Cognitive decline management through theatre therapy, artificial intelligence, and social robots

Abstract— **Cognitive decline is a significant societal challenge, and the development of information and communications technology solutions to manage it is essential. The main challenges include the lack of comprehensive monitoring and assessment of cognitive decline, limited engagement with conventional cognitive stimulation applications, and the need for multi-domain interventions for cognitive function stimulation. In this paper, we present innovative technological solutions for managing more effectively the cognitive function of older adults experiencing mild cognitive impairment that integrates social robots, Internet of Things monitoring, and machine learning. It offers services for dealing with non-invasive monitoring and machine learning assessment of cognitive decline by fusing activity trackers and self-reporting data and personalized social robot-based interventions for cognitive function stimulation and social interaction facilitation using cognitive games and pleasant activities such as theatre therapy or storytelling. We have defined setup of the trials, procedures, and indicators to measure the impact on various care dimensions such as improving the quality of life and cognitive state of older people, Improving the quality of care and the cost efficiency or level of support offered for the informal or formal carers.**

Keywords—active assisted living, social robots, artificial intelligence, cognitive decline, theatre therapy.

I. Introduction

Mild cognitive impairment (MCI) affects older adults' health and wellbeing due to the decline of their cognitive abilities. This includes memory, thinking skills, or the ability to conduct independently activities of daily living (ADL) such as self-care tasks, such as bathing, dressing, eating, and toileting. To manage these negative effects innovative Information and Communication Technology (ICT) solutions can be adopted to engage, support, and coach older adults in stimulating their cognitive functions in personalized manners considering their general state, wishes and needs. Social robots, non-invasive Internet of Things (IoT), and Artificial Intelligence (AI) are key enabling technologies that can be innovatively combined to support the self-management of cognitive decline. Analyzing nowadays cognitive screening models [1], and existing ICT solutions for cognitive stimulation of older adults [2], the critical challenges need to be addressed for developing innovative solutions aiming to improve the quality of life of people with MCI. The literature reports low levels of engagement with traditional cognitive stimulation applications which are mostly based on cognitive games and memory exercises [3]. This is associated with the need for setting up proactive interventions by coaching support and social interaction facilitation to allow the older adults to self-manage their cognitive decline in their homes delaying their institutionalization [4].

There is a high cost and lack of contextual information for traditional MCI screening methods (i.e., based on genetic, neuroimaging biomarkers, questioners, etc.), which affects the early identification of cognitive decline. The drawbacks of nowadays tools are related to the absence of multiparametric contextual monitoring and assessment of decline, and multi-domain intervention addressing all relevant factors such as cognitive stimulation, coaching, and social interaction [5]. The available tools are often not practical and suitable in-home settings nor enjoyable for older adults, as they require complex technological skills. They provide exercises based on general game scenarios (i.e., playing with a ball or flying a plane) and are often considered not age-appropriate or childish by older adults, thus reducing their engagement.

In this paper we present how the above challenges are addressed in a European innovation project called engAGE (Managing cognitivE decliNe throuGh theatre therapy, Artificial intelligence and social robots drivEn interventions) [6]. engAGE aims to develop an ecosystem of services based on an innovative platform that integrates social robots, IoT-based monitoring, and machine learning (ML) to slow down cognitive decline evolution. It offers a holistic approach to the self-management of older adults' cognitive decline from non-invasive monitoring using activity trackers, ML assessment, and up to advanced intervention using social robot-driven coaching, cognitive function stimulation, and social interaction facilitation.

The solution proposed for cognitive intervention is based on social robots which have in general more positive acceptance influenced by the robot's social capabilities. Moreover, the cognitive function stimulation is done using pleasant activities employing theatre therapy (i.e., dialog play with the robot) or memories stories telling. By doing so, we are also tackling one of the issues that the COVID-19 pandemic brought to people experiencing MCI: the loss of the invaluable support offered by art and music-based therapies. Such therapies that have been demonstrated to be effective non-medical interventions [7]. For example, art through its different forms has been used as a therapy to improve quality of life by stimulating enjoyable experiences, preserving the personal identity, reducing stress, and ultimately dealing with the behavioral and emotional challenges of the cognitive decline [8]. Drama and theatre activities can be combined with emotion-oriented care methods to produce a positive impact on behavior and mood people with MCI by enhancing and activating memory functions and lowering the socially isolated behavior [9]. Several studies have shown the positive outcomes of social robots-based therapies for people experiencing MCI [10-11]. They are more effective in engaging people in activities and stimulating their cognitive and physical condition when used together with art-based therapies especially in day care centers [12].

