Ambient Assisted Living and Social Robots: Towards Learning Relations between User's Daily Routines and Mood

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ABSTRACT

Endowing social robots with the ability to learn and predict the user's activities during the day is one of the main aims of research in the field of ambient assisted living. Social robots should support older adults with daily activity and, at the same time, they should contribute to emotional wellness by considering affective factors in everyday situations. The main goal of this research is to investigate whether it is possible to learn relations between the user's affective state and daily routines, made by activities, with the aid of a social robot, Pepper in this case. To this aim, we use the WoMan system able to incrementally learn daily routines and the context in which activities take place. WoMan will be used as a back-end module of the Daily Diary application running on the Pepper robot to collect data concerning daily activities and their relation to emotions and mood. Results of this phase of the research will be used to assess the validity of the approach in ambient assisted living houses for seniors to make the social robot able to provide not only proactive service assistance but also an affective empathic experience.

CCS CONCEPTS

• **Computing methodologies → Machine learning**; • **Human-centered computing → Human computer interaction (HCI)**.

KEYWORDS

social robot, daily routine, emotions

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1 INTRODUCTION

According to the World Health Organization (WHO) the proportion of people over 60 years will reach the 22% by 2050[1]. In this context, the sustainability of care and assistance is getting an increasing importance. Besides the lack of caregivers, since people lives longer, the costs of care increase due to the fact that elderly people often have chronic diseases and comorbidity that requires specific management.

A possible solution to this problem is to empower seniors with technological solutions for enhancing their quality of life and allowing aging actively in their house. In this vision, seniors assistance is delegated to the intelligence embedded in the technology that should not represent a further obstacle for the user. Therefore, it is necessary to put the emphasis on human-technology interaction for making access to services effective and suitable for the user needs [31].

In this vein, vocal assistants and social robots have been used as a natural interface between the user and the smart home services. Then, social robots should support older adults with daily activity, but at the same time they may contribute to emotional wellness by considering affective factors in everyday situation.

Many research works have focused on endowing the the robot with the capability of recognizing human emotions from facial expressions, body poses, voice, and physiological responses [33], but rarely the emotional intelligence of the robot allows to reason on the situation in which emotions occur. Given data that can be captured by a social robot and sensors present in a smart environment over long durations of time, it is possible to discover the context of behaviors of people, including habits and routines [19, 37]. Then, making the robot aware of the user's activities, routines and affective factors could allow reasoning on the user not only for personalizing assistance but also for infer the situations in which emotions occurs.

In a previous work, we focused our effort on developing a system for learning the daily routines of the user both from sensors present in smart environments and from mobile data [5, 12]. In particular, the approach exploits the WoMan (acronym for 'Workflow Management') system to incrementally learn and refine users routines represented in First-Order Logic (FOL) [21]. The WoMan system is able to deal with non-sequential activities and repeated-tasks, and therefore the approach is suited to represent models of user's routines for predicting the user needs.

At the current phase of research, we investigate whether it is possible to use this approach to relate patterns of daily routines to affective factors and how social robots may be used to this purpose. To this aim we designed a dialog application for the Pepper robot, the DailyDiary (DD), that will allow on one side gathering an annotated set of data, to learn the daily routines and to relate activities to emotions and mood, on the other side to use the learned model

[1]https://www.who.int/news-room/fact-sheets/detail/ageing-and-health

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to make the robot aware of the user daily routine and the relation of certain patterns of activities with affective states.

In this phase of the project, we tested the accuracy of the learning module which shows that, with the proposed approach, it is possible to learn daily routines and the relations of activities with affective factors. In our future work, we plan to develop the fully described application and test it. The evaluation will be made in terms of: i) user experience in a smart environment created in our laboratory and ii) accuracy in predicting both activities and mood. The final result of this reasearch will be used to give to the robot the right level of proactivity needed for assistance in smart environments.

2 BACKGROUND AND MOTIVATIONS

Technology-enabled assistive environments offer opportunities to provide personalized care services to older adults to live as much as possible independently in their houses.

To this aim the home environment monitors daily life activities by data coming from sensors that can be embedded in the environment or wearable and used to collect data about physiological parameters, lifestyle, activities, daily routines, social factors and environmental factors [1, 34, 36, 38] These data are collected in order to decide and support the intervention of the smart environment. For instance, many systems use sensors to recognize daily living activities (i.e., walking, running, stepping and falling) and to detect anomalies during these activities [23].

