A Holistic System for Fostering Active Aging: The D3A Project

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Abstract

Recent research highlights the significance of active aging, emphasizing its role in enhancing the well-being of the elderly population. To effectively promote active aging and address the evolving needs of our growing global aging demographic, a fusion of technological innovation and progressive policy strategies is imperative.

In response to this challenge, we introduce the D3A (Digital Assistant for Active Aging) system – a pioneering platform aimed at elevating the quality of life for the elderly. D3A focuses on optimizing interconnected facets of physical and cognitive performance. Within this framework, healthcare professionals can tailor individualized training regimens encompassing both physical and cognitive exercises, which can be experienced in both traditional and virtual reality settings.

D3A leverages artificial intelligence algorithms to assess the efficacy of these exercises, providing valuable support to healthcare providers. Moreover, the platform incorporates wearable devices to monitor users' physiological parameters, serving as crucial indicators of their overall health. Also, D3A employs blockchain technology to ensure robust security and data immutability for access control, activity logs, and health records within the application. This holistic approach to active aging promises a brighter future for our aging population, driven by innovation and evidence-based care.

Keywords

Active Aging, Virtual Assistant, Training Plan, Artificial Intelligence, Virtual Reality, Blockchain

Introduction

According to a UN report [1], aging can be seen as a remarkable success story, celebrating the triumph of public health, medical advancements, and social and economic policies. It is considered one of the four global demographic "megatrends", alongside population growth, international immigration, and urbanization. This trend, spanning the globe, has been a longstanding phenomenon in developed nations since the 20th century, while less developed countries are experiencing it more recently.

Traditionally, we have defined the elderly based on a straightforward criterion: chronological age, typically set at 65 or older. The UN report estimates that by 2050, one in six people worldwide will be over 65, a significant increase from 2019 when this ratio was one in eleven. For instance, the likelihood of reaching the age of 65 has risen from less than 50% in places like Sweden at the end of the 19th century to well over 90% in countries with the highest life expectancy today.

Many societies across the world are reassessing their social policies to better support and engage with the elderly population. Some are in the early stages of managing this important demographic shift, while others are more advanced. The United Nations has established 17 global goals [2], known as Sustainable Development Goals (SDGs), to be achieved by 2030, outlined in

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the “2030 Agenda”. Aging-related themes are prominent within this agenda, including eradicating poverty (SDG 1), ensuring well-being at all ages (SDG 3), promoting gender equality (SDG 5), fostering decent work for all (SDG 8), reducing inequalities between and within countries (SDG 10), and building inclusive, safe, resilient, and sustainable cities (SDG 11).

This is where the concept of *active aging* becomes crucial, as defined by the World Health Organization in the late 1990s. It entails optimizing opportunities for health, participation, and safety to enhance the quality of life as people age – a topic that remains highly relevant [3]. With the global elderly population set to grow, strategies must be devised to maintain elders’ physical and cognitive health, thus reducing the burden on national healthcare systems.

To meet such a challenge, we present the D3A project, which aims to introduce a digital platform for the elderly population, enhancing their quality of life through specialized physical and cognitive exercises designed by a team of experts. Especially, the D3A project aims at implementing a virtual assistant that provides support to both caregivers and operators in the daily physical and cognitive training activities of the elderly. Obviously, D3A do not replace caregivers but offers valuable support to them, aiding the team in decision-making and evaluating each caregiver’s training plan.

The remainder of this paper is structured as follows: Section 2 delves into related work on digital systems in the active aging field. Section 3 presents an overview of D3A, while Section 4 discusses on the innovative methodologies applied in D3A. Finally, Section 5 concludes the paper.

Related work

Preserving both physical and mental functions in the elderly is crucial for promoting healthy aging. As individuals age, there is typically a decline in both physical and cognitive functions, and research has demonstrated a correlation between these two domains [5], underscoring the need to explore strategies that can simultaneously enhance both aspects. Such strategies are needed because the decline in physical and mental functions can significantly increase the risk of impairing elders’ ability to perform daily activities [4].

In terms of physical training, older individuals often experience a decline in their motor skills. This can lead to a loss of independence and challenges in performing even basic daily activities. Implementing tailored exercise programs can offer a valuable solution to help these individuals overcome these physical limitations. However, research has shown that only 31% of the elderly population regularly engage in recommended exercise routines [6].

