Visualization and Interaction Technologies in Serious and Exergames for Cognitive Assessment and Training: A Survey on Available Solutions and Their Validation

CHIARA BASSANO, MANUELA CHESSA, (Member, IEEE), AND FABIO SOLARI
Department of Informatics, Bioengineering, Robotics, and Systems Engineering, University of Genoa, 16126 Genoa, Italy
Corresponding author: Manuela Chessa (manuela.chessa@unige.it)

This work was supported in part by the Interreg ALCOTRA Projects PRO-SOL We-Pro under Grant 4298, and in part by PRO-SOL Senior under Grant 4128.

ABSTRACT Exergames and serious games, based on standard personal computers, mobile devices and gaming consoles or on novel immersive Virtual and Augmented Reality techniques, have become popular in the last few years and are now applied in various research fields, among which cognitive assessment and training of heterogeneous target populations. Moreover, the adoption of Web based solutions together with the integration of Artificial Intelligence and Machine Learning algorithms could bring countless advantages, both for the patients and the clinical personnel, as allowing the early detection of some pathological conditions, improving the efficacy and adherence to rehabilitation processes, through the personalisation of training sessions, and optimizing the allocation of resources by the healthcare system. The current work proposes a systematic survey of existing solutions in the field of cognitive assessment and training. We evaluate the visualization and interaction technologies commonly adopted and the measures taken to fulfil the need of the pathological target populations. Moreover, we analyze how implemented solutions are validated, i.e. the chosen experimental designs, data collection and analysis. Finally, we consider the availability of the applications and raw data to the large community of researchers and medical professionals and the actual application of proposed solutions in the standard clinical practice. Despite the potential of these technologies, research is still at an early stage. Although the recent release of accessible immersive virtual reality headsets and the increasing interest on vision-based techniques for tracking body and hands movements, many studies still rely on non-immersive virtual reality (67.2%), mainly mobile and personal computers, and standard gaming tools for interactions (41.5%). Finally, we highlight that although the interest of research community in this field is increasingly higher, the sharing of dataset (10.6%) and implemented applications (3.8%) should be promoted and the number of healthcare structures which have successfully introduced the new technological approaches in the treatment of their host patients is limited (10.2%).

INDEX TERMS Augmented reality, cognitive assessment, cognitive training, exergames, human-computer interaction, interaction technologies, serious games, virtual reality, visualization technologies.

I. INTRODUCTION

The technological evolution we have witnessed in the recent years has led to important advances in many research fields, among which cognitive assessment and training. Researchers have started developing and validating new solutions, based on serious games (SGs) and exergames (EGs). SGs are digital applications designed for a primary purpose other than pure entertainment, as education, information, enhancement of cognitive and physical functions. They usually emulate activities of daily living (school lessons, doing the shopping, doing housework, exploring environments) and indirectly assess...
participants cognitive functions during gameplay. EGs are videogames which rely on technologies that track body movements and imply a form of physical exercise, as emulating a sport, playing an instrument, exercise or doing racing. Advantages of using SGs and EGs for the ecological assessment and the rehabilitation of cognitive functions are disparate. Firstly, gamification allows to indirectly evaluate patients avoiding causing stress and frustration, which could affect results of standard tests. Moreover, they ensure the creation of safe, controlled, standardized settings and a strict control over experimental conditions and stimulus delivery. Besides, thanks to the integration of different sensors, it is possible to record different measurements, useful for the assessment of patients’ cognitive and motor skills and the monitoring of their well-being state, behaviour and improvements.

Another fundamental advantage is the possibility to create personalized training sessions: in order to be effective and engaging, training difficulty has to match patient ability and to avoid a ceiling effect [1]. Training personalization approaches usually employ two main strategies, i.e. task difficulty adaptation (22.6%) and regulation of the training session duration (0.9%), which are crucial factors especially when training sessions are self-administered without supervision, as home rehabilitation applications. In particular, standard multiple level applications still represent the preferred solution (21.3%). Access to a higher level is often bound to the achievement of a certain score, accuracy or number of consecutive correct trials or to the acquirement of certain performance can lead to a negative level adjustment and, sometimes, inadequate performance can lead to a negative level adjustment [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42]. Alternative solutions include the use of AI techniques, as case-based algorithms, ontology based models, or open learner models, or giving the therapists the permission to intervene in the difficulty level selection. Otherwise, difficulty adjustments can be done real-time, during gameplay, by modifying game parameters according to players performance [51], [52], [53].

The purpose of our review is to provide an analysis of the advancements of research on SGs and EGs applied to the cognitive assessment and training conjointly with the development of new technologies for visualization and interaction, i.e. Virtual Reality (VR) and Augmented Reality (AR) [54], platforms for game deployment, i.e. mobile, computer, consoles and Web platforms, and Artificial Intelligence (AI). Specifically, this review addresses the following research questions:

RQ1 Among the different visualization techniques, from non-immersive (e.g., monitor-based) to fully immersive (e.g., head-mounted displays) methods, which are the most adopted solutions? During the years, was there a rise in the use of immersive VR and AR devices?

RQ2 Among the available interaction techniques, from touchfree (e.g., mice and keyboards, touchscreens and controllers) to touchless (e.g., vision, sensors or voice based), which are the most adopted solutions? Although the wide diffusion of gaming tools, during the years, was there a rising interest on the search of alternate solutions?

RQ3 In consideration of their eventual adoption in the standard clinical practice, how developed solutions are actually validated? Moreover, given the increased number of systems published per year, have we assisted, in parallel, to a growth in the number of available data and finally, subjects/patients effectively using such solutions?

In the following sections, we first describe the adopted procedure to gather data (Section II), then we consider the different technologies available for visualisation (Section III) and interaction (Section IV), their core features, potentials and actual application. We then focus on the validation process, in particular on the experimental designs currently adopted to test proposed solutions (Section V-A) and the way data are collected and analysed, also considering the application of ML algorithms for predicting the onset of certain pathological conditions (Section V-B). Lastly, we evaluate the availability of proposed frameworks and datasets (Section V-C) and the effective adoption of SGs and EGs based solutions by healthcare structures.

II. PROCEDURE

The current survey is the result of a systematic search that we conducted in several high profile databases, i.e. PubMed, Scopus, Web of Knowledge and Science Direct, using the search string

(assessment OR training) AND (((cognitive AND (VR OR AR OR serious game OR exergame OR WebGL OR AI)) OR ((memory OR attention OR executive functions) AND (VR OR AR OR serious game OR exergame))))

We included only articles written in English, both peer-reviewed journal articles and conference proceedings or workshops and excluded abstracts, editorial, book chapters and review articles and we excluded articles for which full text was not available for our University. Finally, due to the constantly evolving nature of the technologies considered, the search was limited to the period 2016 to the present. After the first search and selection phase, summarized in Fig. 1, we have selected 235 works (N = 235, in the following N denotes the number of the works for the considered specific topic), including 197 journal articles, 38 conference proceedings and workshop articles.

Papers included in this survey propose methodologies for the cognitive training (N = 151), assessment (N = 83) or both (N = 1) of heterogeneous target populations: elderly and age related diseases patients (N = 110); subjects with long term acquired disabilities caused by different pathological conditions, as stroke, cancer, MS, epilepsy, traumatic and acquired brain injuries (N = 32), or drugs and alcohol abuse (N = 5);
people suffering of psychiatric, neurological and emotional disorders (N = 26); children and adolescents with learning, social and cognitive impairments (N = 29); visually impaired patients (N = 2). All reported studies aim at the implementation of solutions based on new interactive technologies as a substitute or complementary tool to standard physiotherapy, occupational or pharmacological therapy, in order to improve patients autonomy, cognitive functions and general well-being. Around two third of selected works adopt SGs (N = 173), whereas less explored alternatives are EGs (N = 25), the computerized version of the classic tests (CT, N = 27) or a combination of SGs and EGs (N = 9) and SGs and CTs (N = 1).

During the categorization and data extraction phase, articles were classified considering the visualization and interaction technologies used as well as the chosen validation approaches, adopting the taxonomy further illustrated in Table 1.

III. VISUALISATION TECHNOLOGIES

Our search highlights a strong interest in VR technologies (N = 223), which has become increasingly higher in the last few years, see Fig. 2. The popularity of VR is due to its ability to reproduce realistic and ecologically valid two-dimensional or three-dimensional objects and virtual environments (VE) the user can interact with, while allowing to precisely control test administration and stimulus presentation, to record responses and track participants performance over time [55]. Considering the level of immersion provided, VR setups can be classified in three main categories, non-immersive, semi-immersive and immersive. Non-immersive systems are based on the use of screens (computers, mobile devices, monitors and projectors). The VE is presented to the users without occluding their Field of View (FOV), hence, even if they feel involved and engaged in the task, the sense of being in the real world while interacting with the virtual one persists. Semi-immersive virtual experiences provide users with a partial VE through the use of drive simulators or multiple screens. Sense of presence is moderate, since they will still give the perception of being in a different reality, while remaining connected to the physical surroundings. Finally, immersive systems concern room-filling technologies, such as the CAVE\(^1\) or the CAREN High End,\(^2\) and head-mounted displays (HMDs), both standalone and tethered, e.g. the Oculus\(^3\) or the Vive\(^4\) products. They completely occlude participants FOV enhancing the sense of being physically present in the VE. Moreover, they often include tracking systems, which, on the one hand, are essential for the correct functioning of the system, while, on the other hand, can provide additional information on users movements and behaviour inside the VE.

As shown in Table 2, non-immersive VR is still the most diffused visualization technology (N = 150), followed by immersive VR (N = 59), despite the recent success of VR HMDs and the release of more affordable and performing devices, and despite its benefits, in terms of multisensory stimulation, tracking of the head and body movements and higher sense of presence. The minor interest towards semi-immersive VR systems (N = 4) can be justified by their high cost and by the fact that they require an adequate space for installation and assistance during task execution.

The preference towards non-immersive VR may be partially explained by the fact that these technologies are accessible, affordable and portable, which make them ideal for remote use and home rehabilitation applications. Moreover, target populations mainly include children or adolescents (N = 10) and adults (N = 14), who are used to these technologies, or elderly (N = 25), who can more handily manage a computer or a tablet rather than a headset for immersive VR. Home rehabilitation applications are usually videogames smoothly accessible through Web platforms (N = 25) or playing games directly installed on the devices (N = 24), owned by the participants or provided by the experimenter. The majority of works found are based on non-immersive VR: PC (N = 20), mobile (N = 14), both (N = 8) or console (N = 5).