Another type of sensor that can be use to recognize activities is the camera that can be combined with wearable and ambient sensors for realizing complex monitoring infrastructures [24]. In this case computer Vision approaches can be used to extract relevant information from images and activities can be recognized by analyzing video streams. Relevant approaches in this direction start from the extraction of the skeleton joints of a person in the video through a pose detection software and, subsequently, recognize the activity using models based on LSTMs [25, 28, 39], Graph Convolutional Networks (CGN) as in the work proposed by [7].

These technologies to be successfully used to support users in their daily life should be integrated in natural and engaging interfaces. Social Assistive Robots (SAR) are nowadays seen as key interaction technology for supporting older adults care at home or in care institutions [3, 9]. They provide a social interface to support seniors in performing daily tasks and care. Since SAR have the main goal to provide assistance to human users through social interaction, the emphasis is then on using effective interaction for the purpose of giving assistance to the user [20]. Besides the functional capabilities of the robot (physical activity, cognitive training, physiological therapy, etc.) affective aspects are important since they can help to increase the quality of life of older adults through companionship and social interaction [4].

The Pepper robot developed by SoftBank is a humanoid robot featuring multi-modal communication able to recognize faces and basic human emotions, is capable of human interaction directly through conversation [27]. For the specific use–case of older adult care, Pepper was successfully used in healthcare and older adult-care facilities mainly as narrative-memory-based human–robot companionship [15] and medicine taking reminding, encouraging older adults to keep active and helping them keep in touch with family and friends. Recent research approaches have used Pepper as older adults' companion for suggesting personalized physical activities in the context of active aging [10]. The proposed solution uses deep learning methods on Pepper recorded information to classify the exercises and to schedule personalized physical activities. Both Pepper and Nao robots have been used with good results in cognitive stimulation therapy for people suffering of Mild Cognitive Impairment (MCI). Researchers [26] investigate how patients with dementia relate to humanoid robots and perceive serious games accessed through it, as part of a training program aimed to improve their cognitive status [11, 30].

Social robots have been used and tested in the context of a smart home environments [35]. In [13], a micro-service oriented platform has been developed to endow the social robot with a set of behaviors aimed at monitoring and interacting with elderly people affected by Alzheimer disease in their houses. In [2, 14] projects, social robots have been developed and used for providing services to facilitate independent living at home, assisting the user in the daily tasks. Projects having the main goal of promote independent living through the use of services provided by a smart environment and the social and natural interface of a social robot are growing in number denoting the importance of endowing these artificial entities of rational and emotional intelligence.

3 INCREMENTAL LEARNING OF DAILY ROUTINES

Smart home environments should proactively support users in their activities by anticipating their needs and adapting the environment's behavior. Automatically learning models of daily routines from examples of actual behavior can support this task. To this aim we use the WoMan framework [21, 22] for incremental learning of users' daily routines from a set of annotated data.

3.1 Process Mining: The WoMan Framework

A *process* is a sequence of actions performed by agents. A *task* is a generic type of action, defined to be executed for many cases of the process. An *activity* is the actual execution of a task in a case. WoMan [21, 22] is a *declarative* Process Mining [29] framework that introduced some important novelties in the process mining and management landscape. Experiments proved that it is able to handle efficiently and effectively very complex processes, thanks to its powerful representation formalism and process handling operators. This includes learning people's daily routines and people's paths in an Ambient Assisted Living context. This made it an interesting candidate for application in the work described in this paper. In the following, we briefly and intuitively recall its fundamental notions.

3.2 WoMan Representation Formalism

As all Process Mining systems, WoMan learns process models starting from logs of previous process executions. It allows to specify in log entries more information than most other systems. A WoMan log entry associated to a relevant process event is a 6-tuple of the form $\langle T, E, W, P, A, O \rangle$, where T is the event timestamp, E is the type of the event (one of 'begin_process', 'end_process', 'begin_activity', 'end_activity', 'context_description'), W is the name of the reference workflow, P is the case identifier, A can be either the name of the activity or the contextual information, and O is the progressive number of occurrence of A, in case of name of activity, in that case. The description of the context stored in A is expressed in the form of a list of First-Order Logic (FOL for short) atoms. This formalism allows describing explicitly the concurrent flow of activities in a process execution. More technically, log entries are described as FOL atoms built on the following predicate:

`entry(T,E,W,P,A,O).`

WoMan process models describe the structure of workflows using several predicates. The core information to describe the process' structure consists of *tasks* (the kind of activities that are allowed in the process) and *transitions* (the allowed connection between activities). In particular, transitions express the flow of activities during process execution. A transition $t : I \Rightarrow O$ between two multisets of tasks I and O is enabled if all tasks in I are active; it occurs when, after stopping (in any order) the concurrent execution of all tasks in I, the concurrent execution of all tasks in O is started (again, in any order). Woman can attach probabilities to process components. It can also learn pre-/post-conditions for tasks and transitions in the form of FOL rules based on contextual and control flow information, possibly involving several steps of execution. More technically, this information is described in WoMan's models as a conjunction of atoms built on the following predicates:

- `task(t,C)` : task t occurs in cases C;
- `transition(I,O,p,C)` : transition $p : I \Rightarrow O$ occurs in cases C.