This recalls the need of having specialized guidance and motivation for patients to correctly execute exercises, ultimately improving their physical condition, and enabling remote exercise from the comfort of their homes. Recent years have witnessed the development of various motion tracking systems designed to support healthcare professionals in monitoring movement, engaging patients, and guiding them through exercise routines. Technological advancements in this field have substantially reduced the costs of motion tracking systems, giving rise to Vision-Based Interaction (VBI) systems [7], which have become central to motor training programs. Notably, promising results have emerged from various studies regarding the use of affordable equipment commonly associated with entertainment, such as the Nintendo Wii Remote Controller [8] and different hardware versions of the Microsoft Kinect [9].

For instance, Rodrigues *et al.* [10] examined the effectiveness of Kinect V2 in tracking walking at various speeds (very slow, slow, normal, and fast) over a cycle of 12 repetitions. They analyzed multiple parameters, including walking time, speed, and ankle angle. The study revealed that under normal and fast walking conditions, the Kinect V2 sensor exhibited minimal and mostly negligible errors. However, as walking speed decreased, errors increased due to self-occlusion and error compensation, particularly during the “stance” phase of the foot, causing a latency in recognition of nearly 1 second. These errors resulted from the Time-of-Flight sensor, necessitating preprocessing of images to enhance accuracy through mathematical models and image filtering and fusion algorithms [11]. Finally, Ren *et al.* [25] have demonstrated that with specialized pre-processing and post-processing algorithms, coupled with artificial intelligence techniques and DTW [25], it is possible to enhance the precision of Kinect sensors.

Su *et al.* [24] argue that clinicians typically assess the trajectory and speed of rehabilitation exercise mainly based on their experience and subjective criteria, instead of using more precise and measurable values. For this reason, numerous studies in the literature have explored machine learning and deep learning methodologies to automatically evaluate the performance of patients during the execution of exercises. Osgouei *et al.* [22] compared the performance of *Hidden Markov Model* (HMM) and *Dynamic Time Warping* (DTW) and concluded that both algorithms showed a similar trend in the evaluation of participants' performance. Although the DTW was more sensitive to small changes, the HMM captured an overall evaluation of performance. DTW was also used by Yu *et al.* [23] to develop and validate an approach for the evaluation of physical exercises to support *self-coaching* in a virtual game environment. This algorithm was applied to calculate the similarity of movement between two time series of a single user and a virtual coach. In aid of DTW, *fuzzy* logic was applied to emulate the effect of doctors' subjectivity in evaluations and obtain a truth value ranging from 0 to 1 [23].

In the context of cognitive training, state-of-the-art research primarily focuses on affectivity, encompassing a complex array of mental states including emotions, moods, attitudes, and interpersonal relationships [12]. These states exert a significant influence on behavior, well-being, social interaction, and human cognition. Affective cognition, specifically, deals with the processing of stimuli carrying emotional valence [13].

The scientific community has devoted effort also in developing therapies for emotional function disorders, seeking effective interventions to enhance affective functions and alleviate negative symptoms. A primary goal is to increase the experience of positive emotions while reducing negative ones, significantly contributing to the health and well-being of the elderly population within the context of active aging. Especially, numerous multimedia stimuli, including images, sounds, and videos, have been identified in the literature for their positive effects on the emotional well-being of those receiving assistance. Images, for instance, are widely used due to their low cognitive load nature, making them suitable for a broad range of individuals, including children, the elderly, and individuals with illnesses. The International Affective Picture System (IAPS) [14] offers a library of such images used in experimental studies to influence emotional states.

So far, several studies have utilized IAPS images, establishing IAPS as one of the most employed stimuli sets in contemporary behavioral research. The significance of its role in advancing research cannot be overlooked. Anyway, a more recent image database was proposed by Kurdi *et al.* [32]. They collected 900 pictures depicting a wide range of categories, including humans, animals, scenes, and objects, from open-access online sources and recruited a diverse sample of participants for a norming study to assess their affective responses to the images in terms of valence and arousal.

A further widely used database is the Geneva Affective Picture Database (GAPED) [33]. It consists of 760 pictures divided into six categories: spiders, snakes, human concern pictures, animal mistreatment, neutral, and positive pictures. The images were assessed for arousal and valence by 60 volunteers recruited from a second-year psychology class.