Even if studies focusing on the comparison of immersive and non-immersive solutions exist, results are not...
TABLE 1. Categories used for the classification of articles.

| Category            | Classification                                                                 |
|---------------------|---------------------------------------------------------------------------------|
| Visualization technologies | VR: Non-immersive, Semi-immersive and Immersive                               |
|                     | AR: Trigger-based and View-based                                               |
| Interaction technologies | Touchful: Standard gaming devices and Physiotherapy devices                   |
|                     | Touchless: Movement-based, EMG-based, Vision-based, Eye tracking-based and EEG-based |
|                     | Verbal                                                                         |
|                     | Robotic-based                                                                  |
| Validation          | Experimental design Within subject, Between subject, Compare different population, RCT, One subject Number of participants: n<20, 20<n<60, n>60 Data analysed: Gameplay data, Standart cognitive tests, User Experience tests, Physiological data, Kinematic data, Behavioural data, Real life test comparison and Experiment observations |

A less explored alternative to VR is AR (N = 10), which integrates digital and physical information in real-time and allows the user to interact with virtual and real worlds and objects at the same time. AR related articles have been classified in two overarching categories, i.e. trigger versus view-based augmentation, see Table 2. As shown in Fig. 2, our search reveals an increasingly higher interest in trigger based AR solutions, which include applications for AR see-through headsets and for mobile devices in which markers, body movements and locations are used to initiate the augmentation.

A comparison of the effect of VR and AR spatial memory training on short-term and long-term memory, has shown that, even if VR outperforms AR in the immediate post-training test, AR is better suitable for long-term spatial memory transfer [58]. Nonetheless, physical displacements have been shown to be important in acquiring spatial ability skills [59]. Solutions combining non-immersive VR and AR technologies also exist. Authors in [60] design a tool for screening initial dementia: participants visit a virtual cultural relic exhibition and have to complete a test while visiting the exhibition by scanning the answer’s code shown on a “cognitive board” with a mobile phone.

IV. INTERACTION TECHNOLOGIES

Interaction is another important factor to consider when designing applications in which participants can benefit from active learning and are asked to perform a specific task, which requires to interact with the VE. Thus, intuitive interfaces should be promoted, in order to reduce learning time and optimize the effects of the training. However, the choice of the solution to be adopted is frequently bound to some constraints, since all target populations exhibit cognitive and/or physical impairments, which should be taken into account during the design phase and the choice of the proper interface. Moreover, around half of the studies analysed address older adults, who are less experienced with Information and Communication Technologies (ICTs), may have expectations strictly anchored to mental models developed in their past experiences with certain tools and could lack some basic knowledge required to effectively interact with the technological solutions proposed.

Interaction modalities can be mainly classified in touchful and touchless, as shown in Table 3. In the first case, the user concludes and strongly depend on the target population and on the task. Performance in assessing cognitive functions are usually comparable, whereas preference and usability of HMDs seem to be more consistent, in terms of increased motivation, more intuitive action control and greater enjoyment associated with task fulfillment. However, these studies are often conducted on young subjects, hence, even if results may encourage the use of immersive VR for the assessment and treatment of emotional or neurological disorders, they cannot be easily generalized to the senior population. In [55], researchers specifically address this problem and investigate the effect of the level of immersion (desktop screen and HMD) on seniors and young adults performance in a virtual supermarket shopping task. While young adult group score remains stable regardless of the platform used, seniors’ scores are superior in the non-immersive case, even if their experiences do not differ between the two platforms and only minimal and rare side effects are reported. Moreover, in both groups, trial execution with the HMD seems to be more influenced by fatigue. Opposite results are obtained by authors in [56], who demonstrate that a higher level of immersion can significantly improve inhibitory control and task switching. Similarly, in [57] two different games to train attention and working memory in children with Attention-Deficit/Hyperactivity Disorder (ADHD) in two modes, immersive and non-immersive, are developed and tested on healthy subjects. Electroencephalography (EEG) signals and gameplay data are recorded and analyzed as a measure of participants’ cognitive abilities and temporal cognitive ability changes. Better results are associated to the immersive trials.
is required to handle a device and apply a physical pressure to a surface to trigger events. Whereas, in the second case, no physical interaction with the device is needed. This category includes both different approaches for body posture and hand gesture detection and tracking, such as movement, electromyography (EMG) and vision-based techniques, and interfaces exploiting gaze or brain activation through eye trackers and wearable EEGs.

Touchful devices comprise the widely diffused tools for gaming ($N = 181$) and physiotherapeutic devices ($N = 17$), e.g. treadmills, cycle-ergometers and pressure sensitive plates, which are particularly suitable for rehabilitation programs aimed at improving motor skills in subjects with age-related disorders [15], [50], [89], [95], [112], [147], [148], [149], [150], [204], [209], major neurocognitive disorders (MNCD) [23], stroke [116], [152] and multiple sclerosis (MS) [22]. In general, touchful interfaces ensure stability, reliability and effectiveness. Nonetheless, although the low ICT education level of some subjects, mice and keyboards have been widely used since the last century and can be considered familiar tools. Hence, they represent the most common solution for interaction with a growing interest over the years, see Fig. 3. However, as interaction is achieved by pressing buttons and triggers or sliding fingers on a touchpad, which are not natural hand gestures, the transfer of skills acquired during training to daily life activities could be questionable.

Touchless approaches are often referred to as ecological, as they are designed in order to reuse existing skills, through intuitive gestures requiring a little cognitive effort. Moreover, they potentially allow for nearly unlimited input options, as they theoretically could exploit all the 27 DOFs of the human hand. However, they often present interaction and tracking challenges, as they are prone to occlusion, noisy reconstruction and noisy artifacts, which undermine both their intuitiveness and their stability and efficiency, causing frustration. This explains the increased interest of researchers over the year in the development of vision-based solutions, although to a lesser extent than touchless solutions, as shown in Fig. 3. Less explored alternative are eye tracking ($N = 2$) and EEG ($N = 9$) based interfaces. Eye tracking is used to monitor students with autism spectrum disorders (ASD) during the interaction with their educators and to help direct their attention [234]. Whereas portable EEG devices are employed to create Brain-Computer Interfaces (BCI), where signals detected by the EEG are translated into inputs in the application. These BCI are designed with the aim of training attention and concentration in pre adolescents [84] or ADHD [94], anxiety disorder [51] or Mild Cognitive Impaired (MCI) [73] patients.

A minority of studies explores other solutions, namely verbal ($N = 18$) and robot-based ($N = 6$) interaction. In the first case, the user is usually asked to watch a video [64], [153], observe a scenario [47], [203] or navigate a city [68], [71], [86], [223] or a maze [199] and recall elements, pick up and correctly place objects in a house [193], [201], solve problems by thinking aloud [78], [229], recall a list of items before buying them [173], [218], listen to a list of words and recall them [83], respond to visual or auditory targets [217]. The second case includes hand end-effector robotic devices [24], exoskeleton gait robots [116], [152] and humanoid robots, programmed to substitute therapists during test administration and provide adequate feedback. For example, in [134] Pepper humanoid robot administer a music memory based game, requiring MCI patients to recognise songs from the years they were younger; in [96] Pepper administers and shows the final score of a MoCA-like psychometric assessment; in [126] a tablet is mounted on a Lego robot that moves its arms and legs when the activity is correctly completed.

A classification of articles based both on the interaction and visualization technologies used is shown in Table 4.
FIGURE 4. Experimental designs commonly used to validate the proposed solutions based on the intervention goal, e.g. training, assessment or both.

In addition to the choice of the interaction technology, researchers must pay particular attention to the graphic design of the interface. As participants could suffer from visual and hearing problems or have troubles with attention, visual scenes have to be as simple as possible and search space should be reduced. During gameplay, simple and immediate data as a countdown timer, the number of remained chances to guess an answer, the current score or achieved progress can be correlated with the results of standard pencil-and-paper tests. High correlations suggest the construct validity of the proposed solution, which could become an alternative to standard assessment methods with the advantage of allowing for ecological assessment in a controlled environment.

V. VALIDATION

A. EXPERIMENTAL DESIGN AND DATA ANALYSIS

As highlighted by Fig. 4, games for training are usually validated using three main experimental designs, i.e. within subjects (N = 61), between subjects (N = 27) and randomized control trial (RCT, N = 39). While in the former case, all participants follow the same training procedure, in the latter cases, they are divided in groups and asked to follow two different training procedures, usually the traditional one and the videogame-based one, and results are compared. Test-retest reliability is often used for validation and is obtained by administering standard validated pencil-and-paper tests at different moment of the training schedule, namely before, after and follow-up. Similarly, games for cognitive assessment are usually validated using a within subjects experimental design (N = 48) or comparing healthy control (HC) with patients (N = 25) or young and elderly healthy subjects (N = 2), whereas a between subjects experimental design is only used by [224] to compare different visualization technologies (immersive and non-immersive). In general, participants are asked to play the game, and their performance is correlated with the results of standard pencil-and-paper tests. High correlations suggest the construct validity of the proposed solution, which could become an alternative to standard assessment methods with the advantage of allowing for ecological assessment in a controlled environment.

The increasing number of participants involved in the experimental sessions, as shown in Fig. 5 can be an indicator of the research community’s interest and efforts to develop solutions for cognitive assessment and training as well as the level of progress towards actual practical application in standard clinical practice. In fact, even if studies presenting new prototypes, applications at an initial development phase and user tests, which usually involve less than 20 participants, are common (N = 77), there is an increasing number of works that describe solutions at the validation phase, which typically involve a larger number of participants (N = 158). Representative samples in combination with large sample sizes are fundamental indexes when the goal is collecting informative data and extending the results of a research.

