Review

Artificial Intelligence–Driven Serious Games in Health Care: Scoping Review

Alaa Abd-alrazaq¹, PhD; Israa Abuelezzz², MSc; Asma Hassan², MSc; AlHasan AlSammarraie², MSc; Dari Alhuwail³, PhD; Sara Irshaidat⁴, MD; Hashem Abu Serhan⁵, MD; Arfan Ahmed¹, PhD; Sadam Alabed Alrazak⁶, BSc; Mowafa Househ², PhD

¹AI Center for Precision Health, Weill Cornell Medicine-Qatar, Doha, Qatar
²Division of Information and Computing Technology, College of Science and Engineering, Hamad Bin Khalifa University, Qatar Foundation, Doha, Qatar
³Information Science Department, College of Life Sciences, Kuwait University, Kuwait, Kuwait
⁴Health Informatics Unit, Dasman Diabetes Institute, Kuwait, Kuwait
⁵Department of Pediatrics, King Hussein Cancer Center, Amman, Jordan
⁶Department of Mechanical & Industrial Engineering, Faculty of Applied Science and Engineering, University of Toronto, Toronto, ON, Canada

Corresponding Author:
Mowafa Househ, PhD
Division of Information and Computing Technology, College of Science and Engineering
Hamad Bin Khalifa University
Qatar Foundation
P.O. Box 34110, Doha Al Luqta St, Ar-Rayyan
Doha, 0000
Qatar
Phone: 974 55708549
Email: mhouseh@hbku.edu.qa

Abstract

Background: Artificial intelligence (AI)–driven serious games have been used in health care to offer a customizable and immersive experience. Summarizing the features of the current AI-driven serious games is very important to explore how they have been developed and used and their current state to plan on how to leverage them in the current and future health care needs.

Objective: This study aimed to explore the features of AI-driven serious games in health care as reported by previous research.

Methods: We conducted a scoping review to achieve the abovementioned objective. The most popular databases in the information technology and health fields (ie, MEDLINE, PsycInfo, Embase, CINAHL, IEEE Xplore, ACM Digital Library, and Google Scholar) were searched using keywords related to serious games and AI. Two reviewers independently performed the study selection process. Three reviewers independently extracted data from the included studies. A narrative approach was used for data synthesis.

Results: The search process returned 1470 records. Of these 1470 records, 46 (31.29%) met all eligibility criteria. A total of 64 different serious games were found in the included studies. Motor impairment was the most common health condition targeted by these serious games. Serious games were used for rehabilitation in most of the studies. The most common genres of serious games were role-playing games, puzzle games, and platform games. Unity was the most prominent game engine used to develop serious games. PCs were the most common platform used to play serious games. The most common algorithm used in the included studies was support vector machine. The most common purposes of AI were the detection of disease and the evaluation of user performance. The size of the data set ranged from 36 to 795,600. The most common validation techniques used in the included studies were k-fold cross-validation and training-test split validation. Accuracy was the most commonly used metric for evaluating the performance of AI models.

Conclusions: The last decade witnessed an increase in the development of AI-driven serious games for health care purposes, targeting various health conditions, and leveraging multiple AI algorithms; this rising trend is expected to continue for years to come. Although the evidence uncovered in this study shows promising applications of AI-driven serious games, larger and more rigorous, diverse, and robust studies may be needed to examine the efficacy and effectiveness of AI-driven serious games in different populations with different health conditions.
KEYWORDS

serious games; artificial intelligence; deep learning; machine learning; health care; digital health; eHealth; mobile phone

Introduction

Background

Since its establishment in the 21st century, video games have experienced a boom and become an ever-growing global industry [1]. In recent years, there has been a rapid increase in the accessibility and ubiquity of handheld computers and smart devices (ie, tablets, wearables, and smartphones) as well as major advances in the underlying technology and capability of commercial video game consoles [2], thereby providing a plethora of opportunities to leverage video games for many purposes. Video games used for purposes other than entertainment (eg, education, training, research, rehabilitation, and advertising) are called serious games [3].

In health care, serious games have been used for many purposes such as screening, diagnosing, education, prevention, and rehabilitation [4,5]. For example, serious games have shown promising results in improving health education [6]; acute pain management [7]; cognitive functions (eg, global cognition [8], memory [9], executive functions [10], and processing speed [11]); mental health disorders (eg, depression [12] and anxiety [13]); and functional, motor, and sensory functions [14]. Furthermore, serious games have the potential to diagnose and screen many diseases such as mild cognitive impairment [15], developmental dyslexia [16], and attention-deficit/hyperactivity disorder [17].

Serious games rely on the concept of gamification, which involves the “use of game design elements within non-game contexts” [18] through the structure, design, and methodology of games [19]. According to evidence, gamification typically relies on three elements: (1) game dynamics, including the behaviors, interactions, and experience of the player; (2) pedagogical or instructional design of the game; and (3) the mechanics (ie, procedures and rules) of the game [20]. Typically, gamification relies on the use of points, badges, leader boards, or timed performance [21,22].

Serious games exist in several formats depending on their therapeutic modality such as (1) exergames, which are video games that require physical activity to be played [23]; (2) computerized cognitive behavioral therapy games, which provide the player with structured approaches to address and recognize negative thinking and beliefs [24]; (3) cognitive training games that target improving or maintaining the player’s cognitive abilities, including executive functions, memory, and learning [25]; or (4) biofeedback games that use electrical sensors attached to the player to receive information about the player’s physiological state and in turn influence some of the player’s body functions (eg, heart rate) [26,27].

Experts suggest that artificial intelligence (AI) is positioned to broadly reshape health care and the practice of medicine [28]. Coined by John McCarthy in a lecture at Dartmouth College in 1956 [29], AI is a branch of computer science that involves the development of methods, techniques, and systems that intelligently handle and analyze complex data sets and information. In recent years, AI models have played an increasingly central role in medical research and clinical practice through several applications including personalized screening, diagnosis, prognosis, monitoring, risk modeling, drug discovery, and prediction of response to therapy [30,31].

AI-driven serious games, which are video games combined with AI used for purposes other than entertainment, for health can offer a customizable and immersive experience that adjusts its speed and difficulty, for example, based on the player’s performance [1]. Through the use of AI algorithms, serious games can monitor the performance of players in real time [32]. For example, using data mining, serious games that leverage AI can evaluate players’ behaviors, mood, and personality while playing a serious game [33]. In addition, AI-driven serious games that use data mining techniques can improve players’ knowledge, skills, and training progress through the analysis of the data collected playing the game [34,35].

Research Problem and Aim

Several studies have been conducted on AI-driven serious games in health care. Summarizing the features of the current AI-driven serious games is very important to explore how they have been developed and used and their current state to plan on how to leverage them in the current and future health care needs. Previous reviews did not focus on AI-driven serious games [36] and focused on a specific disease rather than health care in general [8-13]. Therefore, this review aimed to explore the features of AI-driven serious games in health care as reported by previous studies. Thus, this review focused on both AI and serious games together rather than serious games alone. Furthermore, our review is more comprehensive than other reviews, as it targeted serious games for any health condition rather than targeting a specific health condition.