Besides images, also music has demonstrated its impact on emotions and mood at the brain level, but investigations extend beyond music to include all acoustic stimuli, such as speech, noise, and environmental sounds [15], [16].

Kolestra *et al.* [17] introduced DEAP, a database containing 120 pieces of music ranked based on emotional response along two dimensions: activation and valence. In the context of sound databases, Schuller *et al.* [34] present a selection of 390 sound files categorized into eight distinct groups: Animals, Musical instruments, Nature, Noisemakers, People, Sports, Tools, and Vehicles. These audio samples make up the Emotional Sound Database, which underwent evaluation by four postgraduate students specializing in audio processing. Their task involved rating each sound file on two emotional dimensions: Arousal and Valence, using a five-point scale for precision.

In contrast, the Oxford Vocal Sounds database, referred to as "OxVoc," comprises 173 unscripted, spontaneous non-verbal vocalizations from infants, adults, and domestic animals. To gauge the emotional impact of these sounds, two separate studies were conducted, engaging more than 100 volunteers split into distinct groups. The goal was to assess the arousal and valence associated with each sound [35].

It is worth noting that videos possess the potential to elicit a stronger emotional response compared to single images or audio stimuli [36]. However, they are a more intricate stimulus, demanding increased attention and cognitive processing [37]. For video stimuli, Li *et al.* [38] conducted a study involving 60 students, who assessed emotions based on three dimensions: valence, arousal, and dominance. The dataset consisted of 299 brief videos, each lasting 3 seconds and categorized into four groups: people, animals, objects, and scenes.

An exceptional example in this domain is the Aff-Wild2 dataset, employed in the 4th Workshop and Competition on Affective Behavior Analysis in-the-wild (ABAW) [39]. This dataset represents a ground-breaking creation, constituting a large-scale "in-the-wild" database encompassing over 550 videos that capture the reactions of 458 subjects. These videos encompass a broad spectrum of subjects, including various age groups (from babies to the elderly), diverse ethnic backgrounds (Caucasian, Hispanic or Latino, Asian, black, or African American), and a wide range of professions (e.g., actors, athletes, politicians, journalists). The dataset is further enriched with data on head pose, illumination conditions, occlusion, and emotions, making it a valuable resource for research in the field.

Furthermore, Rincon *et al.* [18] introduced the EMERALD system, designed to improve elderly well-being through a platform capable of generating and adapting personalized exercises while recognizing the emotional state of individuals through biosensors like ECG (electrocardiography), EDA (electrodermal activity), and PPG (photoplethysmography). In another study, Chanel *et al.* [40] delved into the potential of utilizing physiological signals to gauge emotions and adapt game difficulty accordingly. The paper outlines a concept aimed at enhancing player engagement by dynamically adjusting in-game challenges based on the player's emotional state, as inferred from physiological signals. To validate this innovative approach, the researchers conducted a comprehensive assessment involving questionnaire responses, electroencephalogram (EEG) readings, and peripheral signals from participants engaged in a Tetris game, spanning three distinct difficulty levels.

For the D3A project, multimedia stimuli will be sourced from the aforementioned reputable and well-established databases, given their reliability and accessibility. Nevertheless, the door is open to exploring additional databases. For instance, there is an intriguing hypothesis of incorporating personalized stimuli contributed by users themselves. This approach holds the potential to elicit heightened levels of valence and arousal, offering a unique avenue for research and experimentation.

D3A in a Nutshell

D3A is a comprehensive system comprising both hardware and software components to create a cognitive and physical assistant that fosters Active Aging. This assistant recommends activities to support a healthy lifestyle regimen, including daily short physical and cognitive training sessions within the comfort of one's home. The D3A virtual assistant functions as a personal coach, guiding users through adaptive physical exercises tailored to their individual needs, as designed by a team of experts, including physiatrists, geriatricians, and physiotherapists. It also facilitates cognitive games for entertainment and mental stimulation.

The system caters to three distinct user roles:

1. **Administrators**: Responsible for content and user management.
2. **Specialists**: Oversee designing, assigning, monitoring, and evaluating cognitive and motor training plans.
3. **Patients**: Individuals engaging in training plans to enhance their mental and physical well-being.