FIGURE 5. Number of participants involved in the experimental sessions over the last five years.
TABLE 3. Classification of articles based on the interaction technologies and devices.

| Classification | Device | Articles | N |
|----------------|--------|----------|---|
| Gaming devices | Mouse and keyboard | [17], [33], [49], [85], [91], [103], [109], [113], [115], [117], [120], [145], [150], [161], [163], [169], [175], [176], [179], [185], [213], [226] | 85 |
| | Touchscreen surface | [13], [51], [57], [61], [63], [66], [71], [74], [77], [81], [84], [86], [91], [97], [99], [101], [103], [109], [113], [115], [117], [120], [145], [150], [161], [163], [169], [175], [176], [179], [185], [213], [226] | 60 |
| | Controller, joystick or gamepad | [6], [14], [15], [17], [20], [25], [31]-[33], [36], [37], [39], [41], [43], [44], [48], [50], [59], [60], [66], [119], [122]-[128], [130]-[146], [161], [169], [200], [226], [233] | 53 |
| Touchful | System for driving simulation | [68], [171], [172] | 3 |
| | 3 Degree of Freedom manipulator | [90] | 1 |
| | 6 Degree of Freedom manipulator | [102] | 1 |
| Physiotherapy devices | Theraband | [95], [115], [147], [152], [218], [219] | 6 |
| | Pressure sensitive plate | [15], [22], [23], [89], [148], [169] | 6 |
| | Cycle-exerciser | [20], [112], [150], [204], [209] | 5 |
| Total | 198 |
| Movement-based | Sensitized gloves | [192] | 1 |
| | Acceleration-based techniques | [8], [12], [232] | 3 |
| EMG-based | EMG sensors | [52], [125] | 2 |
| Vision-based | RGB, RGB-D or 2K cameras with sensors or markers | [5], [9], [25], [28], [30], [33], [40], [46], [56], [58], [61], [69], [72], [73], [75], [86], [93], [146], [153], [155]-[159], [167], [174], [178], [183], [192], [197], [199], [205], [207], [212], [220]-[222], [229], [231], [234] | 43 |
| Eye tracking-based | Eye tracker | [214], [234] | 2 |
| HMD-based | Data wearable device | [3], [35], [71], [73], [76], [94], [111], [146], [235] | 7 |
| Other | Verbal | [27], [66], [68], [71], [78], [83], [86], [153], [173], [193], [199], [201], [203], [217], [218], [223], [229] | 17 |
| | Automatic speech recognition | [114] | 1 |
| Robot-based | Humanized robot | [99], [125], [134] | 3 |
| | Exoskeleton/gait robot | [16], [132] | 2 |
| | Hand-eye-effect robot device | [24] | 1 |

B. DATA COLLECTION AND ANALYSIS

During experimental sessions lots of heterogeneous data can be collected, however, as highlighted by Fig. 6, interest is often mainly focused on gameplay data and standard cognitive test results. Gameplay scores and parameters or log data are recorded for the evaluation of performance and the monitoring of user actions in the VE. These scores are usually compared with standard cognitive pencil-and-paper tests results or, rarely, with performance obtained in real life tasks. In recent years, authors have become more interested in using a user-centered design approach, and validated questionnaires on usability, presence, workload or simulation sickness have emerged as key tools. Behavioural, observational, physiological and kinematic data, useful to monitor patients motor skills, task workload and the possible onset of negative side effects when using a certain technology, instead, have always been poorly exploited, although recordings can be easily acquired using non-invasive methods, which do not interfere with task execution or reduce sense of presence. For example, vision based approaches, as motion tracking systems and cameras, can provide kinematic information on body movements, postures and gait, while wearable sensor, e.g. armbands, bracelets or EEG headsets, allow to obtain physiological measurements, as heart rate, skin conductance or brain activation signals.

Table 5 proposes a classification of articles based on the goal of the intervention, the experimental design, the acquired data and the number of participants, which summarizes the previously reported results.

In some cases, data acquired during gameplay are used in combination with ML techniques for the classification of pathological and non pathological subjects, in particular concerning age related diseases [79], [86], [115], [130], [196], [208] and ADHD [188]. Since some pathological conditions can take long periods before being actually diagnosed with the means currently available, an early diagnosis through prediction methods allows to intervene promptly, preventing or limiting the onset of severe symptoms and debilitating conditions. Digital biomarkers, i.e. kinematics data, gameplay, clinical and neuropsychological data, can be used for the creation of predictive models for the identification of MCI pathological patterns [220], for scoring elderly brain’s ability [201] or for the clinical developmental assessment of preschooler [138]. Authors in [143] use Reinforcement Learning to train bots to generate synthetic data plausibly emulating a large population of players, at various stages of learning, or conversely, various levels of cognitive decline. Subsequently a prediction model is applied to new
| Visualization | Interaction | Articles |
|---------------|-------------|---------|
| **VR Non-Immersive** | | |
| Head gesture | | [11], [10], [11], [14], [28], [34], [45], [62], [65], [69], [70], [74], [77], [81], [82], [84], [85], [91], [92], [97], [99], [103], [109], [113], [115], [117] |
| Touchscreen | | [110] |
| Body tracking | | [61], [75], [93], [98] |
| Hand gesture and body tracking | | [72] |
| Robot | | [34], [96] |
| Voice and text | | [78] |
| EGG | | [71], [73], [74], [94], [111] |
| Treadmill/pressure plate/cycle ergometer | | [22], [81], [85], [112] |
| Mouse and voice | | [114] |
| Mouse/keyboard and cycle-ergometer | | [120] |
| Treadmill and robot | | [116] |
| Touchful and voice | | [64], [71], [83] |
| Touchful/touchless and voice | | [66] |
| Body tracking and EGG | | [73] |
| Keyboard and EGG | | [53] |
| Touchless and AR marker | | [35], [30] |
| Driving tool and voice | | [68] |
| Joystick | | [150] |
| Motion sensor device | | [9] |
| Body tracking | | [154], [155], [171], [159] |
| Pressure plate | | [15] |
| **PC and console** | Mouse/keyboard and body tracking | [9], [560] |
| **Mobile/Tablet** | Controller | [129] |
| Touchscreen | | [133], [138], [26], [31], [37], [90], [41], [43], [44], [123], [125], [127], [128], [130], [133], [135], [137], [139], [141], [144] |
| Touchscreen and robot | | [134] |
| Touchscreen and EGG | | [140] |
| Touchscreen and magnetic sensor | | [56] |
| Touchscreen, robot and EMG | | [126] |
| **PC touchscreen/projector/monitor** | Joystick | [113] |
| Touchscreen | | [4], [5], [7], [119] |
| Body Tracking | | [151] |
| Treadmill cycle-ergometer/pressure plate | | [23], [147] | [150] |
| Treadmill and robot | | [155] |
| Touchful/touchless and voice | | [55] |
| Touchless and touchscreen | | [146] |
| **PC and mobile** | Touchscreen | [52] |
| Touchscreen and mouse/keyboard | | [3], [21], [31], [48], [145], [161], [165], [169] |
| Touchful and body tracking | | [38], [40] |
| **VR Semi-Immersive** | Driving simulator | [171], [172] |
| Multiple screens | Jogging/voice | [73] |
| Body tracking | | [174] |
| **VR Immersive** | Controller/joystick/gamepad | [14], [17], [20], [27], [35], [42], [178], [180], [183], [184], [186], [189], [194], [195], [202], [206], [214], [215], [219], [223], [213] |
| Mouse/keyboard | [179], [176], [179], [185], [213] |
| Hear gesture | | [29], [45], [177], [192], [212] |
| Body tracking | | [182], [183], [197], [198], [205] |
| Voice | | [47], [237] |
| EGG | | [213] |
| Eye Tracking | | [214] |
| Cycle-ergometer and controller | [204], [209] |
| Controller and EGG | | [52] |
| Controller/voce | [193], [199], [201], [203] |
| Treadmill and voice | | [218] |
| Controller and touchless | [4], [207] |
| Room-filling device | Body tracking | [202], [221] |
| Treadmill | | [218] |
| Both | Body tracking and joystick | [223] |
| **VR Non-Immersive and Immersive** | | |
| PC and HMD | Mouse/keyboard and controller | [51], [57] |
| Body tracking and controller | [56] |
| Voice and controller | [223] |
| Written | | [224] |
| Mobile and HMD | IMU and body tracking | [235] |
| Touchful, controller and cycle-ergometer | [90] |
| PC/Mobile and HMD | Mouse/keyboard and controller | [225] |
| **AR Trigger based** | See-through HMD | | |
| Eye tracking | | [334] |
| Controller | [235] |
| Marker based | [230] |
| PC | Body tracking | [331] |
| Marker based/Voice | [229] |
| Mobile | Motion sensor | [121], [232] |
| Touchscreen and sensors | [233] |
| SLAM and Touchscreen | [59] |
| **AR View based** | Holograms | Hand gesture | [336] |
| **VR and AR** | | | |
| HMD and See-through HMD | Hand gesture | [5] |
| PC and smartphone | Marker based | [22] |
### TABLE 5. Classification of articles based on the aim of the study, the experimental design, the data acquired and the number of participants.