Existing studies have already highlighted the importance of early intervention in cognitive decline management [13]. Unfortunately, the cognitive decline in older population is still underdiagnosed. Thus, there is a strong need for holistic solutions, utilizing cutting-edge technology to provide sensitive and acceptable tools for monitoring and detection of cognitive functioning decline [14]. The solution discussed in this paper integrates non-invasive monitoring using activity trackers with self-reporting questioners to assess the cognitive function decline by detecting its effects on activities of daily living (ADL) [15]. Recent research studies have revealed a notable link between cognitive function and daily activities [16]. In our case we will use ML to establish the correlation between the two factors. Predicting cognitive decline using easy-to-collect variables by non-invasive methods will allow the setup of early social robots-based personalized intervention for improving their well-being. We innovatively combine ML and social robots to enable virtual coaching of the older adults supporting them to adopt healthy behaviors that may slow down the cognitive decline. The social robot is not only a companion but also as a tool for engaging older adults in social and fun activities together with their family caregivers or friends. Moreover, it may increase independence and self-esteem of older adults but can also lift some of burden of the formal and informal carriers by reducing their anxieties, worries, and stress.

The remainder of this paper is structured as follows. Section II presents related work in social robot-based therapies. Section III describes the proposed solution architecture, and the foreseen services and Section IV presents the evaluation protocol defined for testing and validation. Finally, Section V summarizes the findings and outlines potential areas for future research.

II. Related Work

Over the past few years, social robots have undergone significant advancements, allowing for their integration in therapies improving people's quality of life and wellbeing. In the care domain, they are an asset for offering personalized assistance, coaching, and interventions. Their main advantage relies on the multi modal communication channels offered such as speech, motor, or touch [2]. The robots' design and physical appearance have also evolved, offering more confidence to the interacting persons, and alleviating the skepticism among individuals who may have been hesitant to use such innovative systems [17].

The adoption of social robots in elderly care centers and modalities in which their human-like appearance influence users' social perceptions was studied in the literature [18]. Social robots offer their users valuable affective and cognitive resources. During the COVID-19 pandemic, social robots have been used for disinfection and sterilization of facilities, assistance and logistics, telemedicine, and remote assistance [19]. At the same time, they can monitor the medical treatment of patients, encourage them to follow a medical plan [20], may assist the tasks done by users with disabilities, or to manage the cognitive state [21]. Social robots can offer support for people living alone via coaching and social interaction functionalities. Pepper featuring a humanoid form is one of the most used in the care domain. It supports nonverbal communication through hand gestures, moves around, monitors the environment, and features multi-modal interaction [22].

The development of care applications integrating social robots and IoT monitoring has been facilitated recently using visual programming [23]. The modelling of social robots' behaviors can be done using script-based, rule-based, state-based, or behavior-based (i.e., behavior trees) approaches [24]. In [25] a behavior control system for social robots used for different therapies is presented, with a focus on personalization in terms of robot behavior and platform-independence (that can be used on multiple robot platforms). The system is based on YARP robot developing framework and is used in different scenarios for NAO and Pepper robots. Different architectures for developing and integrating social robots in care applications and scenarios have been researched. A generalized software architecture that features a template and a common vocabulary for improving a robot's behavior, social skills, and decisions was proposed in [26]. The architecture was grouped into four concentric layers: knowledge base layer, semantic bus layer, capabilities layer and behavior layer. It was used for developing autonomous companion robots as cognitive stimulation tools for people with dementia. In [27] an architecture for controlling autonomous social robots is designed using distributed graphs and behavior trees in combination with finite state machines. It has been used for developing components on various robots such as RB1, Pepper, and TIAGo. Similarly, in [28] specific architectures for social robots' usage in healthcare therapy, are presented. They divided the social robots into three major categories: companion, therapeutic play partner and coach robot. A detailed analysis is conducted for each of them, considering the behavior generation mechanisms, learning mechanisms, or use cases for applications. In [29], the authors propose an architecture for social robots that considers user emotions and motivations, allowing the robots to interact more naturally with humans. It uses input signals from cameras, sensors, radar, or microphones and a genetic algorithm for generating responses to user input.