Methods

Overview

To achieve the abovementioned objective, we conducted a scoping review in line with the guidelines of PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) [37]. Multimedia Appendix 1 shows the PRISMA-ScR checklist for this review. The methods used in this review are described in detail in the following subsections.

Search Strategy

Search Sources

The following databases were searched on January 12, 2022: MEDLINE (via Ovid), PsycINFO (via Ovid), Embase (via Ovid), CINAHL (via EBSCO), IEEE Xplore, ACM Digital Library, and Google Scholar. In the case of Google Scholar, only the
first 100 publications were considered because it retrieved a massive number of publications, and we found that the results quickly lost relevance and applicability beyond the first 100 hits. To identify further studies, we screened the reference lists of the included studies and relevant reviews (ie, backward reference list checking), and we checked the studies that cited the included studies (ie, forward reference list checking) [38].

Search Terms
The search query in this review was developed by consulting 3 experts in digital health and by checking the search queries used in previous reviews within this area. The developed search query is composed of AI-related terms (eg, AI, machine learning, and deep learning) and serious games–related terms (eg, serious games and exergames). The search query used to search each of the 8 databases is shown in Multimedia Appendix 2.

Study Eligibility Criteria
In this review, we included only studies that focused on AI-driven serious games used for any purpose in health care (eg, diagnosis, rehabilitation, prognosis, quantification, screening, and forecasting). We focused only on serious games that are played on any digital platform (eg, computers, consoles, mobile phones, and handheld devices), whereas nondigital games and those used in other fields (eg, education) were excluded. We also focused on serious games provided to health consumers (patients or healthy people) rather than health care providers or caregivers. We excluded studies that provided an overview or proposal for AI-driven serious games. This review included only empirical studies written in English. Although we included peer-reviewed articles, dissertations, conference proceedings, and preprints, we excluded reviews, conference abstracts, proposals, editorials, and commentaries. We did not apply any restrictions on the year of publication, country of publication, study design, population, and outcomes.

Study Selection
The study selection process in this review consisted of three steps: (1) removing duplicates from all retrieved studies using EndNote, (2) screening titles and abstracts of the remaining publications, and (3) reading the entire text of the studies included in the previous step. In the full-text screening, we read the paper from title to conclusion in addition to the supplementary materials. Two reviewers independently performed the study selection process. Disagreements between the reviewers in the second and third steps were resolved by consulting 2 other reviewers. Cohen κ was calculated to measure the reviewer’s agreement [39], and it was 0.81 for title and abstract screening and 0.86 for full-text reading.

Data Extraction
Multimedia Appendix 3 displays the data extraction form used in this review, which was pilot-tested using 5 included studies. Three reviewers independently used Microsoft Excel to extract data related to the characteristics of the included studies, serious games, and AI techniques. Any disagreement between the reviewers was resolved through discussion.

Data Synthesis
A narrative approach was used to synthesize data extracted from the included publications. Specifically, we began by describing the features of serious games used in the included studies in terms of their name, target condition, purpose, therapeutic modality, connectivity, interface, genre, types, and platform. Then, we described the features of the AI techniques used in the included studies in terms of their purposes, AI algorithms, type of data, size of the data set, type of validation, and performance. We used Microsoft Excel to manage data synthesis.

Results

Search Results
The total number of publications retrieved by searching the predefined databases was 1470 (Figure 1). We removed 181 duplicates from those publications. Checking the titles and abstracts of the remainders led to the exclusion of 1117 publications due to several reasons, as shown in Figure 1. After checking the full text of the remaining 172 publications, 129 were excluded for several reasons, as shown in Figure 1. We identified 3 additional studies using backward and forward reference list checking. Accordingly, the final number of included studies was 46 [40-85].
Characteristics of the Included Studies
The included studies were published between 2010 and 2021. The years wherein the largest number of included studies were published were 2018 (8/46, 2%) and 2019 (7/46, 15%). The included studies were conducted in 30 different countries. The countries that published the largest number of studies were the United States and Spain (5/46, 11%). The included studies were published in peer-reviewed journals (26/46, 57%) or in conference proceedings (20/46, 44%). Multimedia Appendix 4 [40-85] presents the characteristics of each included study.

Characteristics of the Serious Games
A total of 64 different serious games were found in the included studies (6 studies used >1 serious game). Of the 64 games, 16 (25%) were not given a specific name. Serious games were used for 20 health conditions. Motor impairment was the most common health condition targeted by the serious games in the included studies (18/46, 39%), followed by attention deficit hyperactivity disorder (4/46, 9%). Serious games were used for 5 purposes: rehabilitation (29/46, 63%), detection of diseases or disorders (10/46, 22%), health and wellness (5/46, 11%), education (2/46, 4%), and the prediction of players’ characteristics (1/46, 2%). The therapeutic modalities in the 29 rehabilitation games were exercise (19/29, 66%), cognitive training (6/29, 21%), and biofeedback (5/29, 17%). The interface of the serious games was 2D in 19 studies, 3D in 23, and 2D and 3D in 4 studies. Serious games in the included studies could be played by a single player (45/46, 98%) or multiplayer (1/46, 2%). Serious games were connected with other devices in 36 studies: nonwearable sensors (18/46, 39%), wearable sensors (15/46, 33%), wearable devices (7/46, 15%), webcam (7/46, 15%), robotic device (3/46, 7%), microphone (3/46, 7%), controllers (2/46, 4%), smartphone (1/46, 2%), monitor (1/46, 2%), speakers (1/46, 2%), and single-board computer (1/46, 2%). Multimedia Appendix 5 [40-85] shows characteristics of the serious games in the included studies.

Characteristics of the AI Techniques
The included studies used algorithms to solve classification problems (41/46, 89%), regression problems (5/46, 11%), and clustering problems (2/46, 4%). Algorithms embedded in serious games were reported in 40 studies, whereas the remaining studies did not report the algorithms used. These studies used 27 different algorithms for serious games. The most common algorithm used in the included studies was support vector machine (14/46, 30%), followed by convolutional neural network (7/46, 15%), artificial neural networks (7/46, 15%), and...
and random forest (7/46, 15%). AI algorithms in the included studies were used for 9 different purposes: detection of disease (13/46, 28%), evaluation of user performance (13/46, 28%), adaptation of difficulty level (7/46, 15%), recognition of gestures (7/46, 15%), recognition of biosignals (5/46, 11%), supporting users to play (3/46, 7%), classification of activity (2/46, 4%), recognition of voice (2/46, 4%), and prediction of user characteristics (1/46, 2%). Multimedia Appendix 6 [40-85] exhibits characteristics of AI techniques leveraged by serious games in the included studies. The AI models in the included studies were developed using the following types of data: kinematic data (22/46, 48%), gameplay data (21/46, 46%), biosignal data (11/46, 24%), demographic data (3/46, 7%), speech data (2/46, 4%), clinical data (1/46, 2%), and laboratory data (1/46, 2%). Data used for developing the models were collected from samples ranging from 3 to 150, as reported in 36 studies. The mean sample size was approximately 36 (SD 39.3). The data set size was reported in 24 studies and ranged from 36 to 795,600, with an average of approximately 52,124 (SD 161,862). The AI models in the included studies were validated using 4 techniques: k-fold cross-validation (13/46, 28%), training-test split validation (13/46, 28%), leave-one-out cross-validation (7/46, 15%), and moving-window cross-validation (1/46, 2%). The performance of the AI models was evaluated in 32 studies using 11 different metrics: accuracy (26/46, 57%), sensitivity (13/46, 28%), \( F_1 \)-score (9/46, 20%), precision (7/46, 15%), specificity (6/46, 13%), negative predictive value (3/46, 7%), area under the curve (3/46, 7%), root mean square error (1/46, 2%), normalized root mean square error (1/46, 2%), kappa (1/46, 2%), and Mathew correlation coefficient (1/46, 2%).