| Goal                  | Experimental design | Data Analysed                                      | Participants | Articles |
|-----------------------|---------------------|----------------------------------------------------|--------------|----------|
| **Assessment**        | Within subjects     | Game data                                          | n=20         | [164], [219]|         |
|                       |                     |                                                   | 20<n=60      | [143]     |          |
|                       |                     |                                                   | n=60         | [108]     |          |
|                       |                     | Standard test                                      | n=60         | [115]     |          |
|                       |                     | EEG data                                           | n=20         | [94]      |          |
|                       |                     |                                                   | 20<n=60      | [151]     |          |
|                       |                     | Behavioral data                                    | 20<n=60      | [235]     |          |
|                       |                     | Game data and standard test                        | n=20         | [33], [75], [76], [125], [187] |
|                       |                     |                                                   | 20<n=60      | [59], [101], [110], [130], [218] |
|                       |                     |                                                   | n=60         | [34], [73], [64], [92], [100], [104], [113], [119], [122], [125], [138], [145] |
|                       |                     | Game data and kinematic data                       | n=20         | [218]     |          |
|                       |                     | Game data and eye tracking                         | n=20         | [104]     |          |
|                       |                     | Game data and usability                            | n=20         | [117]     |          |
|                       |                     |                                                   | 20<n=60      | [105], [211], [32], [214] |
|                       |                     | Standard test and physiological data              | n=20         | [84]      |          |
|                       |                     | Standard test, game and physiological data        | n=60         | [16]      |          |
|                       |                     |                                                   | 20<n=60      | [215]     |          |
|                       |                     | Standard test, game data and usability             | n=60         | [50], [205], [217] |
|                       |                     | Game and physiological data, usability and eye tracking | n=20         | [42]      |          |
|                       | **HC young vs HC old** | Game data and usability                            | n=20         | [169]     |          |
|                       |                     | Standard test, game data and observations          | n=80         | [33]      |          |
|                       | **HC vs patients**  | Game data                                          | n=20         | [205]     |          |
|                       |                     |                                                   | n=60         | [109], [162] |
|                       |                     | Standard test                                      | n=20         | [79]      |          |
|                       |                     |                                                   | n=60         | [130], [184] |
|                       |                     | Eye tracking                                       | n=60         | [24], [131], [185], [206] |
|                       |                     |                                                   | n=60         | [26], [127], [177], [183], [184], [212] |
|                       |                     | Game and kinematic data                            | n=20         | [225]     |          |
|                       |                     | Standard test, game and physiological data        | n=20         | [118]     |          |
|                       |                     | Game and kinematic data                            | n=60         | [194]     |          |
|                       |                     | Standard test, game data and usability             | n=20         | [65]      |          |
|                       |                     | Game data and observations                         | n=20         | [68]      |          |
|                       | **Between subjects** | Standard test, game data and recording and usability | n=60         | [114]     |          |
|                       |                     | Game data                                          | n=20         | [225]     |          |
|                       |                     | One subject                                        | n=20         | [207]     |          |
|                       | **Different experiments** | Standard test, game, kinematic and physiological data, usability and real life task | n=20         | [133]     |          |
|                       |                     |                                                      | n=60         | [226]     |          |
|                       |                     | Standard test and usability                        | n=20         | [135]     |          |
|                       |                     | Game data and usability                            | n=20         | [185]     |          |
|                       |                     |                                                   | n=60         | [185]     |          |
|                       | **Training**        | Game data                                          | n=20         | [48], [58], [78], [187], [235] |
|                       | Within subjects     |                                                   | n=60         | [151]     |          |
|                       |                     | Standard test                                      | n=20         | [229], [172], [182], [133], [183] |
|                       |                     |                                                   | 20<n=60      | [56], [74] |
|                       |                     | Physiological data                                 | n=20         | [176]     |          |
|                       |                     | Eye tracking                                       | n=20         | [223]     |          |
|                       |                     |                                                   | n=20         | [149]     |          |
|                       |                     | Usability                                          | n=20         | [12], [142], [174] |
|                       |                     |                                                   | 20<n=60      | [141]     |          |
|                       |                     | Standard test and game data                        | n=20         | [144]     |          |
|                       |                     |                                                   | 20<n=60      | [57], [69], [71], [85], [195] |
|                       |                     |                                                   | n=60         | [53], [82] |
|                       |                     | Game and physiological data                       | n=20         | [139]     |          |
|                       |                     | Game data and eye tracking                         | n=20         | [155]     |          |
|                       |                     |                                                   | n=60         | [135]     |          |
|                       |                     | Standard test and physiological data              | n=20         | [111]     |          |
|                       |                     | Game data and eye tracking                         | n=20         | [121], [200] |
|                       |                     |                                                   | n=60         | [164]     |          |
|                       |                     | Game data and usability                            | n=20         | [48], [134], [189] |
|                       |                     |                                                   | 20<n=60      | [35], [159], [192], [209] |
|                       | **Between subjects** | Game data and real life task                       | n=20         | [197]     |          |
|                       |                     | Standard test and kinematic data                  | n=20         | [234]     |          |
|                       |                     | Game data and observations                         | n=20         | [201]     |          |
|                       |                     | Standard test and physiological data              | n=20         | [155]     |          |
|                       |                     | Standard test and usability                       | n=20         | [28], [60] |
|                       |                     | Physiological data and usability                  | n=20         | [228]     |          |
|                       |                     | Standard test, game and kinematic data             | n=20         | [198]     |          |
|                       |                     | Standard test, game and physiological data        | n=20         | [120]     |          |
|                       |                     |                                                   | n=60         | [15]      |          |
|                       |                     | Standard test, game data and usability             | n=20         | [79]      |          |
|                       |                     | Standard test, game data and observations          | n=20         | [222]     |          |
|                       |                     | Game and physiological data and eye tracking      | n=20         | [219]     |          |
|                       |                     | Game data and usability                            | n=20         | [297]     |          |
|                       |                     | Game data and usability                            | n=20         | [19]      |          |
|                       |                     | Game data and usability                            | n=20         | [179]     |          |
|                       |                     | Standard test, game data and usability             | n=20         | [65]      |          |
|                       |                     | Standard test, game data and observations          | n=20         | [81]      |          |
|                       |                     | Game data and eye tracking                         | n=20         | [27], [133], [165], [172] |
|                       |                     |                                                   | 20<n=60      | [83], [236] |
|                       |                     | Standard test, game data and observations         | n=20         | [97]      |          |
TABLE 5. (Continued.) Classification of articles based on the aim of the study, the experimental design, the data acquired and the number of participants.

| Classification | Article Count |
|----------------|---------------|
| Standard test and observations | 202 (<60) | 153 |
| Game and physiological data | 202 (<60) | 154 |
| Game and usability | 202 (<60) | 140 |
| Standard test and physiological data | 202 (<60) | 150 |
| Game and usability | 202 (<60) | 140 |
| Standard test and real-life task | 202 (<60) | 129 |
| Real-life task and physiological data | 202 (<60) | 130 |
| Standard test, game data and usability | 202 (<60) | 136 |
| Game and usability | 202 (<60) | 134 |
| Standard test, physiological data and usability | 202 (<60) | 138 |
| Standard test, physiological data and kinematic data | 202 (<60) | 135 |
| Standard test, game data and real-life task | 202 (<60) | 133 |

RCT

| Classification | Article Count |
|----------------|---------------|
| Standard test | 202 (<60) | 106 |
| Game and usability | 202 (<60) | 83 |
| Standard test and game data | 202 (<60) | 138 |
| Standard test and physiological data | 202 (<60) | 147 |
| Standard test and kinematic data | 202 (<60) | 131 |
| Standard test, game and physiological data | 202 (<60) | 148 |
| Standard test, game and usability | 202 (<60) | 50 |
| Game data | 202 (<60) | 158 |
| Usability | 202 (<60) | 157 |
| Standard test, game, EEG and eye tracking data | 202 (<60) | 195 |

Dive subject

| Classification | Article Count |
|----------------|---------------|
| Standard test and game data | 202 (<60) | 175 |
| Game data | 202 (<60) | 99 |
| Usability | 202 (<60) | 228 |
| Standard test, game data and usability | 202 (<60) | 41 |

Both

| Classification | Article Count |
|----------------|---------------|
| Standard test and game data | 202 (<60) | 176 |

TABLE 6. Classification of the articles according to the practical usability of SGs and EGs in healthcare structures and research centres.

| Clinical practice | Articles |
|-------------------|----------|
| Healthcare Structure | [16], [23], [25], [28], [34], [41], [44], [59], [61], [62], [70], [75], [76], [81], [84], [85], [86], [94], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125], [126], [127], [128], [129], [130], [131], [132], [133], [134], [134], [135], [136], [137], [138], [139], [140], [141], [142], [143], [144], [145], [146], [147], [148], [149], [150], [151], [152], [153], [154], [155], [156], [157], [158], [159], [160], [161], [162], [163], [164], [165], [166], [167], [168], [169], [170], [171], [172], [173], [174], [175], [176], [177], [178], [179], [180], [181], [182], [183], [184], [185], [186], [187], [188], [189], [190], [191], [192], [193], [194], [195], [196], [197], [198], [199], [200], [201], [202], [203], [204], [205], [206], [207], [208], [209], [210], [211], [212], [213], [214], [215], [216], [217], [218], [219], [220] |
| Research Center | [15], [25], [47], [65], [66], [71], [80], [83], [95], [105], [106], [114], [118], [124], [127], [134], [135], [141], [146], [164], [166], [167], [168], [188], [189], [200], [203], [209], [211], [218], [220] |

gameplay data to classify different levels of play. These examples suggest the feasibility of the adoption of ML techniques in biomedical applications where the number of patients is small, symptoms could be non-homogeneous and the complexity of the setting can be challenging. In other cases, ML techniques are adopted for runtime analysis of data. In [47] two supervised algorithms, namely random forest and support vector machine, analyse verbal and non-verbal input. Outputs are employed both for the classification of MS and Parkinson Disease subjects and for the recognition and automatic verification of the given verbal answers. Authors in [78] develop a multi-label classification model for driven automatic assessment to track and assess the cognitive and emotional states of individuals with ASD during VR-based training. In [99] authors describe the implementation and efficacy of a linear regression model for the assessment of intrinsic motivation and performance using Big Five personality traits values (openness to experiences, conscientiousness, extraversion, agreeableness, and emotional stability).

C. AVAILABILITY AND EFFECTIVE CLINICAL APPLICATION

Authors frequently do not explicitly share information about the availability of raw data and applications used, though this would be very important for the research community and for the medical doctors. Dataset is sometimes made explicitly available online [49], [215] or from the corresponding author on reasonable request because of privacy policies, ethical or proprietary constraints [10], [15], [19], [23], [30], [34], [44], [60], [78], [80], [108], [110], [113], [115], [121], [137], [153], [174], [176], [209], [214], [216], [218]. Moreover, excluding commercial and proprietary applications, we can still find free download [65], [81], [100], [123], [185], open source [78] and freely accessible Web applications [21], [30], [107].

Finally, considering the effective use of proposed solutions with pathological subjects, patients involved in the experimental sessions usually have a diagnosed disease and are recruited from hospitals, clinics, community-dwelling, specialized day care centers or retirement homes. This implies a collaboration between these structures and research groups, however the nature of this collaboration nor the duration is often unclear, even if specialized research centers having stable and long-lasting collaborations with health facilities exist (12.3%). For this reason, it is difficult to understand the practical feasibility and usability in hospitals, rehabilitation centers and daycare centers of the methodologies proposed.
Nonetheless, as reported in Table 6, we could find some clinics (10.2%), which have successfully integrated the new technological approaches in the treatment of their host patients.

VI. CONCLUSION

The current survey aims at providing an analysis of the research on SGs and EGs for the assessment and training of cognitive dysfunctions related to different pathological conditions, conjointly with technological advancements in visualization and interaction technologies, platform for game deployment and AI, in the last five years. After the first search and selection phase conducted in high profile databases, we categorized articles and extracted data according to the classification shown in Table 1.

Considering RQ1, the analysis of the visualization technologies highlights a greater and increasingly higher interest in VR (94.9%), in particular non-immersive (67.2%) and immersive VR (28.5%), than AR (4.3%). The diffusion of non-immersive with respect to immersive VR, although the recent success and widespread diffusion of immersive VR HMDs, may be justified by the affordability and portability of PCs and mobile devices, their accessibility and easiness of use, even in absence of supervision, which make them particularly suitable for home rehabilitation and applications for target population with a low ICTs level. This could also explain why researchers are becoming more interested in trigger-based AR solutions for mobile devices.

Regarding RQ2, touchful interaction modalities have been the most diffused over the last five years (84.3%), whereas among the touchless solutions, a growing interest for vision-based techniques (18.3%) has been found. Considering touchful interaction approaches, half of the solutions found use the standard gaming tools (51.5%), e.g., mice and keyboards, controllers, joysticks or gamepads, whereas only a minority of works try to combine standard physiotherapy tools (7.2%) or exoskeleton gait robots and end-effector robotic devices (1.3%) with videogame-based training. Among the touchless interactions, excluding vision-based techniques, the application of alternative approaches, such as eye tracking (0.9%) and EEG for attention training is still limited (3.8%), even if the recent integration of eye trackers with newer HMDs (as HTC Vive Pro Eye) could encourage researchers to further investigate its application in the cognitive neuroscience field. Finally, the application of AI techniques for speech recognition and eventual interaction with chat bots or virtual characters (0.4%) or humanoid robots (1.3%) is still poorly exploited, since human therapists still play a prominent role (7.2%).