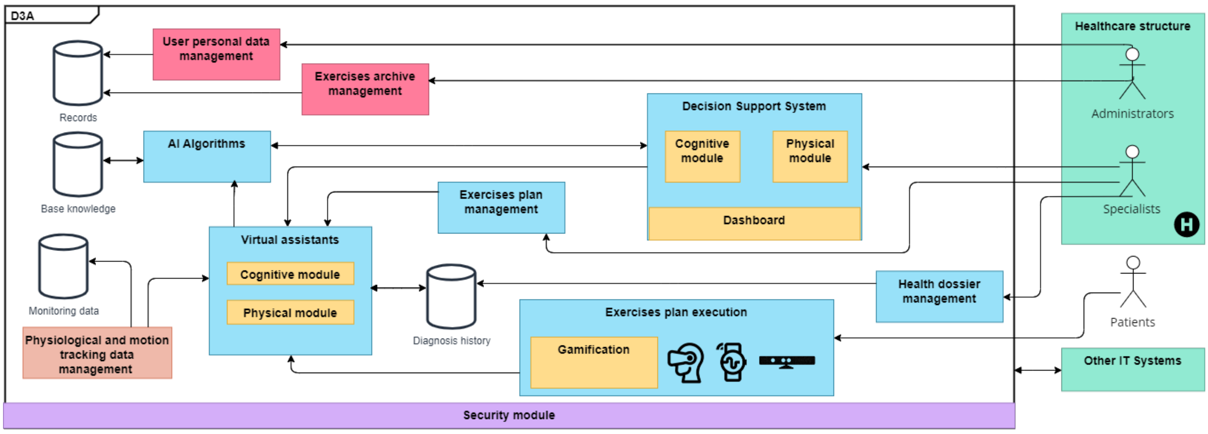

Figure 1 – Functional architecture of D3A system

The D3A platform offers several key functionalities, summarized in Figure 1:

- **Administrative Functions**: Manage user personal data and exercise records.
- **Health and Care Functions**: Utilize virtual assistants via a Decision Support System to define exercise plans and aid users in their execution.
- **Monitoring Functions**: Collect and store motion tracking and physiological data through wearable devices.
- **Security Management**: Employ Blockchain technology for access control and data protection, ensuring compliance with Italian Privacy Law and GDPR regulations.

The architecture of D3A follows a three-tier design model commonly used in software development and deployment, offering benefits such as separation of concerns, scalability, and ease of maintenance. The system is divided into two subsystems: Cognitive and Physical. Both are web-based applications accessible via web browsers, making them available through intranets or the Internet. The D3A Physical subsystem focuses on physical training with sessions monitored by a motion tracking system using sensors like Microsoft Kinect. While the D3A Cognitive subsystem targets users' affective aspects through the delivery of multimedia sequences capable of stimulating particular sensations/emotions. Such a delivery can be performed in standard mode or virtual reality. Both subsystems share components for reading physiological data from wearable devices and incorporate Artificial Intelligence (AI) components to extract valuable insights from collected data, providing decision support to therapists. Gamification elements make training therapies engaging for users, whether they are physical or cognitive.

Innovations Points of D3A

When designing D3A, we have placed significant emphasis on providing comprehensive psychophysical support for the elderly population. Leveraging technological innovations as the cornerstone of our approach, we tried to amalgamate various cutting-edge technologies, including artificial intelligence, blockchain, and virtual reality. This section aims to introduce and substantiate our hypothesis that the synergistic application of these technologies can bring substantial added value to the project's development and tangible benefits to end users.

Artificial intelligence plays a pivotal role in the D3A project. We are developing algorithms that empower operators to assess the effectiveness of exercises performed by elderly individuals and trigger alerts based on vital data gathered from wearable devices. Especially, in D3A, wearable devices serve as data collection tools, with artificial intelligence algorithms interpreting this data to offer decision support to operators, enabling health predictions and continuous monitoring of the assisted population. We employ physiological signals such as heart rate, blood pressure, respiratory rate, and skin conductance to objectively assess the well-being of the elderly, aligning with prior studies in this domain [19, 20, 21].

Our research strategy incorporates the use of several machine learning models, including Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbors (KNN), and Artificial Neural Networks. The choice of these models is contingent upon the specific task at hand and the unique characteristics of the dataset in question. This approach ensures a comprehensive and adaptable methodology that leverages the strengths of each model to address specific challenges and nuances inherent in the data.

