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Systematic Review of AI-Based Cognitive Training Programs: Algorithms, Populations, and Stimulated Cognitive Domains

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Abstract

This article presents a literature review divided into two phases. The first phase exposes the findings from the grey literature on cognitive training programs that implement artificial intelligence strategies with commercial use. The second phase shows the results of the search conducted in scientific databases, focusing on studies that describe the design and implementation of software for cognitive training using artificial intelligence algorithms. The objective has been to identify which intelligent algorithms were implemented, which functionalities or moments within the cognitive training these algorithms intervene, which populations have been studied, and which cognitive domains were stimulated. The review was conducted following the PRISMA protocol (Preferred Reporting Items for Systematic reviews and Meta-Analyzes), guided by a research question that directed both the search for commercial software in the grey literature and the search in seven scientific databases. In the grey literature, 31 commercially available cognitive training platforms that use intelligent algorithms were identified, while 291 records were extracted from scientific journals. Both commercial programs and articles were filtered according to the established inclusion criteria to obtain a final selection of four programs and nine articles used for the purposes of this study in the analysis phase. The findings showed that the most used intelligent algorithms are recommendation systems, particularly collaborative filtering ones, and they are mainly used to propose challenges during training sessions or to vary the difficulty of exercises based on the participants' results. The target population for commercial platforms includes participants of any age, particularly middle-aged adults, while the most studied age groups in the research focus on children with learning disorders and adults aged 60 to 90 years with cognitive decline or brain injuries. In both cases, they aim to stimulate cognitive domains such as attention, memory, and executive functions to a greater extent.

Keywords: cognitive stimulation; cognitive training; cognitive rehabilitation; brain training; computational system; artificial intelligence; intelligent algorithms; system recommendation; cognitive domains; bibliographic review.

Revisión sistemática de programas de entrenamiento cognitivo basados en IA: algoritmos, poblaciones y dominios cognitivos estimulados

Resumen

Este artículo presenta una revisión bibliográfica dividida en dos fases. La primera fase expone los hallazgos encontrados en la literatura gris sobre programas de entrenamiento cognitivo que implementan estrategias de inteligencia artificial (IA) con uso comercial. La segunda fase muestra los resultados de la búsqueda realizada en bases de datos científicas, centrándose en estudios que describen el diseño e implementación de software para entrenamientos cognitivos mediante el uso de algoritmos de IA. El objetivo ha sido identificar qué algoritmos inteligentes fueron implementados, qué funcionalidades o momentos dentro de los entrenamientos cognitivos intervienen estos algoritmos, qué poblaciones se han estudiado y qué dominios cognitivos fueron estimulados. La revisión se ha realizado siguiendo el protocolo PRISMA (por sus siglas en inglés Preferred Reporting Items for Systematic reviews and Meta-Analyzes), guiada por una pregunta de investigación que orientó tanto la búsqueda de software comercial en literatura gris como la realizada en siete bases de datos científicas. En la literatura gris se lograron identificar 31 plataformas de uso comercial para entrenamientos cognitivos que hacen uso de algoritmos inteligentes, mientras que de las revistas científicas se extrajeron 291 registros. Tanto los programas comerciales como los artículos fueron filtrados siguiendo los criterios de inclusión establecidos para obtener una selección final de cuatro programas y nueve artículos que han sido utilizados para los propósitos de este estudio en la fase de análisis. Los hallazgos mostraron que los algoritmos inteligentes más utilizados son los sistemas de recomendación, particularmente los de filtrado colaborativo, y se utilizan en mayor proporción para proponer desafíos durante las sesiones de entrenamiento o para variar la dificultad de los ejercicios a partir de los resultados que obtienen los participantes. El objetivo poblacional en las plataformas comerciales son participantes de cualquier edad, particularmente adultos de edad media, mientras que en las investigaciones los grupos etarios más estudiados se enfocaron en niños con enfermedades o trastornos de aprendizaje y adultos mayores entre los 60 y 90 años con deterioro cognitivo o lesiones cerebrales. En ambos casos, apuntan a estimular en un mayor porcentaje dominios cognitivos como la atención, la memoria y las funciones ejecutivas.

Palabras clave: estimulación cognitiva; entrenamiento cognitivo; rehabilitación cognitiva; ejercicios cognitivos; software; uso del computador; inteligencia artificial; algoritmos inteligentes; sistemas de recomendación; dominios cognitivos; revisión sistemática.