The are several examples of social robots being used effectively in healthcare settings. In [30] socially assistive robots are proposed for cardiac rehabilitation. The solution integrates a set of sensors used to monitor physical exercise that is performed on a treadmill and the NAO social robot. The sensors were used to measure heart rate, weight and blood pressure, treadmill inclination, and speed. The social robot uses the data to motivate and provide advice to users. In [31] a social robot-based solution is used for gait rehabilitation of patients with neurological disorders. Using feedback on patient posture during exercises (e.g., cervical posture feedback, thoracic posture feedback), the robot generates motivational feedback and alerts the therapist when the patient's heart rate is high. Social robots are used in the pediatric field, for hospitalized children showing a positive impact on the emotional status of the children [32]. The Huggable robot used mimics the appearance of a normal toy (i.e., a teddy bear). In [33] the authors present a Human-Robot Interaction (HRI) system which uses IoT sensors to monitor the environment, a social robot as interaction tool and an AI platform to analyze the data. The system offers visual identification, audio-based interaction, and localization as main functionalities. The role of the robot is limited to offering contextual information and redirecting people to appropriate departments.

III. Architecture and services

Figure 1 shows the conceptual architecture of the proposed solution. It defines technology-based services for monitoring and big data processing, ML-based cognitive decline assessment, social robot coaching and cognitive stimulation, and communication and intelligent personalization.

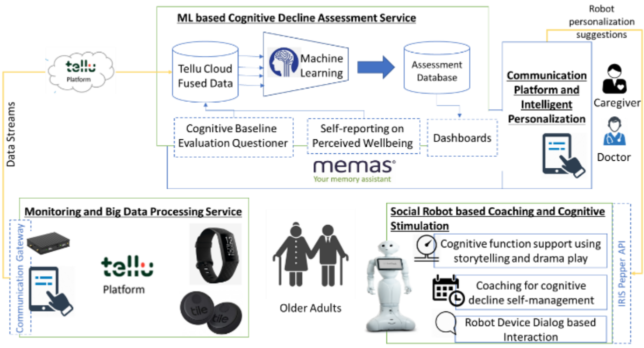

Fig. 1. Architecture, technologies, and services

In the development of these services, we are leveraging on some background technologies: Tellu cognitive and ADL monitoring infrastructure [34], a big data and ML platform previously validated in the healthcare domain [14-15], [35-36], MEMAS communication and personalization platform [37] and a Pepper social robot customization platform [38].

A. Monitoring and Big Data Processing Service

The service deals with the holistic and non-invasive monitoring of older adults with MCI using easy-to-collect variables on ADL using activity trackers. The sensors connect to a gateway device which is a mobile application running on an Android or Apple smartphone or tablet. The gateway device collects data from sensor devices and sends the data streams to a cloud application. The data is ingested into cloud storage and associated with a specific user. The cloud application has connection points for integration with the other services through a dedicated API. For management purposes, the monitoring service has a dedicated web interface for user administration and configuration.

For gathering ADL data, we have integrated an activity tracker as a sensor device (i.e., Fitbit), but the service architecture is generic and can easily integrate any activity tracking device or IoT sensor that makes its data available through an HTTP-based communication API. The Fitbit is a bracelet worn on the wrist, accompanied by a management application installed on the device where the gateway is configured. The gateway will poll the Fitbit API regularly, retrieving the latest collected data and pushing it to cloud storage. The data is made available through a dedicated API to the rest of the services using standardized HL7 FHIR (Fast Health Interoperability Resources) data structures.

B. Social Robot Coaching and Cognitive Stimulation Service

The service offers interactive functionalities for Pepper Robot to encourage older adults with MCI to play different cognitive games and interact during storytelling scenarios. As a result, it will improve their memory and cognitive function. The games and storytelling scenarios on Pepper Robot's tablet are co-created to address the needs discovered by people experiencing MCI. Gestures, movements, and speech of Pepper (e.g., raising hands) are integrated with games and story dynamics increasing the engagement in the learning and cognitive stimulation process. They can be played on Pepper Robot in daycare centers and at home on their tablets or smartphone. Cognitive games have different difficulty levels associated with a specific number of points. The scores will be stored on a leaderboard to analyze the individual and collective progress and are sent to the ML service to be used in the assessment.