**Discussion**

**Principal Findings**

This study summarized the evidence about the features of AI-driven serious games in health care as reported by previous research. The 64 AI-driven serious games uncovered by this study targeted 20 different health conditions, were built for various purposes, and leveraged several therapeutic modalities through the use of multiple AI algorithms. The evidence uncovered in this review points to a rising trend in the use of AI-driven serious games in health care in recent years. The findings reported in this review were consistent with other recent evidence. Although a review by Frutos-Pascual and Zapirain [1] did not solely focus on AI-based serious games for health care purposes, its findings related to AI-based serious games were consistent with our findings with respect to their potential application for health care purposes, AI algorithms used, and the platforms used; there is also agreement about the need for improved testing methodologies to ensure efficacy.

Although the studies included in this review were conducted across the globe, many were conducted in 1 country. Therefore, the evidence remains scarce with respect to the compatibility of AI-driven serious games with the sociocultural practices of consumers playing them. Literature indicates that understanding a community’s sociocultural practices can significantly contribute toward designing and building reliable serious games; hence, more studies in the reported countries, as well as others, are needed [86].

Most of the AI-driven serious games reported in the studies examined in this review were heavily focused on the interventional therapeutics and the detection of diseases or disorders compared with prevention (ie, health and wellness or education). Given the alarmingly rising rates of noncommunicable diseases globally (eg, diabetes and cardiovascular diseases) [87], it is imperative to invest more efforts in developing more AI-driven serious games that focus on prevention and not only treatment and therapy because of the potential of serious games in providing systematic and sustainable means of preventing or delaying the onset of such noncommunicable diseases [5,87,88].

A recent study that developed a smartphone-based serious game that teaches self-management to children aged 8 to 14 years with type 1 diabetes reported that although the developed prototype of the serious game was perceived as useful and engaging by participants, it was not adaptable to players’ knowledge level and provided “information [that] was too basic for participants” [89]. This presents a great opportunity for developing AI-driven serious games that adapt to players’ abilities and knowledge level [1,90,91], making them more engaging and meaningful.

The studies examined in this review that reported the game engine used to develop their AI-driven serious game predominantly used the proprietary game engine Unity (19/38, 50%). There is room for further development of AI-driven serious games on open-source platforms [92], which can make their development collaborative, modular, and modifiable [93]. In addition, half of the studies examined in this review required players to play the AI-driven serious game on a PC. This goes against the fast-paced adoption and ubiquity of smart devices, such as smartphones and tablets.

Although only 4 studies reported the use of virtual reality headsets, we speculate that this number will rise in the years to come with the hype of metaverses and availability as well as affordability of these headsets. This progression comes naturally with the increasing adoption of connected devices, including wearable and nonwearable sensors, as part of the AI-driven serious game. With this in mind, we project that AI-driven serious games will be more adaptable in an unobtrusive and affordable manner [94].

This review found that 3D serious games were slightly more common than 2D serious games, which is in line with the findings of a previous review [36]. This can be attributed to the fact that 3D games are more immersive and attractive to players. Although 4 studies used both 2D and 3D serious games, none of the serious games in these 4 studies had multimodal interfaces. More precisely, each study included >1 serious game, and the interface of each game was either 2D or 3D rather than multimodal (2D and 3D). It is worth noting that none of these studies compared the effectiveness of a 2D serious game with a 3D serious game.
Practical and Research Implications

Practical Implications

Summarizing the features of the current AI-driven serious games helped us explore how they have been developed and used and their current state, and this will help us plan on how to leverage them in the current and future health care needs. Only 10 studies in this review used smart mobile devices (ie, tablets and smartphones). The ubiquity of smart mobile devices, coupled with their increasing capabilities, affordability, and accessibility, makes them more appealing for future applications of AI-driven serious games, and smart mobile devices are certainly more pervasive compared with personal computers and gaming consoles [8]. Estimates of global mobile devices and mobile users are reported to be 15 billion and 7.1 billion, respectively [95].

There is a need to consider the sociocultural context and player demographics when designing and developing AI-driven serious games. In addition, involving multiple stakeholders, including the targeted audience (ie, consumers or patients), is fundamental to the success of an AI-driven serious game [96,97].

Research Implications

Of the 64 studies examined in this review, 14 (22%) did not report the performance of the AI models used in the serious games. The evidence uncovered in this study demonstrates a promising potential for leveraging AI-driven serious games for health care purposes, which in turn can inform future research efforts by demonstrating the status quo of research in this domain. With the increasing adoption of AI in medical software and the development of serious games, and considering that AI models may not be fully explainable at times, it becomes imperative to rigorously test and report the performance of the models, especially in high-stakes use cases such as missing a diagnosis of disease [98].

The studies included in this review had sample sizes ranging from 3 to 150, with many of them in the lower range. More evidence and research are needed on larger sample sizes to determine the generalizability of the findings and the impact of AI-driven serious games. It is also essential to examine the efficacy and effectiveness of AI-driven serious games in different populations with different health conditions. Although many of the studies examined in this review reported the data set size used, numerous studies did not; therefore, we urge researchers to not only report the data set size but also increase it to ensure adequate performance of AI-driven serious games for health care purposes [99]. In addition, more research, including randomized control trials and systematic reviews, may be needed to examine the efficacy and effectiveness of AI-driven serious games in different populations with different health conditions.

Strengths and Limitations

Strengths

To the best of our knowledge, this is the first review of AI-driven serious games in health care. Only 1 previous review focused on serious games in health care; however, it did not focus on AI-driven serious games. Furthermore, this review can be considered the most comprehensive review in this area, given that it focused on all AI-driven serious games in health care regardless of their target health condition, therapeutic modality, game interface, number of players, connectivity, genre, type, game engine, platform, AI techniques, data types, sample size, data set size, and validation methods.

Bias resulting from the study selection was minimal in the review because the 2 reviewers independently performed the study selection process, and any disagreements between them were resolved by consulting 2 other reviewers. Furthermore, bias resulting from data extraction is not a concern in this review, as 3 reviewers independently extracted data from the included studies, and any disagreement between them was resolved through discussion. Bias resulting from missing papers is minimal, given that we sought to retrieve as many relevant studies as possible by searching the most popular databases in the information technology and health fields using a well-developed search query and by conducting backward and forward reference list checking.