Argument C represents a history of those tasks/transitions, and is exploited to compute statistics on their use.

3.3 WoMan Modules

WoMan may run in 3 modes. The learning mode allows to learn a process model from logs of activities. The supervision mode allows to apply a learned model to new cases of the process in order to check that they are compliant with the model. The prediction mode allows to apply a learned model to new cases of the process in order to foresee the most likely subsequent activities that the user will perform at a given moment of the execution. These tasks are carried out by different modules in WoMan's architecture.

WEST (Workflow Enactment Supervisor and Trainer) is WoMan's supervision module. It takes the events in a log as long as they are available, and checks their compliance with the currently available model for the specified process. If an event is compliant it returns 'ok'. If it is syntactically wrong (e.g., closing activities that had never begun, or terminating the process while activities are still running) it returns an 'error'. If it is syntactically correct but deviates from the model, it returns a 'warning' specifying the kind of problem (e.g., unexpected task or transition, preconditions not fulfilled, unexpected resource running a given activity, etc.).

WIND (Workflow INDucer) is WoMan's process discovery module. It can learn *or refine* (in incremental mode) a process model according to new executions. The refinement may affect the structure, the probabilities or the conditions of the model. Whilst all previous approaches in the literature work in 'batch' mode (i.e., they need a –possibly large– set of training cases to learning their models), WIND is *fully incremental*: not only can it refine an existing model according to new cases whenever they become available, it can even start learning from an empty model and a single case. To learn conditions in form of logic theories, WIND relies on the incremental learning system InTheLex [18].

WoGue (Workflow Guesser) is WoMan's module allowing it to make several kinds of predictions while in supervision mode. Specifically, it can predict the process execution outcomes or the next activities that will be carried out during process execution. Its predictions are ranked by confidence, determined based on a heuristic combination of several parameters associated with the current process execution and the probabilities associated to the model's components.

Since each mode deals with a different task, there is no direct relationship between the modes. A typical usage sequence is: WIND is used to learn a process model, then WEST applies the process model to new process executions to check that they are compliant to the model. During the execution, WoGue can be used to predict what is likely to happen next in that process execution.

3.4 Process Mining for Learning Daily Routines

We used WoMan to face two problems: *daily routines learning* and *activity prediction*. Predictions are more complex than in classical process mining domains, because there is much more variability and subjectivity in the users' behavior, and there is no 'correct' underlying model, just some kind of 'typicality' can be expected.

As far as learning the lifestyle of the user by building models of his daily routines is concerned, it can be seen as a set of processes. Therefore, modeling such routines can be cast as a process mining task. A workflow model is a formal specification of how a set of tasks can be composed to result in valid processes, allowing compositional schemes such as sequential, parallel, conditional, or iterative. So, in WoMan we decided to learn models that are represented as workflows. As an example, we provide here the process log represented in WoMan's formalism for the case in Figure 1 (timestamps have been replaced by sequential numbers for readability purposes):

```
entry(1,begin_of_process,monday,day1,start,1).
entry(2,begin_of_activity,monday,day1,read,1).
entry(3,end_of_activity,monday,day1,read,1).
entry(4,begin_of_activity,monday,day1,tv,1).
entry(5,begin_of_activity,monday,day1,eat,1).
entry(6,end_of_activity,monday,day1,eat,1).
entry(7,end_of_activity,monday,day1,tv,1).
entry(8,begin_of_activity,monday,day1,take_pill,1).
entry(9,end_of_activity,monday,day1,take_pill,1).
entry(10,begin_of_activity,monday,day1,play,1).
entry(11,end_of_activity,monday,day1,play,1).
entry(12,begin_of_activity,monday,day1,work_out,1).
entry(13,begin_of_activity,monday,day1,read,2).
...
entry(47,end_of_process,monday,day1,stop,1)
```

As context and activities are detected through sensors or entered by the user, the corresponding entries are provided to the WoMan system that, applying the algorithm described in [21], learns the activities and their inter-relationships.