Concerning RQ3, the most diffused experimental designs for the validation of designed solutions are within subjects (26%), RCT (16.6%) and between subjects (11.5%) for training and within subjects (20.4%) and comparison of healthy control and patients (10.6%) for assessment. During experimental sessions, only gameplay data (63.4%), standard cognitive tests (66%) and validated questionnaires (22.6%) are ordinarily used, whereas physiological (13.2%) and kinematic (5.1%) data are employed by a minority of the works, although they can be easily recorded through non-invasive methods and could provide additional objective quantitative information on the pathological conditions, performance and workload. Moreover, we highlight an increasing interest over the years in the development of validated applications aiming at becoming a standard in the clinical practice, since the majority of proposed solutions have been tested on a number of participants between 20 and 60 (37.9%) or higher than 60 (29.4%). However, the number of subjects/patients effectively using such solutions and their actual adoption by healthcare structures (10.2%) or research centers having stable and long-lasting collaborations with health facilities (12.3%) is still limited. Although results are promising and literature is rich, the exchange and sharing of data and applications within the large community of researchers and medical professionals is limited. In fact, datasets are sometimes available online (0.9%) or can be obtained from the corresponding author on reasonable request (9.8%), whereas implemented applications are rarely freely accessible, i.e. Web applications (1.3%), free downloaded (2.1%) and open source (0.4%), by hampering a real impact of the research works.

REFERENCES

[1] W. J. Boendermaker, T. E. Gladwin, M. Peeters, P. L. M. Prins, and R. W. Wiers, “Training working memory in adolescents using serious game elements: Pilot randomized controlled trial,” *JMR Serious Games*, vol. 6, no. 2, p. e8364, May 2018.
[2] Z. Huang, A. Javaid, V. K. Devabhaktuni, Y. Li, and X. Yang, “Development of cognitive training program with EEG headset,” *IEEE Access*, vol. 7, pp. 126191–126200, 2019.
[3] H.-T. Jung, J.-F. Daneault, H. Lee, K. Kim, B. Kim, S. Park, T. Ryu, Y. Kim, and S. I. Lee, “Remote assessment of cognitive impairment level based on serious mobile game performance: An initial proof of concept,” *IEEE J. Biomed. Health Inform.*, vol. 23, no. 3, pp. 1269–1277, May 2019.
[4] Y. Jyoti and U. Lahiri, “Virtual reality based joint attention task platform for children with autism,” *IEEE Trans. Learn. Technol.*, vol. 13, no. 1, pp. 198–210, Jan. 2020.
[5] Y. Jyoti and U. Lahiri, “Human-computer interaction based joint attention cues: Implications on functional and physiological measures for children with autism spectrum disorder,” *Comput. Hum. Behav.*, vol. 104, Mar. 2020, Art. no. 106163.
[6] Y.-Y. Liao, I.-H. Chen, Y.-J. Lin, Y. Chen, and W.-C. Hsu, “Effects of virtual reality-based physical and cognitive training on executive function and dual-task gait performance in older adults with mild cognitive impairment: A randomized control trial,” *Frontiers Aging Neurosci.*, vol. 11, p. 162, Jul. 2019.
[7] L. Martin, F. Vannetti, L. Fabbrini, F. Gerli, I. Mosca, S. Pazzi, F. Baglio, and L. Bocchi, “GOAL (games for older adults life): A web-application for cognitive impairment tele-rehabilitation,” in *World Congress on Medical Physics and Biomedical Engineering 2018*. Singapore: Springer, 2019, pp. 177–182.
[8] M. Adcock, M. Fankhauser, J. Post, K. Lutz, L. Zislisperger, A. R. Luft, V. Guimarães, A. Schättin, and E. D. de Bruin, “Effects of an in-home multicomponent exergame training on physical functions, cognition, and brain volume of older adults: A randomized controlled trial,” *Frontiers Med.*, vol. 6, p. 321, Jan. 2020.
[9] B. Babuska, M. Hostovecky, M. Smoundr, and L. Huraj, “Spectral analysis of electroencephalographic data in serious games,” *Appl. Sci.*, vol. 11, no. 6, p. 2480, Mar. 2021.
[11] G. Binarelli, M. Lange, M. D. Santos, J.-M. Grellard, A. Lelaidier, L. Tron, S. L. Arborgast, B. Clarisse, and F. Joly, “Multimodal web-based intervention for cancer-related cognitive impairment in breast cancer patients: Cog-Stim feasibility study protocol,” *Cancers*, vol. 13, no. 19, p. 4868, Sep. 2021.

[12] K. Han, K. Park, K.-H. Choi, and J. Lee, “Mobile augmented reality serious game for improving old adults’ working memory,” *Appl. Sci.*, vol. 11, no. 17, p. 7843, Aug. 2021.

[13] A. Jaramillo-Alcázar, E. Venegas, S. Criollo-C, and S. Luján-Mora, “An approach to accessible serious games for people with dyslexia,” *Sustainability*, vol. 13, no. 5, p. 2507, Feb. 2021.

[14] X. Li, K. S. Niskrait, S. Chen, D. Weng, S. Sarcar, and X. Ren, “The impact of a multitasking-based virtual reality motion video game on the cognitive and physical abilities of older adults,” *Sustainability*, vol. 12, no. 21, p. 9106, Nov. 2020.

[15] J. M. Kang, N. Kim, S. K. Woo, G. Park, B. K. Yeon, J. W. Park, J.-H. Youn, S.-H. Ryu, J.-Y. Lee, and S.-J. Cho, “Effect of cognitive training on fully immersive virtual reality on visuospatial function and frontal-opercular functional connectivity in predementia: Randomized controlled trial,” *J. Med. Internet Res.*, vol. 23, no. 5, May 2021, Art. no. e24526.

[16] E. I. Konstantinidis, P. D. Bamidis, A. Billis, P. Kartsidis, D. Petsani, J. M. Kang, N. Kim, S. Y. Lee, S. K. Woo, G. Park, B. K. Yeon, A. Jaramillo-Alcázar, E. Venegas, S. Criollo-C, and S. Luján-Mora, “Design and evaluation of user-centered exergames for patients with multiple sclerosis: Multilevel usability and acceptability study,” *PLoS ONE*, vol. 15, no. 3, Mar. 2020, Art. no. e0230498.

[17] S. Leonardi, M. G. Maggio, M. Russo, A. Bramanti, F. A. Arcadi, A. Naro, R. S. Calabrò, and R. De Luca, “Cognitive recovery in people with relapsing/remitting multiple sclerosis: A randomized clinical trial on virtual reality-based neurorehabilitation,” *Clin. Neurolog. Neurosurg.*, vol. 208, Sep. 2021, Art. no. 106828.

[18] R. Capizzi, M. Fisher, B. Biagianti, N. Ghiassi, A. Currie, K. Fitzpatrick, N. Albertini, and S. Vinogradov, “Testing a novel web-based neurocognitive battery in the general community: Validation and usability study,” *J. Med. Internet Res.*, vol. 23, no. 5, May 2021, Art. no. e25082.

[19] A. L. Faria, M. S. Pinho, and S. B. I. Badia, “A comparison of two per task adaptive and fully immersive virtual reality approaches: A randomized controlled trial with chronic stroke patients,” *J. NeuroEng. Rehabil.*, vol. 17, no. 1, pp. 1–15, Dec. 2020.

[20] S.-J. Eun and J. Y. Kim, “Design and implementation of ADL content with VR sensor at a smart human-care service,” *J. Sensors*, vol. 2020, pp. 1–14, Jul. 2020.

[21] A. L. Faria, M. S. Pinho, and S. B. I. Badia, “A comparison of two per task adaptive and fully immersive virtual reality approaches: A randomized controlled trial with chronic stroke patients,” *J. NeuroEng. Rehabil.*, vol. 17, no. 1, pp. 1–15, Dec. 2020.

[22] H.-T. Jung, J.-F. Daneault, T. Nanglo, H. Lee, B. Kim, Y. Kim, and S. I. Lee, “Effectiveness of a serious game for cognitive training in chronic stroke survivors with mild-to-moderate cognitive impairment: A pilot randomized controlled trial,” *Appl. Sci.*, vol. 10, no. 19, p. 6703, Sep. 2020.

[23] J. W. Park, J.-H. Youn, S.-H. Ryu, J.-Y. Lee, and S.-J. Cho, “Effect of game-based cognitive training programs on cognitive learning of children with intellectual disabilities,” *Appl. Sci.*, vol. 11, no. 18, p. 8582, Sep. 2021.

[24] N. Mistarz, A. S. Nielsen, K. Andersen, A. E. Goudriaan, L. Skøt, S.-J. Eun, and J. Y. Kim, “Development of a novel mobile-based game for using to assess cognitive control among children and adolescents,” *PLoS ONE*, vol. 13, no. 19, May 2021, Art. no. e0212038.

[25] A. M. Terrer, M. G. Maggio, M. C. De Cola, C. Zichittella, C. Carmela, B. Porcari, G. la Rosa, R. De Luca, A. Naro, and R. S. Calabrò, “Beyond motor recovery after stroke: The role of hand robotic rehabilitation plus virtual reality in improving cognitive function,” *J. Clin. Neurosci.*, vol. 92, pp. 11–16, Oct. 2021.

[26] A. L. Faria, M. S. Cameirão, J. F. Couras, J. R. O. Aguiar, G. M. Costa, and S. Bermúdez I Badia, “Combined cognitive-motor rehabilitation in virtual reality improves motor outcomes in chronic stroke—A pilot study,” *Frontiers Psychol.*, vol. 9, p. 854, May 2018.

[27] L. Zając-Lamparska, M. Wilkońska-Dębczyńska, A. Wojciechowiec, M. Podhorecka, A. Polak-Szabela, L. Warchol, K. Kędziora-Kornatowska, A. Araszkiewicz, and P. Izdebski, “Effects of virtual reality-based cognitive training in older adults living without and with mild dementia: A pretest–posttest design pilot study,” *BMC Res. Notes*, vol. 12, no. 1, pp. 1–14, Dec. 2019.

[28] A. Chaldogeridis and T. Tsiatsos, “Implementation and evaluation of a serious game for working memory enhancement,” *Appl. Sci.*, vol. 10, no. 24, p. 9128, Dec. 2020.
K. E. Greenwood, R. Smith, A.-M. Jones, D. Pearson, and T. Wykes, “Virtual shopping: A viable alternative to direct assessment of real life function?” Schizophrenia Res., vol. 172, nos. 1–3, pp. 206–210, Apr. 2016.