Limitations

This review may have missed some relevant studies, given that we excluded proposals of AI-driven serious games (ie, a conceptual framework of a serious game), studies written in a language other than English, and studies focused on AI-driven serious games for health care providers and caregivers. Furthermore, it is likely that we missed some relevant papers, given that we did not search on Scopus and Web of Science. Therefore, it is likely that we missed other applications and features of AI-driven serious games. It was difficult to synthesize data related to the performance of AI-driven serious games for the following reasons: (1) the included studies had considerable heterogeneity in terms of game features (eg, target health condition, therapeutic modality, game interface, genre, and type), AI techniques (eg, their purpose, data type, and validation methods), and performance metrics and (2) conclusions drawn from such synthesis of games’ performance may be misleading because the risk of bias in the included studies was not assessed in this review. Therefore, this review could not comment on the performance of AI-driven serious games.

Conclusions

The last decade witnessed an increase in the development of AI-driven serious games for health care purposes, and this rising trend is expected to continue for years to come. In this review, the 64 AI-driven serious games had varying data set sizes, ranging from only 36 to 795,000; these games reported targeting various health conditions, with motor impairment being the most common, and were mainly used for several therapeutic modalities, with rehabilitation being the most reported. In addition, these AI-driven serious games reported leveraging multiple AI algorithms, with support vector machines being the most used. Although the evidence uncovered in this study shows promising applications of AI-driven serious games, and considering the rate and rapid advances in AI and its pervasive use in serious games in the last decade, larger, more rigorous, diverse, and robust studies may be needed to examine the efficacy and effectiveness of AI-driven serious games in
different populations with different health conditions. AI-driven serious games are expected to be a popular source to inspire the development and design of nearly realistic health-related and preventive interventions. Further evidence is necessary to determine their efficacy and performance.

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Conflicts of Interest
None declared.

Multimedia Appendix 1
PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) checklist. [DOCX File, 107 KB-Multimedia Appendix 1]

Multimedia Appendix 2
Search strategy. [DOCX File, 31 KB-Multimedia Appendix 2]

Multimedia Appendix 3
Data extraction form. [DOCX File, 21 KB-Multimedia Appendix 3]

Multimedia Appendix 4
Characteristics of each included study. [DOCX File, 26 KB-Multimedia Appendix 4]

Multimedia Appendix 5
Characteristics of the serious games in the included studies. [DOCX File, 40 KB-Multimedia Appendix 5]

Multimedia Appendix 6
Characteristics of artificial intelligence techniques leveraged by serious games in the included studies. [DOCX File, 31 KB-Multimedia Appendix 6]

References
1. Frutos-Pascual M, Zapirain BG. Review of the use of AI techniques in serious games: decision making and machine learning. IEEE Trans Comput Intell AI Games 2017 Jun;9(2):133-152. [doi: 10.1109/tciaig.2015.2512592]
2. Bonnechère B, Langley C, Sahakian BJ. The use of commercial computerised cognitive games in older adults: a meta-analysis. Sci Rep 2020 Sep 17;10(1):15276 [FREE Full text] [doi: 10.1038/s41598-020-72281-3] [Medline: 32943742]
3. Chicchi Giglioli IA, de Juan Ripoll C, Parra E, Alcañiz Raya M. EXPANSE: a novel narrative serious game for the behavioral assessment of cognitive abilities. PLoS One 2018 Nov 9;13(11):e0206925 [FREE Full text] [doi: 10.1371/journal.pone.0206925] [Medline: 30412614]
4. Manera V, Ben-Sadoun G, Aalbers T, Agopyan H, Askenazy F, Benoit M, et al. Recommendations for the use of serious games in neurodegenerative disorders: 2016 Delphi panel. Front Psychol 2017 Jul 25;8:1243 [FREE Full text] [doi: 10.3389/fpsyg.2017.01243] [Medline: 28790945]
5. Wiemeyer J, Kliem A. Serious games in prevention and rehabilitation—a new panacea for elderly people? Eur Rev Aging Phys Act 2011 Dec 08;9(1):41-50. [doi: 10.1007/s11556-011-0093-x]
6. Sharifzadeh N, Kharrazi H, Nazari E, Tabesh H, Edalati Khodabandeh M, Heidari S, et al. Health education serious games targeting health care providers, patients, and public health users: scoping review. JMIR Serious Games 2020 Mar 05;8(1):e13459 [FREE Full text] [doi: 10.2196/13459] [Medline: 32134391]
7. Smith V, Warty RR, Sursas JA, Payne O, Nair A, Krishnan S, et al. The effectiveness of virtual reality in managing acute pain and anxiety for medical inpatients: systematic review. J Med Internet Res 2020 Nov 02;22(11):e17980 [FREE Full text] [doi: 10.2196/17980] [Medline: 33136055]
8. Abd-Alrazaq A, Alajlani M, Alhuwail D, Toro CT, Giannicchi A, Ahmed A, et al. The effectiveness and safety of serious games for improving cognitive abilities among elderly people with cognitive impairment: systematic review and meta-analysis. JMIR Serious Games 2022 Mar 10;10(1):e34592. [FREE Full text] [doi: 10.2196/34592] [Medline: 35266877]

9. Abd-Alrazaq A, Alhuwail D, Al-Jafar E, Ahmed A, Shuweihdi F, Reagu SM, et al. The effectiveness of serious games in improving memory among older adults with cognitive impairment: systematic review and meta-analysis. JMIR Serious Games 2022 Aug 09;10(3):e35202. [FREE Full text] [doi: 10.2196/35202] [Medline: 35943792]

10. Abd-Alrazaq A, Alhuwail D, Ahmed A, Househ M. Effectiveness of serious games for improving executive functions among older adults with cognitive impairment: systematic review and meta-analysis. JMIR Serious Games 2022 Jul 25;10(3):e36123. [FREE Full text] [doi: 10.2196/36123] [Medline: 35877166]

11. Abd-Alrazaq A, Ahmed A, Alali H, Aldardour AM, Househ M. The effectiveness of serious games on cognitive processing speed among older adults: systematic review and meta-analysis. JMIR Serious Games 2022 Sep 09;10(3):e36754. [FREE Full text] [doi: 10.2196/36754] [Medline: 36083623]

12. Abd-Alrazaq A, Al-Jafar E, Alajlani M, Toro C, Alhuwail D, Ahmed A, et al. The effectiveness of serious games for alleviating depression: systematic review and meta-analysis. JMIR Serious Games 2022 Jan 14;10(1):e32331. [FREE Full text] [doi: 10.2196/32331] [Medline: 35209530]

13. Abd-Alrazaq A, Alajlani M, Alhuwail D, Schneider J, Akhu-Zaheya L, Ahmed A, et al. The effectiveness of serious games in alleviating anxiety: systematic review and meta-analysis. JMIR Serious Games 2022 Feb 14;10(1):e29137. [FREE Full text] [doi: 10.2196/29137] [Medline: 35156932]