Two cognitive games (Shell Game and Sensors-Memory Game) and four interactive storytelling scenarios have been developed so far (see Fig. 2). However, in future iterations, new games and stories will be developed considering the following categories: family games, quizzes to train memory, physical games to sustain health issues related to MCI and stories to go deeper in memory training.

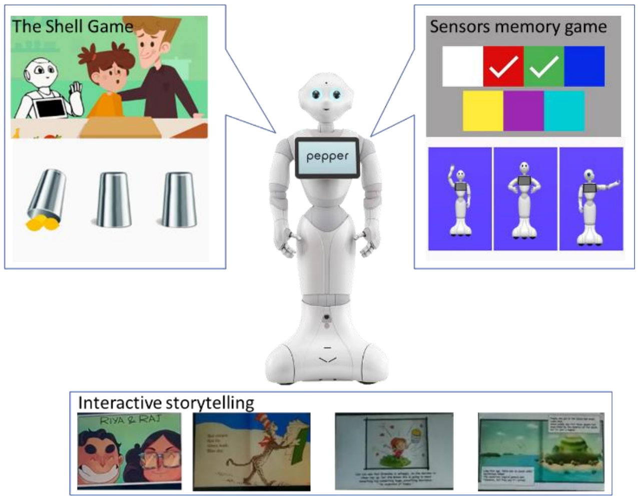

Fig. 2. Cognitive games and storytelling on Pepper robot.

The Shell Game (or the Glasses Game) is a memory game in which the older adults will find themselves in common contexts of everyday life (e.g., shopping, at home, etc.) and will have to remember under which of the glasses they can find the object they are looking for. Initially, the story behind the game is presented to familiarize the users with the game. To earn winning points, the older adults must select the correct cup containing the desired object/product and help Pepper to put all the purchases in the shopping bags.

The Sensors-Memory Game is an interactive game that uses many sensors and interaction elements of the Pepper robot, such as tactile sensors on the robot's hands, head, and base, led on the robot's ears, the tablet, voice communication, and movements. The robot will stimulate the older adults' memory with exercises related to color or sound identification and Pepper's correct position selection.

C. Communication Platform and Intelligent Personalization Service

The platform (MEMAS) offers a life mastering assistant especially targeted towards people with MCI that has several dashboards to show information concerning the cognitive baseline, ADL monitoring, self-reporting, and cognitive decline assessment and to enable interaction and communication of all types of interested actors with the system. It features the ability to remind or show step-by-step instructions on conducting ADL (e. taking medication, drinking water, etc.) and will allow the configuration of personal services by the carer (family or professional) connected to the primary user. Other functionalities of this service are video communication with friends and family to support the social component of older adults' life.

The service is divided into 1) a web-based administration module (see Fig. 3), where secondary users or carers can configure the service functionalities and 2) a user-centered web application for the primary user that runs on a physical device, usually a tablet. In the administrative component, the secondary user can manage an activity calendar, access a dashboard indicating the cognitive state of the primary user, define cognitive games, and instructions for daily help in the form of videos, series of images and spoken commands, build albums with photos and videos, configure access to favorite radio channels and newspapers, etc. The dashboard is build based on information from the ML service offering additional insights for his/her ADL As the cognitive state of the person with MCI deteriorates, the secondary user may remove some of the functionality from the primary user's device.

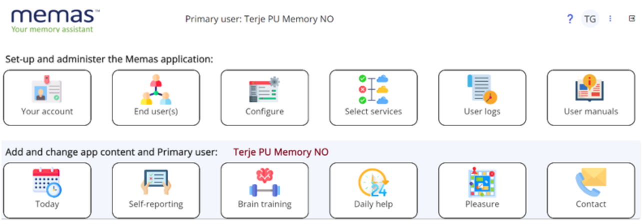

Fig. 3. Home page of the MEMAS platform

An important component of the user-centered part of the service is the self-reporting questionnaires that are used to capture care dimensions such as medication intake, mood and well-being, cognition, and bodily discomfort. This information is sent to the ML service for corelating the context of the older adult with the sensors monitoring data. Other services available for the primary user are different cognitive games (brain training), instruction material for daily help, entertaining functionalities, etc.