The model learned from this case would be:

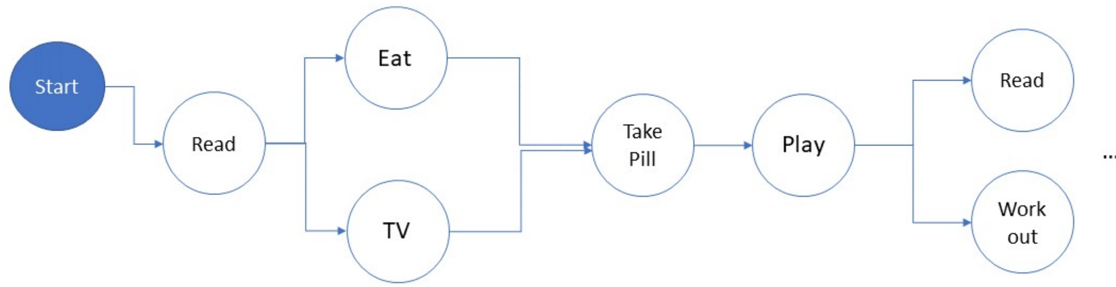

Figure 1: Graphical representation of the activities involved in a process execution referred to 'Monday' daily routine

```
task(stop,[1-1]).
...
task(act_work_out,[1-1]).
task(act_play,[1-1]).
task(act_take_pill,[1-1]).
task(act_eat,[1-1]).
task(act_tv,[1-1]).
task(act_read,[1-2]).
task(start,[1-1]).

transition([act_play]-[act_work_out,act_read],[1-1],2).
transition([act_take_pill]-[act_play],[1-1],3).
transition([act_eat,act_tv]-[act_take_pill],[1-1],4).
transition([act_read]-[act_eat,act_tv],[1-1],5).
transition([start]-[act_read],[1-1],6).
...
```

where the numbers in brackets report the number of occurrences of each item in each case (e.g., $[1-1]$ means that the item occurred once in case 1; $[1-2]$ means that the item occurred twice in case 1; etc.). Note that, being the model a declarative one, the order of task and transition atoms is irrelevant (so, 'stop' being the first task in the list does not mean it is the first task to be applied — the order of task application is controlled by transitions).

The main aim of this new phase of research is to test the approach and learn a model of daily routines in which activities and patterns are related to information about emotions and mood.

To this aim we asked 5 older adults (3 males and 2 females from 60 to 78 years old) to write a diary of their daily activities and mood using a dedicated chat on their phone for 1 month. Two of them (1 male and 1 female) were not able to do it by themselves and, for them, we asked their caregivers to do it. Everyday the senior or the caregiver had to write the schedule of the daily tasks, the relevant events of the day and the mood. An example of entry is:

9:00 Watching news on TV, anxious
11:00 Prepare lunch, calm
12:30 Eat lunch, sad
13:30 Watch TV, relaxed
14:30 Sleep,-
16:00 Read Book, happy
...

In total we collected 1350 entries that were used to extract the knowledge, in terms of activities and mood (we mapped the labels of affective states into their valence in order to simplify the labelling of the mood), needed to learn daily routines.

We formalized these data according to the WoMan formalism and then we learned the daily routine models for each week day (Monday-Sunday) using WoMan in 'learning' mode.

The following is an example of collected trace:

```
entry(1, begin_of_process, a, c1, start, ).
entry(2, context_description, a, c1, [anxious], 1).
entry(3, begin of activity, a, c1, watch_tv_news, 1).
entry(4, end_of_activity, a, c1, watch_tv_news, 1).
entry(5, context_description, a, c1, [calm], 1).
entry(6, begin_of_activity, a, c1, prepare_lunch, 1).
entry(7, end of activity, a, c1, prepare_lunch, 1).
entry(8, context_description, a, c1, [sad], 1).
entry(9, begin_of_activity, a, c1, eat_lunch, 1).
entry(10, end of activity, a, c1, eat_lunch, 1).
entry(11, context_description, a, c1, [none], 1).
entry(12 begin_of_activity, a, c1, sleep, 1).
entry(13, end of activity, a, c1, sleep, 1).
entry(14, context_description, a, c1, [happy], 3).
entry(15, begin_of_activity, a, c1,  read_book, 1).
entry(16, end_of_activity, a, c1, read_book, 1).
...
```