14. Vieira C, Ferreira da Silva Pais-Vieira C, Novais J, Perrotta A. Serious game design and clinical improvement in physical rehabilitation: systematic review. JMIR Serious Games 2021 Sep 23;9(3):e20066. [FREE Full text] [doi: 10.2196/20066] [Medline: 34554102]

15. Pazzi S, Falleri V, Puricelli S, Tost PD, von Barnekow A, Grau S, et al. A Serious Games platform for early diagnosis of mild cognitive impairments. In: Proceedings of the 4th Conference on Gaming and Playful Interaction in Healthcare. 2014 Presented at: GFHEU '14; October 27-28, 2014; Utrecht, The Netherlands p. 110-113. [doi: 10.1007/978-3-658-07141-7_15]

16. Gaggi O, Palazzi CE, Ciman M, Galiazzo G, Franceschini S, Ruffino M, et al. Serious games for early identification of developmental dyslexia. Comput Entertain 2017 Apr 04;15(2):1-24. [doi: 10.1145/2629558]

17. Serrano-Barroso R, Siugzdaitie R, Guerrero-Cubero J, Molina-Cantero AJ, Gomez-Gonzalez IM, Lopez JC, et al. Detecting attention levels in ADHD children with a video game and the measurement of brain activity with a single-channel BCI headset. Sensors (Basel) 2021 May 06;21(9):3221. [FREE Full text] [doi: 10.3390/s21093221] [Medline: 34066492]

18. Deterding S, Dixon D, Khaled R, Nacke L. From game design elements to gamefulness: defining “gamification”. In: Deterding S, Dixon D, Khaled R, Nacke L. From Game Design Elements to Gamefulness: Defining “Gamification”. 2011 Presented at: The 15th International Academic MindTrek Conference: Envisioning Future Media Environments. 2011 Presented at: MindTrek '11; September 28-30, 2011; Tampere, Finland p. 9-15. [doi: 10.1145/2181037.2181040]

19. Fitzgerald M, Ratcliffe G. Serious games, gamification, and serious mental illness: a scoping review. Psychiatr Serv 2020 Feb 01;71(2):170-183. [doi: 10.1176/appi.ps.201800567] [Medline: 3160521]

20. Wood LC, Reiners T. Gamification. In: Khosrow-Pour M, editor. Encyclopedia of Information Science and Technology. 3rd edition. Hershey, PA, USA: IGI Global; 2015:3039-3047.

21. Buckley J, DeWille T, Exton C, Exton G, Murray L. A gamification–motivation design framework for educational software developers. J Educ Technol Syst 2018 Jun 20;47(1):101-127. [doi: 10.1177/0047239518783153]

22. van Gaalen AE, Brouwer J, Schönrock-Adema J, Bouwkamp-Timmer T, Jaarsma AD, Georgiadis JR. Gamification of health professions education: a systematic review. Adv Health Sci Educ Theory Pract 2021 May;26(2):683-711. [FREE Full text] [doi: 10.1007/s10459-020-10000-3] [Medline: 33128662]

23. Xu W, Liang HN, He Q, Li X, Yu K, Chen Y. Results and guidelines from a repeated-measures design experiment comparing standing and seated full-body gesture-based immersive virtual reality exergames: within-subjects evaluation. JMIR Serious Games 2020 Jul 27;8(3):e17972. [FREE Full text] [doi: 10.2196/17972] [Medline: 32716004]

24. Stawarz K, Preist C, Tallon D, Wiles N, Coyle D. User experience of cognitive behavioral therapy apps for depression: an analysis of app functionality and user reviews. J Med Internet Res 2018 Jun 06;20(6):e10120. [FREE Full text] [doi: 10.2196/10120] [Medline: 29875087]

25. Leung NT, Tam HM, Chu LW, Kwok TC, Chan F, Lam LC, et al. Neural plastic effects of cognitive training on aging brain. Neural Plast 2015;2015:535618. [FREE Full text] [doi: 10.1155/2015/535618] [Medline: 26417460]

26. Jafarova O, Mazhirina K, Shtark M. Self-regulation strategies and heart rate biofeedback training. Appl Psychophysiol Biofeedback 2020 Jun;45(2):87-98. [doi: 10.1007/s10484-020-09460-5] [Medline: 32277303]

27. Zafar MA, Ahmed B, Rihawi RA, Gutierrez-Osuna R. Gaming away stress: using biofeedback games to learn paced breathing. IEEE Trans Affective Comput 2020 Jul 1;11(3):519-531. [doi: 10.1109/taf.2018.2816945]

28. Rajipurkar P, Chen E, Banerjee O, Topol EJ. AI in health and medicine. Nat Med 2022 Jan;28(1):31-38. [doi: 10.1038/s41591-021-01614-0] [Medline: 35085819]

29. Bini SA. Artificial intelligence, machine learning, deep learning, and cognitive computing: what do these terms mean and how will they impact health care? J Arthroplasty 2018 Aug;33(8):2358-2361. [doi: 10.1016/j.arth.2018.02.067] [Medline: 29656964]
30. Rajkomar A, Dean J, Kohane I. Machine learning in medicine. N Engl J Med 2019 Apr 04;380(14):1347-1358. [doi: 10.1056/NEJMra1814259] [Medline: 30943338]

31. Abd-Alrazaz A, Alajlan M, Alhwail D, Schneider J, Al-Kuawi S, Shah Z, et al. Artificial intelligence in the fight against COVID-19: scoping review. J Med Internet Res 2020 Dec 15;22(12):e20756 [FREE Full text] [doi: 10.2196/20756] [Medline: 33284779]

32. Kamal O, Mehdi T, Kamar O, Mohamed B. Artificial intelligence a major asset for serious games. EasyChair 2021 Apr 6:5283.

33. Keshhtkar F, Burkett C, Li H, Graesser AC. Using data mining techniques to detect the personality of players in an educational game. In: Peña-Ayala A, editor. Educational Data Mining: Applications and Trends. Cham, Switzerland: Springer; 2014:125-150.

34. Alonso-Fernández C, Cano AR, Calvo-Morata A, Freire M, Martinez-Ortiz I, Fernández-Manjón B. Lessons learned applying learning analytics to assess serious games. Comput Human Behav 2019 Oct;99:301-309 [FREE Full text] [doi: 10.1016/j.chb.2019.05.036]

35. Skinner G, Walmsley T. Artificial intelligence and deep learning in video games a brief review. In: Proceedings of the IEEE 4th International Conference on Computer and Communication Systems. 2019 Presented at: ICCCS '19; February 23-25, 2019; Singapore, Singapore p. 404-408. [doi: 10.1109/comms.2019.8821783]

36. Wattanasoontorn V, Boada I, García R, Sbert M. Serious games for health. Entertain Comput 2013 Dec;4(4):231-247 [FREE Full text] [doi: 10.1007/s10671-013-0138-0]

37. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Ann Intern Med 2018 Oct 02;169(7):467-473 [FREE Full text] [doi: 10.7326/M18-0850] [Medline: 31078033]

38. Wohlin C. Guidelines for snowballing in systematic literature studies and a replication in software engineering. In: Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering. 2014 May Presented at: EASE '14; May 13-14, 2014; London, UK p. 1-10. [doi: 10.1145/2601248.2601268]

39. Higgins JP, Deeks JJ. Chapter 7: Selecting studies and collecting data. In: Higgins JP, Green S, editors. Cochrane Handbook for Systematic Reviews of Interventions: Cochrane Book Series. Hoboken, NJ, USA: John Wiley & Sons; 2008.