C. R. Oliveira, B. J. P. Lopes Filho, C. S. Esteves, T. Rossi, D. S. Nunes, M. M. B. P. Lima, T. Q. Irigary, and I. I. L. Argimon, “Neurophysiological assessment of older adults with virtual reality: Association of age, schooling, and general cognitive status,” Frontiers Psychol., vol. 9, p. 1085, Jun. 2018.

P. Gamito, J. Oliveira, C. Alves, N. Santos, C. Coelho, and R. Brito, “Virtual reality-based cognitive stimulation to improve cognitive functioning in community elderly: A controlled study,” Cyberpsychol., Behav., Soc. Netw., vol. 23, no. 3, pp. 150–156, Mar. 2020.

S. Serino, E. Pedrolí, C. Tuenaa, G. De Leo, M. Stramba-Badiale, K. Goulene, N. G. Mariotti, and G. Riva, “A novel virtual reality-based training protocol for the enhancement of the ‘mental frame syncing’ in individuals with Alzheimer’s disease: A development-of-concept trial,” Frontiers Aging Neurosci., vol. 9, p. 240, Jul. 2017.

S. I. L. Chua, N. C. Tan, W. T. Wong, J. C. Allen, Jr., J. H. M. Quah, R. Malhotra, and T. Östbye, “Virtual reality for screening of cognitive function in older persons: Comparative study,” J. Med. Internet Res., vol. 21, no. 8, Aug. 2019, Art. no. e14821.

G. Lecouvey, A. Morand, J. Gonneaud, P. Pluim, E. Orriols, A. Pélerin, L. F. D. Silva, V. de La Sayette, F. Eustache, and B. Desgranges, “An impairment of prospective memory in mild Alzheimer’s disease: A ride in a virtual town,” Frontiers Psychol., vol. 10, p. 241, Feb. 2019.

T. Fasulis, P. Patrikelis, A. Siatouni, A. Aoudia, V. Vetromiti, L. zachou, and S. G. Zatozis, “A pilot study and brief overview of rehabilitation via virtual environment in patients suffering from dementia,” Psychiatriki, vol. 29, no. 1, pp. 42–51, Apr. 2018.

A. Alloni, E. Sinfortiani, C. Zacchella, G. Sandrini, S. Bernini, B. Cattani, T. D. Parréld, S. Quaglini, and C. Pistarini, “Computer-based cognitive rehabilitation: The CoRe system,” Disability Rehabil., vol. 39, no. 4, pp. 407–417, Feb. 2017.

I. Amado, L. Brüngnacht-Herné, E. Orriols, C. Desombre, M. D. Santos, Z. Prost, M.-O. Krebs, and P. Pluim, “A serious game to improve cognitive functions in schizophrenia: A pilot study,” Frontiers Psychiatry, vol. 7, p. 64, Apr. 2016.

P. Barros, M. Almeida, A. Breda, and E. Rocha, “A digital puzzle game for the elderly,” in Proc. EDULEARN, Palma, Spain, Jul. 2019, pp. 3435–3443.

S. Jarayacharoen, P. Israsena, S. Pan-Ngum, and S. Menrungroj, “Brain exercising games with consumer-grade single-channel electroencephalogram feedback: Pre-post intervention study,” JMIR Serious Games, vol. 9, no. 2, Jun. 2021, Art. no. e26872.

R. T. Azuma, “A survey of augmented reality,” Presence, vol. 6, no. 6, pp. 355–385, Aug. 1997.

A. Plechátová, V. Sahulha, D. Fayette, and I. Fajnerová, “Age-related differences with immersive and non-immersive virtual reality in memory assessment,” Frontiers Psychol., vol. 10, p. 1330, Jun. 2019.

K.-T. Huang, “Exergaming executive functions: An immersive virtual reality-based cognitive training for adults aged 50 and older,” Cyberpsychol., Behav., Soc. Netw., vol. 23, no. 3, pp. 143–149, Mar. 2020.

B. Wan, Q. Wang, K. Su, C. Dong, W. Song, and M. Pang, “Measuring the impacts of virtual reality games on cognitive ability using EEG signals and game performance data,” IEEE Access, vol. 9, pp. 18326–18344, 2021.

N. R. Caluya, A. Plopski, J. F. Ty, C. Sandor, T. Taketomi, and H. Kato, “Transferability of spatial maps: Augmented versus virtual reality training,” in Proc. 4th EAI Int. Conf. Smart Objects Technol. Social Good, 2018, pp. 214–219.

C. Karapapas and C. Goumopoulos, “Mild cognitive impairment detection using machine learning models trained on data collected from serious games,” Appl. Sci., vol. 11, no. 17, p. 8184, Sep. 2021.

N. Hocine, “Personalized serious games for self-regulated attention training,” in Proc. 27th Conf. User Modeling, Adaptation Personalization, Jan. 2019, pp. 251–255.

F. Borgnis, F. Baglio, E. Pedrolí, F. Rossetto, G. Riva, and P. Cipresso, “A simple and effective way to study executive functions by using 360° videos,” Frontiers Neurosci., vol. 15, p. 296, Apr. 2021.

D. Baschieri, M. Gasparrì, and F. Zini, “A planning-based serious game for cognitive rehabilitation in multiple sclerosis,” in Proc. 4th EAI Int. Conf. Smart Objects Technol. Social Good, 2018, pp. 214–219.

K. Tsaikas, E. Barakova, J. V. Khan, and P. Markopoulos, “BrainHood: Towards an explainable recommendation system for self-regulated cognitive training in children,” in Proc. 13th ACM Int. Conf. Pervasive Technol. Rel. Assistive Environments, Jun. 2020, pp. 1–6.

R. Y. C. Kwan, J. Y. W. Liu, K. N. K. Fong, J. Qin, P. K.-Y. Leung, O. S. K. Sin, Y.-H. Hon, L. W. Suen, M.-K. Tse, and C. K. Lai, “Feasibility and effects of virtual reality motor-cognitive training in community-dwelling older people with cognitive frailty: Pilot randomized controlled trial,” JMIR Serious Games, vol. 9, no. 3, Aug. 2021, Art. no. e28400.
G. Shochat, S. Maoz, A. Stark-Inbar, B. Blumenfeld, D. Rand, S. Preminger, and Y. Sacher, “Motion-based virtual reality cognitive training targeting executive functions in acquired brain injury community-dwelling individuals: A feasibility and initial efficacy pilot,” in Proc. Int. Conf. Virtual Rehabil. (ICVR), Jun. 2017, pp. 1–9.

A. Nagle, R. Rienzer, and P. Wolf, “Personality-based reward contingency selection: A player-centered approach to gameplay customization in a serious game for cognitive training,” Entertainment Comput., vol. 28, pp. 70–77, Dec. 2018.

P. Gamito, D. Morais, J. Oliveira, P. Ferreira Lopes, L. F. Picareli, M. Matias, S. Correia, and R. Brito, “Systemic lithium battery: Normative data for memory and attention assessments,” JMIR Rehabil. Assist. Technol., vol. 3, no. 1, p. e5, May 2016.

P. Gamito, J. Oliveira, D. Alghazzawi, H. Fardoun, P. Rosa, T. Sousa, I. Maia, D. Morais, P. Lopes, and R. Brito, “The art gallery test: A preliminary comparison between traditional neuropsychological and ecological VR-based tests,” Frontiers Psychol., vol. 8, p. 1911, Nov. 2017.

C. Mei, B. T. Zahed, L. Mason, and J. Ouarles, “Towards joint attention training for children with ASD—a VR game approach and eye gaze exploration,” in Proc. IEEE Conf. Virtual Reality 3D User Interfaces (VR), Mar. 2018, pp. 289–296.

D. Martínez-Pernía, J. Núñez-Huasa, Á. del Blanco, A. Ruiz-Tagle, J. Velásquez, M. Gomez, C. Blesius, A. Ibáñez, B. Fernández-Manjón, and A. Slachekovsky, “Using game authoring platforms to develop screen-based simulated functional assessments in persons with executive dysfunction following traumatic brain injury,” J. Biomed. Inform., vol. 74, pp. 71–84, Oct. 2017.

P. Gamito, J. Oliveira, M. Matias, E. Cunha, R. Brito, P. F. Lopes, and A. Deus, “Virtual reality cognitive training among individuals with alcohol use disorder undergoing residential treatment: Pilot randomized controlled trial,” J. Med. Internet Res., vol. 23, no. 1, Jan. 2021, Art. no. e18482.

J. Oliveira, P. Gamito, T. Souto, R. Conde, M. Ferreira, T. Corotnean, A. Fernandes, H. Silva, and T. Neto, “Virtual reality-based cognitive exercise to improve functional outcomes,” Addict. Behav., vol. 100, no. 8, pp. 1400–1408, Aug. 2019.

K. Prior, E. Salemink, R. W. Wiers, B. A. Teachman, M. Piggott, N. C. Newton, M. Teesson, A. J. Baillie, V. Manning, L. F. McLellan, A. Mahoney, and L. A. Stapinski, “A web-based cognitive bias modification intervention (re-train your brain) for emerging adults with co-occurring social anxiety and hazardous alcohol use: Protocol for a multiarm randomized controlled pilot trial,” JMIR Res. Protocols, vol. 10, no. 7, Jul. 2021, Art. no. e28667.

J. Güsten, G. Ziegler, E. Düüzel, and D. Berron, “Age impairments in mnemonic discrimination of objects more than scenes: A web-based, large-scale approach across the lifespan,” Cortex, vol. 137, pp. 138–148, Apr. 2021.

P. Barzykowski, M. Wereszczyński, S. Hajdas, and R. Radel, “An inquisit-web protocol for calculating composite inhibitory control capacity score: An individual differences approach,” MethodsX, vol. 8, Jan. 2021, Art. no. 101530.

C. Hogan, P. Cornwell, J. Fleming, D. W. K. Man, and D. H. K. Shum, “Assessment of prospective memory after stroke utilizing virtual reality,” Virtual Reality, vol. 21, pp. 1–14, Sep. 2021.

B. Wang, Z. Xu, T. Luo, and J. Fan, “EEG-based closed-loop neurofeedback for attention modulation to mitigate cognitive decrements in young adults,” J. Healthcare Eng., vol. 2021, pp. 1–13, Jun. 2021.

D. Salisbury, T. Plocher, and A. Deus, “Virtual reality cognitive training among individuals with alcohol use disorder undergoing residential treatment: Pilot randomized controlled trial,”JMIR Res. Protocols, vol. 10, no. 7, Jul. 2021, Art. no. e28667.

J. Güsten, G. Ziegler, E. Düüzel, and D. Berron, “Age impairments in mnemonic discrimination of objects more than scenes: A web-based, large-scale approach across the lifespan,” Cortex, vol. 137, pp. 138–148, Apr. 2021.

