on use cases from people involved in the robot development and retirement home personnel. Using this information, we developed several classifiers that score the use cases. These scores create an ordered list of use cases in which the use case with the highest score comes first.

The agent in charge of switching the use case is the *Adaptation Agent* (see Fig. 2). This agent cooperates with the *Planner Agent* by sending the use case that should be active. *Adaptation Agent* behaves by executing periodically the flow diagram depicted in Fig. 4. The agent first considers the use cases with the highest priority. In the current version of our robot, they are first *Charging* and second *Musical Therapy*. If any of these cases is not selected, preference learning is applied. Our preference learning algorithm considers the users' information in front of the robot to select the best use case for them. However, it is possible that this use case cannot be active due to the time of the day or the robot's current location. For example, the *Reminder* can only be active if the user is not in the adequate room. To remove these cases, a filter after the preference learning process removes them from the ordered list of use cases. After the filtering, the first use case of the list is sent to the *Planner Agent*.

## 7 Experiments

A pilot study has been conducted for one month (July 2024) in a retirement home to evaluate the functionality of the proposed system. Up to 9 residents interacted with the robot daily. Experiments took place in a multipurpose room of the Vitalia Teatinos retirement home (Málaga, Spain) (Fig. 1.b). The room is equipped with furniture that is usually moved to different positions, so the configuration of the room cannot be predicted. During the experiments, some residents and occasional workers moved around walking, using a walker or wheelchair, or pushing food trolleys. The robot was allowed to work in the room from Monday to Friday, but only from 11:00 to 13:30, due to the restrictions imposed by the schedule of the retirement home.

The evaluation group was recruited from residents following these inclusion criteria: (i) adequate cognitive abilities, i.e. a score of 26 or higher out of 30 in the Montreal Cognitive Assessment (MoCA) [12], and a score of 23 or higher



**Fig. 4.** Adaptation loop for smart use case switching.

in the Lobo’s Minimental scale [10]; (ii) ability to hear and/or see displayed tests; (iii) expected to stay in the retirement home for at least one month. The evaluation group finally included 9 residents, aged between 59 and 95 years (mean age 78.75 years). There were 7 female and 2 male participants. Only two have previous computer experience, and 7 use mobile phones occasionally. Two of them have no previous experience with technology.

The proposed system has been compared against a system similar to the one used in [2], in which the SAR performs each planned interaction sequentially, starting and ending the use case from the charging station. Each system has been tested for 10 days during the evaluation. For the sequential system (named *Seq* in the paper, and evaluated in weeks #2 and #4), the *Menu Selection* use case was assigned a daily time slot of 45 minutes (from 11:00 to 11:45). The *Cognitive Therapy* also had a time slot of 45 minutes (from 11:45 to 12:30), the *Musical Therapy* was carried out from 12:30 to 12:45. Finally, the robot reminded the residents of the daily menu from 12:45 to 13:30 (just before lunch). The *Bring me water!* use case was always executed on demand. The opportunistic context-aware system proposed in this paper (named *C.A.*, and evaluated in weeks #1 and #3) used the entire available time slot (from 11:00 to 13:30) to execute use cases according to the algorithm described in Section 6. The *Musical Therapy* was programmed from 12:30 to 12:45. The functionality of the system is measured by the following set of results:

- *Success Rate (SR)*: It is the ratio of successful use cases performed. The maximum number of use cases to be performed is 208: 18 menus (1 weekly menu per person), 90 cognitive therapies (one daily use case per person), 90 reminders, and 10 music therapies. The number of *Bring me water!* use cases to be executed cannot be predicted, hence this use case is not considered for

this metric. A higher  $SR$  value is better: for example, if all the menus are properly collected, but the robot does nothing more, the  $SR$  is 18/208.

- *Distance travelled ( $dist_{total}$ )*: The total distance traveled by the robot until it completes all the daily use cases (excluding *Bring me water!* use cases).
- *Time efficiency ( $t_{eff}$ )*: It is the ratio of actively interacting with a person. It is calculated by dividing the time the SAR spends actively interacting with a person by the time the SAR spends executing meaningful use cases (*Wandering* and *Charging* are excluded).