40. Alchalabi AE, Elsharnouby M, Shirmohammadi S, Nour Eddin A. Feasibility of detecting ADHD patients’ attention levels by classifying their EEG signals. In: Proceedings of the 2017 IEEE International Symposium on Medical Measurements and Applications. 2017 Presented at: MeMeA '17; May 7-10, 2017; Rochester, MN, USA p. 314-319. [doi: 10.1109/memea.2017.7985895]

41. Alchalabi AE, Shirmohammadi S, Eddin AN, Elsharnouby M. FOCUS: detecting ADHD patients by an EEG-based serious game. IEEE Trans Instrum Meas 2018 Jul;67(7):1512-1520. [doi: 10.1109/tim.2018.2838158]

42. Aljumaili M, McLeod R, Friesen M. Serious games and ML for detecting MCI. In: Proceedings of the 2019 IEEE Global Conference on Signal and Information Processing. 2019 Presented at: GlobalSIP '19; November 25-28, 2019; Cairo, Egypt p. 397-402. [doi: 10.1109/3377325.3377495]

43. Aljalili M. Serious games and applications for health and exergaming using wearable sensors. IEEE J Biomed Health Inform 2014 Sep;18(5):1636-1646. [doi: 10.1109/jbhi.2013.2287504] [Medline: 2435280]

44. Azam P, Shabana A, Delafield-Butt JT. Toward the Autism Motor Signature: gameplay identify children with autism. Sci Rep 2016 Aug 24;6:31107 [FREE Full text] [doi: 10.1038/srep31107] [Medline: 27553971]

45. Ascar I, Silva L, Pereira R. Personalized gestural interaction applied in a gestural interactive game-based approach for people with disabilities. In: Proceedings of the 25th International Conference on Intelligent User Interfaces. 2020 Mar Presented at: IUI '20; March 17-20, 2020; Cagliari, Italy p. 100-110. [doi: 10.1145/3377325.3377495]

46. Avola D, Cinque L, Foresti GL, Marini MR. An interactive and low-cost full body rehabilitation framework based on 3D immersive games. J Biomed Inform 2019 Jan;89:81-100 [FREE Full text] [doi: 10.1016/j.jbi.2018.11.012] [Medline: 30521854]

47. Baur K, Wolf P, Riener R, Duarte JE. Making neurorehabilitation fun: multiplayer training via damping forces balancing differences in skill levels. IEEE Int Conf Rehabil Robot 2017 Jul;2017:876-881. [doi: 10.1109/icorr.2017.8009359] [Medline: 28813931]

48. Beurd A, Kim N, Polistico K, Kadara A, Grampurohit N, Roll D, et al. Assistive game controller for artificial intelligence-enhanced telehabilitation post-stroke. Assist Technol 2021 May 04;33(3):117-128 [FREE Full text] [doi: 10.1080/10400435.2019.1593260] [Medline: 31180276]

49. Chen HY, Lin TY, Huang LY, Chen AC, Zheng YC, Wang HM, et al. HP2: using machine learning model to play serious game with IMU smart suit. In: Proceedings of the 17th International Conference on Mobile and Ubiquitous Multimedia. 2018 Nov Presented at: MUM '18; November 25-28, 2018; Cairo, Egypt p. 397-402. [doi: 10.1145/3282894.3289731]

50. Chiu YH, Chen TW, Chen YJ, Su CI, Hwang KS, Ho WH. Fuzzy logic-based mobile computing system for hand rehabilitation after neurological injury. Technol Health Care 2018;26(1):17-27. [doi: 10.3233/THC-171403] [Medline: 29060950]
51. Sadeghi Esfahiani S, Butt J, Shirvani H. Fusion of artificial intelligence in neuro-rehabilitation video games. IEEE Access 2019 Jul 1;7:102617-102627. [doi: 10.1109/ACCESS.2019.2926118]

52. Farahani F, Nambiappan H, Jaiswal A, Kyrarini M, Makedon F. HAND-REHA: dynamic hand gesture recognition for game-based wrist rehabilitation. In: Proceedings of the 13th ACM International Conference on PERvasive Technologies Related to Assistive Environments. 2020 Jun Present at: PETRA '20; June 30-July 3, 2020; Corfu, Greece p. 1-9. [doi: 10.1145/3389189.3392608]

53. Frutos-Pascual M, Garcia-Zapirain B. Assessing visual attention using eye tracking sensors in intelligent cognitive therapies based on serious games. Sensors (Basel) 2015 May 12;15(5):11092-11117 [FREE Full text] [doi: 10.3390/s150511092] [Medline: 25985158]

54. Villacific Silva CJ, Fuertes Diaz WM, Toulkeridis T. Intelligent agents, voice and facial recognition applied in videogames in order to stimulate cognitive development of children - a case study of Tictactoe in 3D. In: Proceedings of the 2017 SAI Computing Conference. 2017 Presented at: SAI’17; July 18-20, 2017; London, UK. [doi: 10.1109/sait.2017.8252235]

55. Garcia-Agundez A, Reuter C, Becker H, Konrad R, Caserman P, Miede A, et al. Development of a classifier to determine factors causing cybersickness in virtual reality environments. Games Health J 2019 Dec;8(6):439-444. [doi: 10.1089/g4h.2019.0005] [Medline: 31295007]

56. Gielig K, Vanden Abeele ME, Verbert K, Tournoy J, De Voc M, Vanden Abeele V. Detecting mild cognitive impairment via digital biomarkers of cognitive performance found in klondike solitaire: a machine-learning study. Digit Biomark 2021 Feb 19;5(1):44-52 [FREE Full text] [doi: 10.1159/000514105] [Medline: 33791448]

57. Heller MD, Roots K, Srivastava S, Schumann J, Srivastava J, Hale TS. A machine learning-based analysis of game data for attention deficit hyperactivity disorder assessment. Games Health J 2013 Oct;2(5):291-298. [doi: 10.1089/g4h.2013.0058] [Medline: 26169629]

58. Huang X, Naghdy F, Naghdy G, Du H. Clinical effectiveness of combined virtual reality and robot assisted fine hand motion rehabilitation in subacute stroke patients. IEEE Int Conf Rehabil Robot 2017 Jul;2017:511-515. [doi: 10.1109/ICORR.2017.8009299] [Medline: 28813871]

59. Jung HT, Lee H, Kim K, Kim B, Park S, Ryu T, et al. Estimating mini mental state examination scores using game-specific performance values: a preliminary study. Annu Int Conf IEEE Eng Med Biol Soc 2018 Jul;2018:1518-1521. [doi: 10.1109/EMBC.2018.8512516] [Medline: 30460681]