3.5 Analysis of the Collected Data

In order to have an insight of the learning system's performance, we tested the accuracy of the learned models using a 10-fold cross-validation procedure. For the considered dataset the system reached 85,63% average accuracy with a standard deviation of 10,84. After the learning step, we removed noisy (i.e., infrequent) pieces of the model, using a feature of WoMan that takes in input a percentage frequency and ignores in the model all items that occurred in less than that percentage of cases. Specifically, we told WoMan to ignore transitions and activities that were encountered in less than 4% of the training cases (a percentage that was experimentally determined so as to preserve the general behavior). Then, we ran WoMan in 'supervision' mode using the denoised models and the training cases, in order to collect for each day the warnings returned by

WoMan, denoting deviations from the routines. After this, the cases were sorted in chronological order, and a histogram of the warnings in each day was drawn. The curves of mood variations, calculated as a function of valence, were finally superimposed to this histogram, normalizing the warning bars to their range [-1,1]. Specifically, for each day the average value of each parameter was plotted in these curves. This allowed to detect correlations between positive or negative valence and days with many warnings, which would confirm the influence of mood over routinary behavior.

4 PEPPER DAILY DIARY

To collect a dataset of entries containing annotated data about activities and emotions for learning the daily routine, we designed the the Daily Diary (DD) application that uses a combination of natural language dialogues, touch-based input on the Pepper's tablet and computer vision modules. The application allows to manage a ToDoList and a context-aware Reminder.

The DD application will be composed by different modules useful for the annotation purpose: user identification, emotion recognition, a todolist manager, activity reminder, activity recognition and a dialogue manager.

- ***User Identification***: this module will be used for recognizing a user by face and keeps the information of each user about personal (user's picture, user's age, gender, name, family,friends and physicians contacts) and medical aspects (chronic diseases, allergies, therapies, etc.). Face recognition on the Pepper robot is performed with the ALFaceDetection API of the NaoQi SDK (http://doc.aldebaran.com/2-5/naoqi/peopleperception/alfacedetection-api.html).
- ***Emotion Recognition***: For the analysis of the emotion from the face of the elderly people, we developed a software to classify the facial expressions according to the following classes: angry, disgust, fear, happy, sad, and surprise [17]. The neutral expression was also considered to indicate the absence of emotions. The recognition of facial expressions in older adults remains a challenging task since aging has an effect on facial expressions. In particular, there are age-related structural changes in the face, such as wrinkles and facial muscles decay, that can be recognized as emotions (usually the neutral expression of elderly people is recognized as sadness) recognition. For this reason, to recognize the facial expressions in elderly faces more efficiently, we developed a classifier trained on the FACES dataset [16] containing images of older adults. Our model, described in [6], uses, as features, the presence and intensity (expressed as a float from 0 to 5) of 17 facial AUs (Action Units) extracted with the OpenFace software. Due to the low number of examples for each class in the dataset, we did not consider approaches based on deep learning. The model is based on Random Forest that reached an accuracy of 97% tested according to the stratified k-fold cross-validation with k=10 and 83% in the wild.
- ***To Do List Manager***: this module will allow to insert event and things to do in an internal calendar application through a combination of dialog and touch-based interface on the Pepper's tablet.

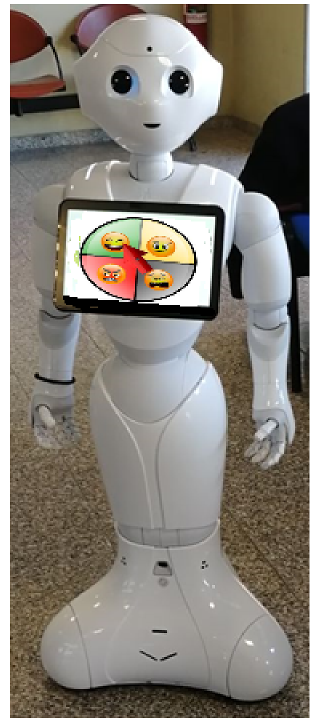

Figure 2: An example on how mood information will be required during the dialog.

- ***Dialog***: the dialog will be handled using using Choregraphe, Python scripts and NaoQi.
- ***Activity Recognition***: a module for activity recognition based on [8] approach has been developed to recognize user activities in real time and will be adapted to the application.

In terms of implementation, the DD application will use a server component on which several webservices, that implement the WoMan and Computer Vision functionalities, will be present and invoked opportunely.

The DD application will send the entries about activities and the context to the WoMan system according to the formalism described previously. Figure 2 shows Pepper and the interface for mood input.