P. Barzykowski, M. Wereszczyński, S. Hajdas, and R. Radel, “An inquisit-web protocol for calculating composite inhibitory control capacity score: An individual differences approach,” MethodsX, vol. 8, Jan. 2021, Art. no. 101530.

C. Hogan, P. Cornwell, J. Fleming, D. W. K. Man, and D. H. K. Shum, “Assessment of prospective memory after stroke utilizing virtual reality,” Virtual Reality, vol. 21, pp. 1–14, Sep. 2021.

B. Wang, Z. Xu, T. Luo, and J. Fan, “EEG-based closed-loop neurofeedback for attention modulation to mitigate cognitive decrements in young adults,” J. Healthcare Eng., vol. 2021, pp. 1–13, Jun. 2021.

D. Salisbury, T. Plocher, and A. Deus, “Virtual reality cognitive training among individuals with alcohol use disorder undergoing residential treatment: Pilot randomized controlled trial,”JMIR Res. Protocols, vol. 10, no. 7, Jul. 2021, Art. no. e28667.

J. Güsten, G. Ziegler, E. Düüzel, and D. Berron, “Age impairments in mnemonic discrimination of objects more than scenes: A web-based, large-scale approach across the lifespan,” Cortex, vol. 137, pp. 138–148, Apr. 2021.

P. Barzykowski, M. Wereszczyński, S. Hajdas, and R. Radel, “An inquisit-web protocol for calculating composite inhibitory control capacity score: An individual differences approach,” MethodsX, vol. 8, Jan. 2021, Art. no. 101530.

C. Hogan, P. Cornwell, J. Fleming, D. W. K. Man, and D. H. K. Shum, “Assessment of prospective memory after stroke utilizing virtual reality,” Virtual Reality, vol. 21, pp. 1–14, Sep. 2021.

B. Wang, Z. Xu, T. Luo, and J. Fan, “EEG-based closed-loop neurofeedback for attention modulation to mitigate cognitive decrements in young adults,” J. Healthcare Eng., vol. 2021, pp. 1–13, Jun. 2021.

D. Salisbury, T. Plocher, and A. Deus, “Virtual reality cognitive training among individuals with alcohol use disorder undergoing residential treatment: Pilot randomized controlled trial,”JMIR Res. Protocols, vol. 10, no. 7, Jul. 2021, Art. no. e28667.

J. Güsten, G. Ziegler, E. Düüzel, and D. Berron, “Age impairments in mnemonic discrimination of objects more than scenes: A web-based, large-scale approach across the lifespan,” Cortex, vol. 137, pp. 138–148, Apr. 2021.

P. Barzykowski, M. Wereszczyński, S. Hajdas, and R. Radel, “An inquisit-web protocol for calculating composite inhibitory control capacity score: An individual differences approach,” MethodsX, vol. 8, Jan. 2021, Art. no. 101530.

C. Hogan, P. Cornwell, J. Fleming, D. W. K. Man, and D. H. K. Shum, “Assessment of prospective memory after stroke utilizing virtual reality,” Virtual Reality, vol. 21, pp. 1–14, Sep. 2021.

B. Wang, Z. Xu, T. Luo, and J. Fan, “EEG-based closed-loop neurofeedback for attention modulation to mitigate cognitive decrements in young adults,” J. Healthcare Eng., vol. 2021, pp. 1–13, Jun. 2021.

D. Salisbury, T. Plocher, and A. Deus, “Virtual reality cognitive training among individuals with alcohol use disorder undergoing residential treatment: Pilot randomized controlled trial,”JMIR Res. Protocols, vol. 10, no. 7, Jul. 2021, Art. no. e28667.

J. Güsten, G. Ziegler, E. Düüzel, and D. Berron, “Age impairments in mnemonic discrimination of objects more than scenes: A web-based, large-scale approach across the lifespan,” Cortex, vol. 137, pp. 138–148, Apr. 2021.

P. Barzykowski, M. Wereszczyński, S. Hajdas, and R. Radel, “An inquisit-web protocol for calculating composite inhibitory control capacity score: An individual differences approach,” MethodsX, vol. 8, Jan. 2021, Art. no. 101530.
A. García-Rudolph, A. García-Molina, E. Opisso, J. M. Tornos, V. I. Madai, D. Frey, and M. Bernabeu, “Neuropsychological assessments of patients with acquired brain injury: A cluster analysis approach to address heterogeneity in web-based cognitive rehabilitation,” Frontiers Neurol., vol. 12, p. 1288, Aug. 2021.

G. Klaybunar, I. Fradgula-Gurab, and O. Yilmaz, “The effects of virtual reality augmented robot-assisted gait training on dual-task performance and functional measures in chronic stroke: A randomized controlled single-blind trial,” Eur. J. Phys. Rehabil. Med., vol. 57, no. 2, pp. 227–237, May 2021.

M. Chessa, C. Bassano, and F. Solari, “A WebGL virtual reality exergame for assessing the cognitive capabilities of elderly people: A study about digital autonomy for web-based applications,” in Proc. Int. Conf. Pattern Recognit. Cham, Switzerland: Springer, 2021, pp. 163–170.

V. Vallejo, P. Wyss, L. Rampa, A. V. Mitache, R. M. Müri, U. P. Mosimann, and T. Nef, “Evaluation of a novel serious game based assessment tool for patients with Alzheimer’s disease,” PLoS ONE, vol. 12, no. 5, May 2017, Art. no. e0175999.

S. Bottirolli, S. Bernini, E. Cavallini, E. Sinforiani, C. Zucchella, S. Pazzi, P. Cristiani, T. Vecchi, D. Tost, G. Sandrini, and C. Tassorelli, “The smart aging platform for assessing early phases of cognitive impairment in patients with neurodegenerative diseases,” Frontiers Psychol., vol. 12, p. 500, Mar. 2021.

L. Qi, Y. Yin, L. Bu, Z. Tang, L. Tang, and G. Dong, “Acute VR competitive cycling exercise enhanced cortical activations and brain functional network efficiency in MA-dependent individuals,” Neurosci. Lett., vol. 757, Jul. 2021, Art. no. 135969.

C.-J. Hou, Y.-T. Chen, M. Capilayan, Y.-S. Lin, M.-W. Huang, and J.-H. Huang, “Analysis of heart rate variability in response to serious games in elderly people,” Sensors, vol. 21, no. 19, p. 6549, Sep. 2021.

S. Bottirolli, C. Tassorelli, M. Lamonica, C. Zucchella, E. Cavallini, S. Bernini, E. Sinforiani, S. Pazzi, P. Cristiani, T. Vecchi, D. Tost, and G. Sandrini, “Smart aging platform for evaluating cognitive functions in aging: A comparison with the MoCA in a normal population,” Frontiers Aging Neurosci., vol. 9, p. 379, Nov. 2017.

V. Vallejo, P. Wyss, A. Chesham, A. V. Mitache, R. M. Müri, U. P. Mosimann, and T. Nef, “Evaluation of a new serious game based multitasking assessment tool for cognition and activities of daily living: Comparison with a real cooking task,” Comput. Hum. Behav., vol. 70, pp. 500–506, May 2017.

S. Valladares-Rodríguez, M. J. Fernández-Iglesias, L. Anido-Rifón, D. Facal, C. Rivas-Costa, and R. Pérez-Rodríguez, “Touchscreen games to detect cognitive impairment in senior adults. A user-interaction pilot study,” Int. J. Med. Inform., vol. 127, pp. 52–62, Jul. 2019.

T. Tong, M. Chignell, M. C. Tierney, and J. Lee, “A serious game for clinical assessment of cognitive status: Validation study,” JMIR Serious Games, vol. 4, no. 4, p. e7, May 2016.

L. Lopez-Samaniego and B. Garcia-Zapirain, “A robot-based tool for physical and cognitive rehabilitation of elderly people using biofeedback,” Int. J. Environ. Res. Public Health, vol. 13, no. 12, p. 1176, Nov. 2016.

S. Zygoziris, P. Iliadou, E. Lazarou, D. Giakoumis, K. Votis, A. Alexiadis, and A. Triantafyllidis, “Detection of mild cognitive impairment in an at-risk group of older adults: Can a novel self-administered serious game-based screening test improve diagnostic accuracy?” J. Alzheimer’s Dis., vol. 78, no. 1, pp. 1–8, 2020.

S. Bhavnani, D. Mukherjee, S. Bhopal, K. K. Sharma, J. Dsgupta, G. Divan, S. Soremekun, R. Roy, B. Kirkwood, and V. Patel, “The association of a novel digital tool for assessment of early childhood cognitive development, ‘develasment on an E-platform (DEEP)’, with growth in rural India: A proof of concept study,” eClinicalMedicine, vol. 37, Jul. 2021, Art. no. 100964.

B. Bonnechère, J.-C. Bier, O. V. Hove, S. Sheldon, S. Samadoulougou, F. Kirakoya-Samadoulougou, and M. Klass, “Age-associated capacity to progress when playing cognitive mobile games: Ecological retrospective observational study,” JMIR Serious Games, vol. 8, no. 2, Jun. 2020, Art. no. e17121.

Y. A. Selkhavat, “Collaboration or battle between minds? An attention training game through collaborative and competitive reinforcement,” Entertainment Comput., vol. 34, May 2020, Art. no. 100360.

T. G. Stavropoulos, I. Lazarou, D. Strantsalis, S. Nikolopoulos, I. Kompatisiaris, G. Kounamanos, F. Mouda, and M. Tsolaki, “Human factors and requirements of people with mild cognitive impairment, their caregivers and healthcare professionals for eHealth systems with wearable trackers,” in Proc. IEEE Int. Conf. Hum.-Mach. Syst. (ICHMS), Sep. 2020, pp. 1–6.

P. Xu, V. Subbaraju, C. H. Cheong, A. Wang, K. Kang, M. Bashir, Y. Dong, L. Li, and J.-H. Lim, “Personalized serious games for cognitive intervention with lifelog visual analytics,” in Proc. 26th ACM Int. Conf. Multimedia, Oct. 2018, pp. 328–336.

M. Aljumali, M. McLeod, and M. Friesen, “Serious games and ML for detecting MCI,” in Proc. IEEE Global Conf. Signal Inf. Process. (GlobalSIP), Nov. 2019, pp. 1–5.

M. Ciman, G. Gaggi, T. M. Sgarrella, L.Nota, M. Bortoluzzi, and I. Pinelli, “Serious games to support cognitive development in children with cerebral visual impairment,” Mobile Netw. Appl., vol. 23, no. 6, pp. 1703–1714, Dec. 2018.