60. Kariyawasam R, Nadeeshani M, Hamid T, Subasinghe I, Ratnayake M. Application of SVM for evaluation of training performance in exergames for neurorehabilitation. Annu Int Conf IEEE Eng Med Biol Soc 2014;2014:1230-1233. [doi: 10.1109/EMBC.2014.6943819] [Medline: 25570187]

61. Lee M, Morando M, Trombini M, Dellepiane S. Application of SVM for evaluation of training performance in exergames for motion rehabilitation. In: Proceedings of the 2019 International Conference on Intelligent Medicine and Image Processing. 2019 Presented at: ICAC ’19; December 5-7, 2019; Malabe, Sri Lanka p. 156-161. [doi: 10.1109/icac49085.2019.9103336]

62. Liu S, Shen Z, McKeown MJ, Leung C, Miao C. A fuzzy logic based Parkinson's disease risk predictor. In: Proceedings of the 2014 IEEE International Conference on Fuzzy Systems. 2014 Presented at: FUZZ-IEEE ‘14; July 6-11, 2014; Beijing, China p. 1624-1631. [doi: 10.1109/fuzz-ieee.2014.6891613]

63. Macintosh A, Vignais N, Desaillly E, Biddiss E, Vigneron V. A classification and calibration procedure for gesture specific home-based therapy exercise in young people with cerebral palsy. IEEE Trans Neural Syst Rehabil Eng 2021;29:144-155. [doi: 10.1109/TNSRE.2020.3038370] [Medline: 33206605]

64. Mansart C, Sukitphitayanon S, Pantongkhum P, Thacharoen S. Go run go: an android game-story application for aiding motivation to exercise. In: Proceedings of the 2015 IEEE International Symposium on Multimedia. 2015 Presented at: ISM'15; December 14-16, 2015; Miami, FL, USA p. 407-410. [doi: 10.1109/ism.2015.49]

65. Marín-Morales J, Carrasco-Ribelles LA, Alcañiz M, Giglioli IA. Applying machine learning to a virtual serious game for neuropsychological assessment. In: Proceedings of the 2021 IEEE Global Engineering Education Conference. 2021 Presented at: EDUCON ’21; April 21-23, 2021; Vienna, Austria p. 946-949. [doi: 10.1109/educon46332.2021.9454138]

66. Mavandadi S, Dimitrov S, Feng S, Yu F, Sikora U, Yaglidere O, et al. Distributed medical image analysis and diagnosis through crowd-sourced games: a malaria case study. PLoS One 2012;7(5):e37245 [FREE Full text] [doi: 10.1371/journal.pone.0037245] [Medline: 22606353]

67. Morando M, Trombini M, Dellepiane S. Application of SVM for evaluation of training performance in exergames for motion rehabilitation. In: Proceedings of the 2nd International Conference on Intelligent Medicine and Image Processing. 2019 Presented at: IMIP ’19; April 19-22, 2019; Bali, Indonesia p. 1-5. [doi: 10.1109/3332340.3332342]

68. Munoz JE, Rios LH, Henao OA. Low cost implementation of a Motor Imagery experiment with BCI system and its use in neurorehabilitation. Annu Int Conf IEEE Eng Med Biol Soc 2014;2014:1230-1233. [doi: 10.1109/EMBC.2014.6943819] [Medline: 25570187]

69. Najeek RS, Uthayan J, Lojini RP, Vishaliney G, Alosius J, Gamage A. Gamified smart mirror to leverage autistic education - Aliza. In: Proceedings of the 2nd International Conference on Advancements in Computing. 2020 Presented at: ICAC '20; December 10-11, 2020; Malabe, Sri Lanka p. 428-433. [doi: 10.1109/icac51239.2020.9357065]

70. Nasri N, Orts-Escolano S, Cazorla M. An sEMG-controlled 3D game for rehabilitation therapies: real-time time hand gesture recognition using deep learning techniques. Sensors (Basel) 2020 Nov 12;20(22):6451 [FREE Full text] [doi: 10.3390/s20226451] [Medline: 33198083]

71. Oliver M, Teruel MA, Molina JP, Romero-Ayuso D, González P. Ambient intelligence environment for home cognitive telerehabilitation. Sensors (Basel) 2018 Oct 29;18(11):3671 [FREE Full text] [doi: 10.3390/s18113671] [Medline: 30380634]
71. Ortiz-Catalan M, Guðmundsdóttir RA, Kristoffersen MB, Zepeda-Echavarria A, Caine-Winterberger K, Kulbacka-Ortiz K, et al. Phantom motor execution facilitated by machine learning and augmented reality as treatment for phantom limb pain: a single group, clinical trial in patients with chronic intractable phantom limb pain. Lancet 2016 Dec 10:388(10062):2885-2894. [doi: 10.1016/S0140-6736(16)31598-7] [Medline: 27916234]

72. Perez-Muñoz A, Robles-Bykbaev Y, Robles-Bykbaev V, Pérez-Muñoz D, Ingavélez-Guerra P, León-Cadme M. An interactive task based on serious games and fuzzy logic to support the motor development and rehabilitation of children with disabilities. In: Proceedings of the 2018 Congreso Argentino de Ciencias de la Informática y Desarrollos de Investigación. 2018 Presented at: CACID 18; November 28-28, 2018; Buenos Aires, Argentina p. 1-6. [doi: 10.1109/cacidi.2018.8584349]

73. Postolache O, Cary F, Girão PS, Duarte N. Physiotherapy assessment based on Kinect and mobile APPs. In: Proceedings of the 6th International Conference on Information, Intelligence, Systems and Applications. 2015 Presented at: IISA '15; July 6-8, 2015; Corfu, Greece p. 1-6. [doi: 10.1109/issa.2015.7388013]

74. Puzenat D, Verlut I. Behavior analysis through games using artificial neural networks. In: Proceedings of the 3rd International Conference on Advances in Computer-Human Interactions. 2010 Presented at: ACHI '10; February 10-15, 2010; Saint Maarten, Netherlands Antilles p. 134-138. [doi: 10.1109/achi.2010.26]

75. Rohani DA, Sorensen HB, Puthusserypady S. Brain-computer interface using P300 and virtual reality: a gaming approach for treating ADHD. Annu Int Conf IEEE Eng Med Biol Soc 2014;2014:3606-3609. [doi: 10.1109/EMBC.2014.6944403] [Medline: 25570771]

76. Sakoda W, Tadayon R, Kishishita Y, Yamamoto M, Kurita Y. Ski exergame for squat training to change load based on predicted locomotive risk level. In: Proceedings of the 2020 IEEE/SICE International Symposium on System Integration. 2020 Presented at: SII '20; January 12-15, 2020; Honolulu, HI, USA p. 289-294. [doi: 10.1109/siisi46433.2020.9026280]

77. Sourial M, El Naggar A, Reichardt D. Development of a virtual coach scenario for hand therapy using LEAP motion. In: Proceedings of the 2016 Future Technologies Conference. 2016 Presented at: FTC '16; December 6-7, 2016; San Francisco, CA, USA p. 1071-1078. [doi: 10.1109/ftec.2016.7821736]