To do so, users will be asked but not forced to input explicitly information about their emotions in the following situations: after the user wakes up in the morning, when the user takes voluntarily the initiative and talks to Pepper, after four hours after the last input, when an activity is foreseen to happen, when a new activity is detected. This is done by initiating a dialog with the user. In this way we can capture a user's self-reported emotions and mood in relation to activities and context. In addition the emotion recognition module will run in the background to detect the emotion automatically. In deciding how to represent mood information we decided to adopt the two-dimensional approach (valence and arousal) described in the Circumplex model [32] and, in particular, we defined 4 possible states corresponding to the four quadrants: 1) Tense/Anxious, 2) Sad/Bored 3) Calm/Relaxed, 4) Happy/Cheerful. Besides the user answer to the Pepper's question ("how do you feel today), we display also an input interface on the Pepper's tablet in which we used a circle divided in four quadrants representing the main moods associated to the combinations of the two dimensions of the model and an arrow that allows indicating also intermediate states. In order to avoid confusion and misunderstandings, we put representative faces in the quadrants. When the user states his moods only by vocal input we map the provided affective state into on of the four quadrants described previously according to its valence and the arousal.

We plan to perform an evaluation of the application in our laboratory where we will create a space furnished like a living room testing the application. We will involved adults older than 60 years old. We plan to evaluate the user experience with the robot and how much the approach allows to collect annotations that are precise and useful to learn and refine incrementally the daily routines and their relation with affective state with the WoMan system.

5 CONCLUSIONS AND FUTURE WORK

In this paper we reported the possibility to apply the WoMan system to the task of learning daily routines and their relation to variation of affective states. In order to do so, we designed an application for the Pepper robot, the Daily Diary, that, besides providing the typical functions of a to do list, allows to collect an annotated dataset of activities related to emotions and context features. In order to investigate on this, we first learned models of user activity and mood using WoMan, and then we used WoMan in supervision mode, checking the co-occurrence of significant changes in mood and deviations from the routine. Moreover we are combining data collected with DD with those that can be detected in indoor situations from indoor sensors of a smart environment. In the near future we plan to develop the application and evaluate the user experience with the robot and how much the approach allows to collect annotations that are precise and useful to learn and refine incrementally the daily routines. In addition we will exploit the learned model to endow the robot with a proactive behavior based on activity prediction and mood inference.