One of our key objectives is to harness machine learning algorithms to compare movements captured by a motion tracking system [41]. This entails evaluating two sets of data: one representing the optimal movements recorded by a physiotherapist and the other reflecting the actual movements performed by the elderlies. The primary aim here is to automatically distinguish sessions that meet the physiotherapist's criteria for well-executed movements from those containing significant errors. However, for precise evaluation, it is imperative to employ distinct models for different exercises. We anticipate that variations in performance outcomes will be substantial for each exercise type and the specific limbs monitored during the exercises. Hence, our approach necessitates the development of individual predictive models for each exercise, rather than applying a global model across all exercises.

In addition, our research endeavors include the implementation of Convolutional Neural Networks (CNN) for the interpretation of vital signs obtained from wearable devices, particularly in the context of elderly individuals. Given the substantial volume of data with high sampling rates, CNNs emerge as the most fitting choice. We aim to tap into existing datasets, such as WESAD [42] and Non-EEG [43], and leverage pre-trained models to tackle new tasks or diverse types of data. This approach enables us to apply transfer learning techniques, capitalizing on the knowledge accrued by the pre-trained models to enhance generalization and adaptability in novel scenarios.

Turning to the blockchain, we have observed its increasing relevance in the healthcare sector. Previous efforts, such as [26], primarily focused on incorporating blockchain into Active Aging services, albeit limited to access management. More recently, Velmovitsky *et al.* [27] addressed the issue of consent for personal data processing, proposing a blockchain-based solution. Blockchain, renowned for its immutability and decentralization, enhances transparency through consent mechanisms. In D3A we massively employ blockchain technology to ensure robust security and data immutability for access control, activity logs, and health records within the application.

As for virtual reality, its unique appeal lies in its unparalleled immersiveness, surpassing traditional stimulus presentation methods [28]. For this reason, in D3A the delivery of cognitive stimuli can be performed also in a virtual environment. Indeed, some researchers have leveraged natural environments within virtual reality to activate the parasympathetic system, reducing fear, anger, and stress, in line with the Stress Reduction Theory [31]. In D3A we followed such a line of research to offer different stimuli and improve the cognitive ability and the celebrating health of the elderly. It is worth noting that in D3A the delivery of cognitive stimuli can be performed also in standard mode, without the use of virtual reality. The possibility of offering stimuli in standard mode and virtual mode is suggested by the need to deal with side effects of virtual reality, such as motion-induced discomfort like dizziness and nausea [29], which may affect emotional responses and research outcomes [30].

In summary, the design of D3A revolves around leveraging cutting-edge technologies, such as artificial intelligence, blockchain, and virtual reality, to provide comprehensive psychophysical support to the elderly population. These technologies offer the promise of enhanced healthcare outcomes and improved quality of life for our target users.

Conclusion and Future Work

This paper introduces the D3A system, a software solution designed to enhance the overall well-being of the elderly population by promoting an active lifestyle. The D3A system leverages a virtual assistant and motion tracking technology, enabling daily cognitive and physical training sessions from the comfort of one's home, eliminating the need for a therapist's presence.

The realization of this project involves addressing three key technical and scientific challenges:

- **Comprehensive Psychophysical Support**: To ensure end-users receive adequate psychophysical support, the system offers continuous monitoring of physiological parameters through synchronized wearable devices integrated within the system. Simultaneously, AI algorithms are employed by a team of specialists to automatically analyze the collected data and provide valuable insights into the progress of the training plan.
- **Enhanced Security with Blockchain**: The Blockchain module is implemented to safeguard the activities and sensitive data of connected users while fortifying the system's resilience against cyber threats.
- **Engagement through Gamification**: To boost user engagement, the D3A system incorporates various gamification strategies, including step-by-step challenges and collective routes with rankings and scores.

In conclusion, the D3A system represents a significant step towards improving the lives of the elderly by promoting an active lifestyle and harnessing technology to provide comprehensive support and security, with the potential for far-reaching positive impacts on healthcare and quality of life. Looking ahead, there are exciting possibilities for system extensions that could introduce new functionalities. One such extension could involve the creation of a true Ambient Assisted Living (AAL) environment. This would incorporate home automation solutions featuring environmental sensors to enhance the living comfort of elderly individuals, promoting autonomy and overall satisfaction in their living spaces.

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