78. Valladares-Rodriguez S, Pérez-Rodriguez R, Fernandez-Iglesias JM, Anido-Rifón LE, Facal D, Rivas-Costa C. Learning to detect cognitive impairment through digital games and machine learning techniques. Methods Inf Med 2018 Sep;57(4):197-207. [doi: 10.3414/ME17-02-0011] [Medline: 30248709]

79. van Diest M, Stegenga J, Wörtche HJ, Roerdink JB, Verkerke GJ, Lamoth CJ. Quantifying postural control during exergaming using multivariate whole-body movement data: a self-organizing maps approach. PLoS One 2015 Jul 31;10(7):e0134350 [FREE Full text] [doi: 10.1371/journal.pone.0134350] [Medline: 26230655]

80. Varga G, Stoiuc-Tivadar L, Nicola S. Serious gaming and AI supporting treatment in rheumatoid arthritis. Stud Health Technol Inform 2021 May 27;281:699-703. [doi: 10.3233/SHTI210262] [Medline: 34042666]

81. Vonstad EK, Vereijken B, Bach K, Su X, Nilsen JH. Assessment of machine learning models for classification of movement patterns during a weight-shifting exergame. IEEE Trans Human Mach Syst 2021 Jun;51(3):242-252. [doi: 10.1109/thms.2021.3059716]

82. Wang C, Peng L, Hou ZG, Luo L, Chen S, Wang W. sEMG-based torque estimation using time-delay ANN for control of an upper-limb rehabilitation robot. In: Proceedings of the 2018 IEEE International Conference on Cyborg and Bionic Systems. 2018 Presented at: CBS '18; October 25-27, 2018; Shenzhen, China p. 855-591. [doi: 10.1109/cbs.2018.8612261]

83. Yeh SC, Huang MC, Wang PC, Fang TY, Su MC, Tsai PY, et al. Machine learning-based assessment tool for imbalance and vestibular dysfunction with virtual reality rehabilitation system. Comput Methods Programs Biomed 2014 Oct;116(3):311-318. [doi: 10.1016/j.cmpb.2014.04.014] [Medline: 24894180]

84. Zainal N, Faied MZ, Kahaki SM, Hussain H, Bahari M, Ismail W. Prediction scoring in exergames for rehabilitation patients using K-means clustering. In: Proceedings of the 6th International Conference on Research and Innovation in Information Systems. 2019 Presented at: ICRiS '19; December 2-3, 2019; Johor Bahru, Malaysia p. 1-6. [doi: 10.1109/criis48246.2019.9073659]

85. Zhang H, Miao C, Yu H. Fuzzy logic based assessment on the adaptive level of rehabilitation exergames for the elderly. In: Proceedings of the 2017 IEEE Global Conference on Signal and Information Processing. 2017 Presented at: GlobalSIP '17; November 14-16, 2017; Montreal, Canada p. 423-427. [doi: 10.1109/globalsip.2017.8308677]

86. Islam MN, Elnaggar A, Reichardt D. Development and validation of a mobile game for culturally sensitive child sexual abuse prevention education in Tanzania: mixed methods study. JMIR Serious Games 2021 Nov 08;9(4):e30350 [FREE Full text] [doi: 10.2196/30350] [Medline: 33069326]

87. Malamsha MP, Sauli E, Luhanga ET. Development and validation of an upper-limb rehabilitation robot. In: Proceedings of the 2018 IEEE International Conference on Signal and Information Processing. 2018 Presented at: GlobalSIP '18; November 14-16, 2018; Montreal, Canada p. 423-427. [doi: 10.1109/globalsip.2018.8308677]

88. Ruggiero L. Diabetes prevention and management: what does a serious game have to do with it? Games Health J 2015 Oct;4(5):333-334. [doi: 10.1089/g4h.2015.0055] [Medline: 26287923]

89. Norlev J, Derosche C, Sondrup K, Hejlesen O, Hangaard S. Using distance communication for the user-centered design of a smartphone-based serious game for children with type 1 diabetes: participatory design approach. JMIR Serious Games 2022 Mar 29;10(1):e33955 [FREE Full text] [doi: 10.2196/33955] [Medline: 35348466]
90. Nørlev J, Sondrup K, Derosche C, Hejlesen O, Hangaard S. Game mechanisms in serious games that teach children with type 1 diabetes how to self-manage: a systematic scoping review. J Diabetes Sci Technol 2022 Sep;16(5):1253-1269 [FREE Full text] [doi: 10.1177/19322968211018236] [Medline: 34024156]

91. Thompson D. Designing serious video games for health behavior change: current status and future directions. J Diabetes Sci Technol 2012 Jul 01;6(4):807-811 [FREE Full text] [doi: 10.1177/193229681200600411] [Medline: 22920806]

92. Toftedahl M, Engström H. A taxonomy of game engines and the tools that drive the industry. In: Proceedings of the 2019 DiGRA International Conference: Game, Play and the Emerging Ludo-Mix. 2019 Presented at: DiGRA ’19; August 6–10, 2019; Kyoto, Japan.

93. Paton C, Karopka T. The role of free/libre and open source software in learning health systems. Yearb Med Inform 2017 Aug;26(1):53-58 [FREE Full text] [doi: 10.15265/IY-2017-006] [Medline: 28480476]

94. Mitsis K, Zarkogianni K, Kalafatis E, Dalakleidi K, Jaafar A, Mourkousis G, et al. A multimodal approach for real time recognition of engagement towards adaptive serious games for health. Sensors (Basel) 2022 Mar 23;22(7):2472 [FREE Full text] [doi: 10.3390/s22072472] [Medline: 35408088]

95. Mobile Statistics Report, 2021-2025. The Radicati Group. 2020. URL: https://www.radicati.com/wp/wp-content/uploads/2021/Mobile_Statistics_Report,_2021-2025_Executive_Summary.pdf [accessed 2022-08-20]

96. Balli F. Developing digital games to address airway clearance therapy in children with cystic fibrosis: participatory design process. JMIR Serious Games 2018 Nov 21;6(4):e18 [FREE Full text] [doi: 10.2196/games.8964] [Medline: 30463835]

97. Verschueren S, Buffel C, Vander Stichele G. Developing theory-driven, evidence-based serious games for health: framework based on research community insights. JMIR Serious Games 2019 May 02;7(2):e11565 [FREE Full text] [doi: 10.2196/11565] [Medline: 31045496]

98. Ghassemi M, Oakden-Rayner L, Beam AL. The false hope of current approaches to explainable artificial intelligence in health care. Lancet Digit Health 2021 Nov;3(11):e745-e750 [FREE Full text] [doi: 10.1016/S2589-7500(21)00208-9] [Medline: 34711379]

99. van Assen M, Lee SJ, De Cecco CN. Artificial intelligence from A to Z: from neural network to legal framework. Eur J Radiol 2020 Aug;129:109083. [doi: 10.1016/j.ejrad.2020.109083] [Medline: 32526670]

Abbreviations

AI: artificial intelligence
PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews

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