L. Chen, L. Lin, J. Weizhou, S. Lin, and W. Lin, “The research of cognitive rehabilitation training system for ADHD children,” in Proc. 11th Int. Conf. E-Educ., E-Bus., E-Manag., E-Learn., Oct. 2020, pp. 422–425.

E. K. Zigman, A. R. Solorio, and G. E. Alexander, “Effects of simultaneous cognitive and aerobic exercise training on dual-task walking performance in healthy older adults: Results from a pilot randomized controlled trial,” BMC Geriatrics, vol. 20, no. 1, pp. 1–10, Dec. 2020.

P. García-Redondo, T. García, D. Areces, J. C. Núñez, and C. Rodríguez, “Serious games and their effect improving attention in students with learning disabilities,” Int. J. Environ. Res. Public Health, vol. 16, no. 14, p. 2480, Jul. 2019.

M. Simoes, R. Abreu, H. Goncalves, A. Rodrigues, I. Bernardino, and M. Castelo-Branco, “Serious games for aging: A pilot interventional study in a cohort of heterogeneous cognitive impairment,” in Proc. IEEE 7th Int. Conf. Serious Games Appl. Health (SeGAH), Aug. 2019, pp. 1–8.

M. Manca, F. Paternò, C. Santoro, E. Zedda, C. Braschi, R. Franco, and A. Sale, “The impact of serious games with humanoid robots on mild cognitive impairment older adults,” Int. J. Hum.-Comput. Stud., vol. 145, Jan. 2021, Art. no. 102501.
L. Colautti, D. Baldassini, V. Colombo, S. Mottura, M. Sacco, M. Sozzi, M. Corbo, M. L. Rusconi, and A. Antonietti, “CREC: The role of serious games in improving flexibility in thinking in neuropsychological rehabilitation,” Brit. J. Educ. Technol., vol. 49, no. 4, pp. 717–727, Jul. 2018.

B. C. Braun, “Innovative method for visual acuity and memory functions evaluation and recovery due to ‘serious games on tablet and smart phone gadgets,’ in Proc. E-Health Bioeng. Conf. (EBHC), Nov. 2019, pp. 1–4.
VOLUME 10, 2022

[198] P. H. Chau, Y. J. Kwok, M. K. M. Chan, K. Y. D. Kwan, K. L. Wong, Y. H. Tang, K. L. P. Chau, S. W. M. Lau, Y. Y. Y. Yiu, M. Y. F. Kwong, W. T. T. Lai, and M. K. Leung, “Feasibility, acceptability, and efficacy of virtual reality training for older adults with disabilities: Single-arm pre-post study,” J. Med. Internet Res., vol. 23, no. 5, May 2021, Art. no. e27640.

[199] J. Varela-Aldásg, G. Palacios-Nava-Joro, R. Amargiolo, and J. García-Magariño, “Head-mounted display-based application for cognitive training,” Sensors, vol. 20, no. 22, p. 6552, Nov. 2020.

[200] E. Reddinger, B. Glas, and Y. Rong, “Impact of screen size on cognitive training task performance: An HMD study,” Int. J. Psychophysiol., vol. 166, pp. 166–173, Aug. 2021.

[201] M. Intraaraprasit, W. Sunhem, and C. Jinjakam, “Interaction behavior of younger adults with immersive virtual reality application for cognitive training,” in Proc. 3rd Int. Conf. Comput. Commun. Syst. (ICCCS), Apr. 2018, pp. 506–510.

[202] L. Ma, A.-W. Krujit, A.-K. Ek, G. Åabyhammar, T. Furmark, G. Andersson, and P. Carlbring, “Seeking neutral: A VR-based person-identity-matching task for instructional bias modification—A randomised controlled experiment,” Internet Intervent., vol. 21, Sep. 2020, Art. no. 100334.

[203] F. Y. Liao, H.-Y. Tseng, Y.-J. Lin, C.-J. Wang, and W.-C. Hsu, “Using virtual reality-based training to improve cognitive function, instrumental activities of daily living and neural efficiency in older adults with mild cognitive impairment,” Eur. J. Phys. Rehabil. Med., vol. 56, no. 1, pp. 1–11, Feb. 2020.

[204] C. Huang, S. Li, B. Sun, H. Lyu, W. Xu, J. Jiao, F. Pan, J. Hu, J. Chen, Y. Chen, M. Huang, and Y. Xu, “Verification of using virtual reality to evaluate deficiencies in cognitive function among patients with schizophrenia in the remission stage: A cross-sectional study,” BMC Psychiatry, vol. 21, no. 1, pp. 1–8, Dec. 2021.

[205] A. Chirico, T. Giovannetti, P. Neroni, S. Simone, L. Gallo, F. Galli, F. Giancamilli, M. Predazzi, F. Lucidi, G. De Pietro, and A. Giordano, “Virtual reality for the assessment of everyday cognitive functions in older adults: An evaluation of the virtual reality action test and two interaction devices in a 91-year-old woman,” Frontiers Psychol., vol. 11, p. 123, Feb. 2020.

[206] C.-F. Tsai, C.-C. Chen, E. H.-K. Wu, C.-R. Chung, C.-Y. Huang, P.-Y. Tsai, and S.-C. Yeh, “A machine-learning-based assessment method for early-stage neurocognitive impairment by an immersive virtual supermarket,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 29, pp. 2124–2132, Dec. 2021.

[207] M. Mouzakidis, E. M. Karathanasi, N. Petridou, M. Tsolaki, C. Mouzakidis, E. M. Karathanasi, N. Petridou, M. Tsolaki, P. Zikas, G. Evangelou, P. Papagiannis, G. Bellis, C. Kokkotis, S. R. Panagiotopoulou, G. Giakas, and Y. Theodorakis, “A virtual reality app for physical and cognitive training of older people with mild cognitive impairment: Mixed methods feasibility study,” JMIR Serious Games, vol. 9, no. 4, 2021, Art. no. e24170.

[208] M. Rodrigo-Yanguas, M. Martín-Moratinos, A. Menendez-Garcia, C. González-Tardón, A. Royuela, and H. Blasco-Fontecilla, “A virtual reality game (the secret trail of moon) for treating attention-deficit/hyperactivity disorder: Development and usability study,” JMIR Serious Games, vol. 6, no. 3, Sep. 2021, Art. no. e26824.

[209] P. Koutseris, S. Collina, L. A. Doumas, and S. E. MacPherson, “Psychologically valid examination of event-based and time-based prospective memory using immersive virtual reality: The effects of delay and task type on everyday prospective memory,” Memory, vol. 29, no. 4, pp. 1–21, 2021.

[210] W. T. Wong, N. C. Tan, J. E. Lim, J. C. Allen, W. S. Lee, J. H. M. Quah, M. Paulpandi, T. A. Teh, S. H. Lim, and R. Malhotra, “Comparison of time taken to assess cognitive function using a fully immersive and automated virtual reality system vs. the Montreal cognitive assessment,” Frontiers Aging Neurosci., vol. 13, Nov. 2021, Art. no. 756891.
R. M. Williams, K. Alikhademi, and J. E. Gilbert, “Design of a toolkit for real-time executive function assessment in custom-made virtual experiences and interventions,” Int. J. Hum.–Comput. Stud., vol. 158, Feb. 2022, Art. no. 102734.

F. Borghin, F. Baglio, E. Pedrol, F. Rossetto, S. Isernia, L. Uccellatore, G. Riva, and P. Cipresso, “EXECutive-functions innovative tool: (EXIT 360°): A usability and user experience study of an original 360°-based assessment instrument,” Sensors, vol. 21, no. 17, p. 5867, Aug. 2021.

V. Delvigne, H. Wannous, T. Dutoit, L. Ris, and J.-P. Vandebarre, “Phy-DDA: Physiological dataset assessing attention,” IEEE Trans. Circuits Syst. Video Technol., vol. 32, no. 5, pp. 2612–2623, May 2022.

Y. Pratved, V. Deschodt-Arsac, F. Larrue, and L. M. Arsac, “Reliability of the Dynavision task in virtual reality to explore visuo-motor phenotypes,” Sci. Rep., vol. 11, no. 1, pp. 1–12, Dec. 2021.

A. Voinescu, K. Petrini, D. S. Fraser, R.-A. Lazarovicz, I. Papavă, Y. Pratviel, V. Deschodt-Arsac, F. Larrue, and L. M. Arsac, “Reliability of visuospatial cognitive functions in virtual reality environment,” in Proc. Int. Conf. Virtual Reality (ICVR), Jun. 2017, pp. 1–6.

S. Cavedoni, A. Chirico, E. Pedrol, P. Cipresso, and G. Riva, “Digital biomarkers for the early detection of mild cognitive impairment: Artificial intelligence meets virtual reality,” Frontiers Hum. Neurosci., vol. 14, p. 245, Jul. 2020.

K. Seo, A. Lee, J. Kim, H. Ryu, and H. Choi, “Measuring the kinematics of daily living movements with motion capture systems in virtual reality,” J. Visualized Exp., vol. 134, Apr. 2018, Art. no. e57284.

S. Korecko, B. Sobota, M. Hudak, R. F. Edorco, and M. Sivy, “Testing of visuospatial cognitive functions in virtual reality environment,” in Proc. 18th Int. Conf. Emerg. eLearn. Technol. Appl. (ICETA), Nov. 2020, Art. no. e30184.

A. V. Bayahya, W. AlHalabi, and S. H. Al-Amri, “Virtual reality in dementia diseases,” Proc. Comput. Sci., vol. 163, pp. 275–282, Jan. 2019.

F. Savazzi, S. Isernia, J. Jonsdottir, S. Di Tella, S. Pazzi, and F. Baglio, “Engaged in learning neurorehabilitation: Development and validation of a serious game with user-centered design,” Comput. Educ., vol. 125, pp. 53–61, Oct. 2018.

Z.-Y. Hoe, I.-J. Lee, C.-H. Chen, and K.-P. Chang, “Using an augmented reality-based training system to promote spatial visualization ability for the elderly,” Universal Access Inf. Syst., vol. 18, no. 2, pp. 327–342, Jun. 2019.

J. Zhang, X. Xia, R. Liu, and N. Li, “Enhancing human indoor cognitive map development and wayfinding performance with immersive augmented reality-based navigation systems,” Adv. Eng. Informat., vol. 50, Oct. 2021, Art. no. 101432.

D. Avila-Pesantez, L. A. Rivera, L. Vaca-Cardenas, S. Aguayo, and L. Zuniga, “Towards the improvement of ADHD children through augmented reality serious games: Preliminary results,” in Proc. IEEE Global Eng. Educ. Conf. (EDUCON), Apr. 2018, pp. 843–848.

**Open Access funding provided by ‘Università degli Studi di Genova’ within the CRUI CARE Agreement**