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REFERENCES

[1] Aitor Almeida, Rubén Mulero, Piercosimo Rametta, Vladimir Urošević, Marina Andrić, and Luigi Patrono. 2019. A critical analysis of an IoT—aware AAL system for elderly monitoring. *Future Generation Computer Systems* 97 (2019), 598–619.
[2] Farshid Amirabdollahian, Rieks Op den Akker, Sandra Bedaf, Richard Bormann, Heather Draper, Vanessa Evers, Gert Jan Gelderblom, Carolina Gutierrez Ruiz, David Hewson, Ninghang Hu, et al. 2013. Accompany: Acceptable robotiCs COMPanions for AgeiNG Years—Multidimensional aspects of human-system interactions. In *2013 6th International Conference on Human System Interactions (HSI)*. IEEE, 570–577.
[3] Ionut Anghel, Tudor Cioara, Dorin Moldovan, Marcel Antal, Claudia Daniela Pop, Ioan Salomie, Cristina Bianca Pop, and Viorica Rozina Chifu. 2020. Smart environments and social robots for age-friendly integrated care services. *International Journal of Environmental Research and Public Health* 17, 11 (2020), 3801.
[4] Joost Broekens, Marcel Heerink, Henk Rosendal, et al. 2009. Assistive social robots in elderly care: a review. *Gerontechnology* 8, 2 (2009), 94–103.
[5] Berardina De Carolis, Stefano Ferilli, and Domenico Redavid. 2015. Incremental learning of daily routines as workflows in a smart home environment. *ACM Transactions on Interactive Intelligent Systems (TiiS)* 4, 4 (2015), 1–23.
[6] Giovanna Castellano, Berardina De Carolis, Nicola Macchiarulo, and Olimpia Pino. 2022. Detecting Emotions During Cognitive Stimulation Training with the Pepper Robot. In *Human-Friendly Robotics 2021*. Springer, 61–75.
[7] Yuxin Chen, Ziqi Zhang, Chunfeng Yuan, Bing Li, Ying Deng, and Weiming Hu. 2021. Channel-wise Topology Refinement Graph Convolution for Skeleton-Based Action Recognition. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 13359–13368.
[8] Yuxin Chen, Ziqi Zhang, Chunfeng Yuan, Bing Li, Ying Deng, and Weiming Hu. 2021. Channel-wise Topology Refinement Graph Convolution for Skeleton-Based Action Recognition. *CoRR* abs/2107.12213 (2021). arXiv:2107.12213 https://arxiv.org/abs/2107.12213
[9] Gabriella Cortellessa, Riccardo De Benedictis, Francesca Fracasso, Andrea Orlandini, Alessandro Umbrico, and Amedeo Cesta. 2021. AI and robotics to help older adults: Revisiting projects in search of lessons learned. *Paladyn, Journal of Behavioral Robotics* 12, 1 (2021), 356–378.
[10] Angelo Costa, Ester Martinez-Martin, Miguel Cazorla, and Vicente Julian. 2018. PHAROS—PHysical Assistant RObot System. *Sensors* 18, 8 (2018). https://www.mdpi.com/1424-8220/18/8/2633
[11] Berardina De Carolis, Valeria Carofiglio, I Grimandli, Nicola Macchiarulo, G Palestra, and O Pino. 2020. Using the pepper robot in cognitive stimulation therapy for people with mild cognitive impairment and mild dementia. In *Proceedings of ACHI-The Thirteenth International Conference on Advances in Computer-Human Interactions*. 452–457.
[12] Berardina De Carolis and Stefano Ferilli. 2014. Towards Learning Relations Between User Daily Routines and Mood.. In *UMAP Workshops*. Citeseer.
[13] Claudia Di Napoli and Silvia Rossi. 2019. A layered architecture for socially assistive robotics as a service. In *2019 IEEE international conference on systems, man and cybernetics (SMC)*. IEEE, 352–357.
[14] Alessandro Di Nuovo, Frank Broz, Ning Wang, Tony Belpaeme, Angelo Cangelosi, Ray Jones, Raffaele Esposito, Filippo Cavallo, and Paolo Dario. 2018. The multi-modal interface of Robot-Era multi-robot services tailored for the elderly. *Intelligent Service Robotics* 11, 1 (2018), 109–126.
[15] Peter Ford Dominey, Victor Paléologue, Amit Kumar Pandey, and Jocelyne Ventre-Dominey. 2017. Improving quality of life with a narrative companion. In *2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*. IEEE, 127–134.
[16] Natalie C Ebner, Michaela Riediger, and Ulman Lindenberger. 2010. FACES—A database of facial expressions in young, middle-aged, and older women and men: Development and validation. *Behavior research methods* 42, 1 (2010), 351–362.
[17] Paul Ekman. 1999. Basic emotions. *Handbook of cognition and emotion* 98, 45-60 (1999), 16.
[18] Floriana Esposito, Giovanni Semeraro, Nicola Fanizzi, and Stefano Ferilli. 2000. Multistrategy theory revision: Induction and abduction in inthelex. *Machine Learning* 38, 1 (2000), 133–156.
[19] Iram Fatima, Muhammad Fahim, Young-Koo Lee, and Sungyoung Lee. 2013. A unified framework for activity recognition-based behavior analysis and action prediction in smart homes. *Sensors* 13, 2 (2013), 2682–2699.
[20] David Feil-Seifer and Maja J Mataric. 2005. Defining socially assistive robotics. In *9th International Conference on Rehabilitation Robotics, 2005. ICORR 2005*. IEEE, 465–468.
[21] S. Ferilli. 2014. WoMan: Logic-based Workflow Learning and Management. *IEEE Transaction on Systems, Man and Cybernetics: Systems* 44 (2014), 744–756. Issue 6.
[22] Stefano Ferilli, Floriana Esposito, Domenico Redavid, and Sergio Angelastro. 2016. Predicting process behavior in woman. In *Conference of the Italian Association for Artificial Intelligence*. Springer, 308–320.
[23] Hemant Ghayvat, Muhammad Awais, Sharnil Pandya, Hao Ren, Saeed Akbarzadeh, Subhas Chandra Mukhopadhyay, Chen Chen, Prosanta Gope, Arpita Chouhan, and Wei Chen. 2019. Smart aging system: uncovering the hidden wellness parameter for well-being monitoring and anomaly detection. *Sensors* 19, 4 (2019), 766.
[24] Chih-Lin Hu, Chitrin Bamrung, Wasita Kamintra, Somchoke Ruengittinun, Pattanasak Mongkolwat, Lin Hui, and Shih-Hsiang Lo. 2019. Using camera array to detect elderly falling and distribute alerting media for smart home care. In *2019 8th International Conference on Innovation, Communication and Engineering (ICICE)*. IEEE, 98–101.
[25] Jun Liu, Amir Shahroudy, Dong Xu, and Gang Wang. 2016. Spatio-Temporal LSTM with Trust Gates for 3D Human Action Recognition. In *Computer Vision – ECCV 2016*, Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling (Eds.). Springer International Publishing, Cham, 816–833.
[26] Marco Manca, Fabio Paternò, Carmen Santoro, Eleonora Zedda, Chiara Braschi, Roberta Franco, and Alessandro Sale. 2021. The impact of serious games with humanoid robots on mild cognitive impairment older adults. *International Journal of Human-Computer Studies* 145 (2021), 102509.
[27] Amit Kumar Pandey and Rodolphe Gelin. 2018. A mass-produced sociable humanoid robot: Pepper: The first machine of its kind. *IEEE Robotics & Automation*