Table 1 shows the number of use cases executed for both approaches during the pilot study, against the maximum number of use cases to be executed (e.g., 15/18 means the robot could execute 18 use cases but performed 15). The proposed context-aware (*C.A*) approach obtains better results, particularly for the *Menu Selection* use case, where the robot improved  $SR$  from 66.67% (12/18) to 100% (18/18). It took the occupational therapist an average of 45 minutes to collect the weekly menus for 9 residents, not including the time spent searching for them in the retirement home. She pointed out that she could now use this time for more meaningful activities with the residents.

**Table 1.** Use cases successfully executed each week

Approach	Menu Select	Cognit. Therapy	Remind	Bring me water!	Musical Therapy
<i>C.A</i> (Week 1)	9/9	24/45	12/45	16/-	5/5
<i>C.A</i> (Week 3)	9/9	29/45	20/45	21/-	5/5
<i>Seq</i> (Week 2)	5/9	12/45	7/45	13/-	5/5
<i>Seq</i> (Week 4)	7/9	17/45	5/45	28/-	5/5
<b><i>C.A</i> (TOTAL)</b>	18/18	53/90	32/90	37/-	10/10
<b><i>Seq</i> (TOTAL)</b>	12/18	29/90	12/90	41/-	10/10

The results of the tests (see Table 2) shows that the context-aware approach outperforms the previously employed sequential approach in  $SR$ . Even when the context-aware approach stays in the *Wandering* use case when no meaningful use case is to be executed, and the charging station is close to the operating area, the sequential approach still covered a larger space (1.66 km more), but executed only 104 use cases against 150. The opportunistic nature of the *C.A* approach led the robot to efficiently execute sets of use cases once a resident had been engaged in an interaction (e.g., after collecting the menu, the robot asked to start cognitive therapy exercises). This resulted in a higher  $t_{eff}$  value.

The  $SR$  is relatively low due to a recurrent issue: not all the residents are in the room every day, even after the experimental procedure had been agreed upon with them. This situation is widespread in these settings. It encourages moving to more flexible, opportunistic decision-making procedures for the SAR, allowing the robot to make the most of its interactions. Routine tasks that are time-consuming for the professionals, but are not urgent or bound by very strict time slots (e.g., *Menu Selection*) are the best candidates for inclusion in the repertoire of the SAR. This repertoire should be as wide as possible to make the SAR a helpful tool in the retirement home.

**Table 2.** Metrics obtained for both approaches

<i>SR</i> (%)		<i>dist<sub>total</sub></i> (km)		<i>t<sub>eff</sub></i> (%)	
<i>C.A</i>	<i>Seq</i>	<i>C.A</i>	<i>Seq</i>	<i>C.A</i>	<i>Seq</i>
54.32	30.28	19.44	21.1	28.03	21.86

## 8 Conclusions

This paper presents a context-aware cognitive architecture for a SAR. The proposal has been tested in a retirement home in a pilot study lasting for one month and involving 9 residents and 2 professionals. The results of the experiments show a significant improvement over previous sequential approaches in terms of efficiency, mainly because the robot can leverage interactions flexibly and opportunistically. The proposed system also adapts its behaviour according to the user profile. The current pilot study reveal some research actions that will be carried out, such as: (i) learning the routines to modulate behaviours; (ii) including additional interaction mechanisms for the users to provide data to the robot (e.g. button-based devices); (iii) reinforcing system capabilities and efficiency (e.g. person recognition processes) with meta data provided by sensors integrated in the smart environment, previous experience and user profiles.

Future work will address the inclusion of user profiles in the ontology to enhance scalability, interoperability, and semantic reasoning. Deeper comparative studies involving other state-of-the-art cognitive architectures will also be conducted. Regarding user experience and social impact analysis for this proposal, a six-month study is currently being carried out according to the AUSUS methodology [9], to evaluate the functionality and user experience in terms of acceptability, utility, and accessibility. The full impact of the proposed adaptive behaviour will be analyzed after this experimentation phase.

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