D. *ML-based Cognitive Decline Assessment Service*

The service integrates different types of data in the machine learning process: features extracted from the monitored data on ADL (sleep, effort, activity types, etc.), game results/scores, and contextual features related to the baseline cognitive function, age, and subjective reports on health state and well-being done through self-reporting. The latest studies have shown that differences in the timing and patterns of DLAs throughout the day can be linked to MCI diagnoses [39]. Thus, the main goal of the service is to assess and correlate the daily physical activity to offer a window of MCI progress. For example, it can identify higher daily activity fragmentation with a similar mean of total activity and duration per day for a person or lower activity counts and minutes spent actively.

Fig. 4 presents the flow of activities implemented in the service for the ML analysis. Data pre-processing and cleaning will prepare the data to be programmatically processed following a well-defined data model scheme. Feature selection aims to collapse the characteristics considered in the learning algorithms by eliminating the ones which do not influence the results. Cross Validation is splitting the historical monitored data into two subsets, one for training the machine learning algorithms and one for estimating the performance of the algorithms. The machine learning algorithms are trained on the training data to learn a model that will be then used on the monitored data received daily. Finally, the model is evaluated based on the test data to determine its performance and afterwards on monitored data of the older adult.

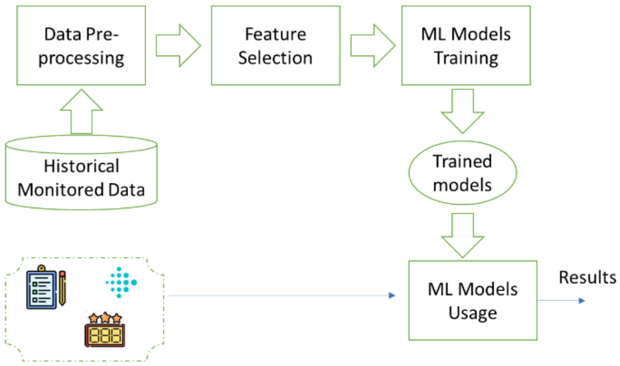

Fig. 4. ML service component flow.

The service allows the training and ensemble of different ML models using the collected data as well as using offline datasets from the literature for analyzing and fine tuning the algorithms. Several alternatives we been integrated using Mcfly deep learning framework [40] such as convolutional neural network, DeepConvLSTM or InceptionTime.

IV. EVALUATION PROTOCOL

In the project a field trial will be set up to introduce, install and evaluate the engAGE platform in the natural environment of older people with MCI that need assistance and physical and cognitive stimulation. The field trial takes place both in healthcare organizations and older people's homes and will allow us to evaluate the platform usability, impact on quality of life, etc. using a set of defined Key Performance Indicators (KPIs). The field trial will follow strictly defined ethical values and principles and data security and privacy recommendations.

A. *Field trial setup*

The field trial will be conducted in three countries Italy, Switzerland, and Norway. It is organized as a controlled longitudinal study, where the observations are made on a series of enrolled individuals using the developed services, with the control group, with data collected before and after the installation and use of the technical solution. The goal of trial evaluation is to assess the technology integration into everyday life, effectiveness in mitigating the cognitive decline, acceptance over six months, security, and reliability of developed services as well as the business perspective reflecting the market demand (e.g., willingness to pay). The field trial in Norway will be performed at two day-centers in Arendal municipality in the southern part of the country. The recruited participants will use the robot at the day-center and the Memas-app when they are in their own home. The inclusion and exclusion criteria summarized in Table I are used to recruit older adults with MCI to participate in the trials.

TABLE I. FIELD TRIAL INCLUSION AND EXCLUSION CRITERIA

	End-user	**Criteria**
Inclusion	Older adults	Over 65 years old age having: MoCA score 21 – 25, MAC-Q $\geq$ 25, Reisberg scale 2 – 4, Clinical Frailty Scale score 1 – 3, 4-items GDS score $\leq$ 1.
	Informal caregivers	Primary informal caregiver of the user having over 18 years old age.
	Formal caregivers	Psychologists, neurologists, occupational therapists, nurses from health care facilities,

		or paid by the participants with > 1-year experience.
Exclusion	- Concomitant participation in other studies. - Lack of written informed consent. - Not meeting the inclusion criteria - Previous diagnosis of dementia or other neurodegenerative diseases. - Psychiatric illnesses that could affect cognitive functioning. - Chronic neurological or systemic disorders not compensated pharmacologically that could affect cognitive functioning.	