Magazine 25, 3 (2018), 40–48.
[28] S.U. Park, J.H. Park, M.A. Al-masni, M.A. Al-antari, Md.Z. Uddin, and T.-S. Kim. 2016. A Depth Camera-based Human Activity Recognition via Deep Learning Recurrent Neural Network for Health and Social Care Services. *Procedia Computer Science* 100 (2016), 78–84. https://doi.org/10.1016/j.procs.2016.09.126 International Conference on ENTERprise Information Systems/International Conference on Project MANagement/International Conference on Health and Social Care Information Systems and Technologies, CENTERIS/ProjMAN / HCist 2016.
[29] M. Pesic and W. van der Aalst. 2006. A declarative approach for flexible business processes management. In *Proceedings of the 2006 international conference on Business Process Management Workshops* (Vienna, Austria) *(BPM'06)*. Springer-Verlag, 169–180.
[30] Olimpia Pino, Giuseppe Palestra, Rosalinda Trevino, and Berardina De Carolis. 2020. The humanoid robot NAO as trainer in a memory program for elderly people with mild cognitive impairment. *International Journal of Social Robotics* 12, 1 (2020), 21–33.
[31] Carlos Ramos, Juan Carlos Augusto, and Daniel Shapiro. 2008. Ambient intelligence—the next step for artificial intelligence. *IEEE Intelligent Systems* 23, 2 (2008), 15–18.
[32] James A Russell. 1980. A circumplex model of affect. *Journal of personality and social psychology* 39, 6 (1980), 1161.
[33] Matteo Spezialetti, Giuseppe Placidi, and Silvia Rossi. 2020. Emotion Recognition for Human-Robot Interaction: Recent Advances and Future Perspectives. *Frontiers in Robotics and AI* 7 (2020). https://doi.org/10.3389/frobt.2020.532279
[34] Ioan Susnea, Luminita Dumitriu, Mihai Talmaciu, Emilia Pecheanu, and Dan Munteanu. 2019. Unobtrusive monitoring the daily activity routine of elderly people living alone, with low-cost binary sensors. *Sensors* 19, 10 (2019), 2264.
[35] Elena Torta, Franz Werner, David O Johnson, James F Juola, Raymond H Cuijpers, Marco Bazzani, Johannes Oberzaucher, John Lemberger, Hadas Lewy, and Joseph Bregman. 2014. Evaluation of a small socially-assistive humanoid robot in intelligent homes for the care of the elderly. *Journal of Intelligent & Robotic Systems* 76, 1 (2014), 57–71.
[36] Md Uddin, Weria Khaksar, Jim Torresen, et al. 2018. Ambient sensors for elderly care and independent living: a survey. *Sensors* 18, 7 (2018), 2027.
[37] Jan Vanus, Jana Belesova, Radek Martinek, Jan Nedoma, Marcel Fajkus, Petr Bilik, and Jan Zidek. 2017. Monitoring of the daily living activities in smart home care. *Human-centric Computing and Information Sciences* 7, 1 (2017), 1–34.
[38] Ju Wang, Nicolai Spicher, Joana M Warnecke, Mostafa Haghi, Jonas Schwartze, and Thomas M Deserno. 2021. Unobtrusive health monitoring in private spaces: The smart home. *Sensors* 21, 3 (2021), 864.
[39] Wentao Zhu, Cuiling Lan, Junliang Xing, Wenjun Zeng, Yanghao Li, Li Shen, and Xiaohui Xie. 2016. Co-Occurrence Feature Learning for Skeleton Based Action Recognition Using Regularized Deep LSTM Networks. *Proceedings of the AAAI Conference on Artificial Intelligence* 30, 1 (Mar. 2016). https://ojs.aaai.org/index.php/AAAI/article/view/10451