The field trial procedure will be divided into three phases, after the recruitment of the participants. The baseline evaluation (T0, M1) deals with the first real contact with the users and their families, before the start of the field trial. The mid-term evaluation (T1, M3) aims to collect useful information on the use of the developed system and services after a short period of use for detecting and analyzing the technology acceptance and usability issues. The final evaluation (T2, M6) collects useful information on the whole benefits perceived by the users after a meaningful period of use of the system. The final evaluation will be conducted after the system de-installation, to detect and analyze the impact of the system in the daily life of the older people and their family. Moreover, the final evaluation aims to gain knowledge on elderly technology acceptance and usability issues to be compared with mid-term results (T1), to assess the long-term acceptance and provide methodological approach for further studies in the field.

B. *Key Performance Indicators*

The defined qualitative and quantitative KPIs will be used to assess the degree to which the developed technology meets the older adults with MCI needs such as achieving better engagement, social interaction, and measurement of cognitive decline. The field trials will conduct only a partial evaluation of the effectiveness of services in relation to some dimensions of cognitive status of older people with MCI. Additionally, KPIs are defined to measure (see Table II): the improvement of the quality of care and the cost efficiency and the level of support offered to informal / formal carers.

The measurements collected from the real-life trials will assess the ecosystem performance and validate the success of the developed technologies. For KPIs measurement, we will use a before and after strategy assessing the baseline value before technology introduction and after usage in trials.

TABLE II. KPIS TO BE EVALUATED IN THE PROJECT

KPI	Measurement procedures	Target values
Improving the quality of life of older people		
Quality of Life	Quality of Life–Alzheimer's Disease (QoL-AD): a scale of 1–4 (poor, fair, good, or excellent) to rate a variety of life domains, including the patient's physical health, mood, relationships, activities, and ability to complete tasks. *Measured for each older adult at T0 and T2.*	Most of the measurements after the trial should be clustered on 3 or 4 values.
Mental wellbeing	WEMWBS (Psychological well-being Scale): used to enable the measuring of mental wellbeing in the general population. *Measured for each older adult and formal/informal caregivers at T0 and T2.*	Improvement/ stability of the psychological well-being between T0 and T2
Feelings of loneliness	UCLA scale (social connectedness): measures one's subjective feelings of loneliness as well as feelings of social isolation. *Measured for each older adult and formal/informal caregivers at T0 and T2.*	Improvement/ stability of the social connectedness between T0 and T2
Improving the quality of care and the cost efficiency		
Cognitive state	Montreal Cognitive Assessment (MoCA): screening assessment for detecting cognitive impairment. *Measured for each older adult in the recruitment phase and as an evaluation point at T2.*	Stability or improvement of the score.
Memory state	Memory assessment clinics-questionnaire (MAC-Q): useful for measuring age-related memory decline. *Measured for each older adult in the recruitment phase and as an evaluation point at T2.*	Stability or improvement of the score.
Health measure	EQ Visual Analogue Scale (EQ VAS): used as a quantitative measure of health as judged by the individual respondents.*Measured daily in the trial.*	Improvement of final values with respect to initial ones.
Providing support to informal or formal carers		
Reducing work pressure	Zarit Burden Interview (ZBI) is a caregiver self-report measure to assess the level of support offered to caregivers by using engAGE platform. *Will be used in the recruitment phase, at T0 and T2.*	Decrease of overall score

V. CONCLUSIONS

In this paper, we have presented the design of technological-based services for managing the cognitive decline of older adults experiencing MCI as well as the setup of the trial and KPIs to measure the impact on various care dimensions. We estimate that the proposed services will improve the quality of life and health for older people and their caregivers by developing and commercializing solutions that allow the detection and management of cognitive decline that constitute nowadays a profound societal challenge. Their adoption will make older adults feel safer and more confident, keep their participation in social life, and lead an active lifestyle.

The proposed services can contribute to the efficiency and sustainability of the care system. Family caregivers can have an objective measure to monitor their loved one's cognitive function, thus reducing the stress and anxiety, and financial burden of MCI care. Healthcare professionals and care organizations may significantly improve their practice efficacy and reduce costs by having a reliable source for activity, cognitive, or care data of their patients. The innovative approach of fusing the human perspective with the activity trackers and cognitive games score by using machine learning algorithms helps in establishing baseline values, detecting, and inferring function state and potential decline enabling the early setup of intervention.

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