1. Introduction

The literature review presented in this article is based on a rigorous research methodology, focusing on the formulation of clear and specific questions, a systematic search of commercial software, relevant studies and articles, and the application of predefined inclusion criteria. The review follows the PRISMA protocol to ensure transparency and thoroughness of the process. The PICO model (Patient, Intervention, Comparison, Outcomes) was employed to structure the research questions, focusing on identifying and analyzing cognitive training programs that use artificial intelligence algorithms available both commercially and developed through scientific research in the last ten years (O'Connor et al., 2008).

Human daily activities, which allow adaptation and interaction with the environment, are regulated by a series of cognitive abilities responsible for developing the motor, functional, and emotional skills necessary to fulfill this purpose (Villalba & Espert, 2014). These abilities evolve as environmental relationships become more complex, implying that individuals take in information from their surroundings through their senses, relate it to previous knowledge stored in their memory, and produce knowledge through interaction with other cognitive processes (Shahmoradi et al., 2022). Through transfer processes, these abilities intervene between situations, building and transforming individuals' mental structures and behaviors, providing them with the competencies necessary to function smoothly in their context and strengthening their cognitive abilities as they age (Jara, 2008).

Villalba & Espert (2014) define cognitive stimulation (CS) as a "set of techniques and strategies aimed at optimizing the efficiency of the functioning of various cognitive capacities and functions (perception, attention, reasoning, abstraction, memory, language, orientation processes, and praxias) through a series of specific situations and activities structured in what are called cognitive training programs" (p. 74). Trápaga-Ortega et al. (2018) add that CS includes "activities aimed at improving overall cognitive performance or some of its processes and components, such as attention, memory, language, executive functions, among others, whether in healthy subjects or patients with some type of central nervous system injury" (p. 24). CS is based on the premise that the lack of cognitive activity accelerates cognitive decline, therefore, implementing compensation and cognitive reserve strategies to improve neuroplasticity and maintain cognitive capacity for as long as possible (Rocha et al., 2023).

Tetlow & Edwards (2017) classify cognitive interventions into CS, which can involve routine recreational or leisure activities, such as board games, dancing, or reading, or guided cognitive training, which consists of routines containing a set of cognitive activities and challenges structured according to each person's capacities and abilities. The intention is to strengthen a specific cognitive ability; depending on the domain or domains expected to improve, the training specifies the frequency of execution, the difficulty level of the exercises, and a series of factors that will be measured during the exercise, also conditioned by age, education level, the stimulation goal, and the cognitive level of the subject before the training.

Cognitive training has gained interest due to the results obtained in clinical studies, where it has been implemented as a non-pharmacological alternative to prevent the effects of aging on mental functions (Garamendi et al., 2010; Rocha et al., 2023). The benefits include the ability to analyze new tasks, enhance logical reasoning, identify, relate, solve, transfer, and extrapolate concepts, and in preventive therapies for cognitive decline caused by aging, promoting

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active aging through the maintenance of autonomy and preservation of cognitive functions in old age, extending the quality, productivity, and life expectancy (Rosell, 2018; Villalba & Espert, 2014; Synaptikon GmbH, s.f.; Zamarrón, 2007).

The inclusion of technology in these treatments has increased their popularity due to the independence it provides, allowing training to be conducted at any time and place, accessible from a device. The growth of artificial intelligence has opened a field of study that promises to transform the understanding and strengthening of mental development, proposing a synergy between CS and intelligent systems to analyze gaming and learning patterns, offering personalized exercises and activities tailored to the individual needs and capacities of each user or patient.

In this review, platforms such as Lumosity, CogniFit, BrainHQ, and NeuroNation were identified, which conduct cognitive training through challenges to improve and train cognitive domains such as memory, attention, and language skills. These applications propose personalized cognitive training plans based on an initial diagnostic test, configuring activities, frequency, and stimulus difficulty to stimulate a particular cognitive skill. These programs usually have a cost for accessing more specialized plans and are aimed at any audience, regardless of age.

In the scientific literature, studies describe in more detail the implementation of recommendation systems combined with K-means algorithms, models based on fuzzy logic, or machine learning models to learn from each interaction with participants, improving exercise suggestions over time or modifying exercise difficulty. These strategies ensure that the more the system is used, the more personalized and effective it becomes in stimulating cognitive abilities.

In conclusion, this review provides an overview of the market-available programs for conducting cognitive training with adaptive characteristics through the use of intelligent algorithms, available commercially or developed in scientifically grounded studies.

2. Materials and Methods

The bibliographic review is based on a rigorous research methodology that begins with a clear research question, a systematic search for relevant studies and articles, and the application of pre-determined inclusion criteria. This process includes the description of the studies, data synthesis, and interpretation of the results, with the aim of collecting, analyzing, synthesizing, and evaluating the most prominent studies on a specific topic.

2.1. Formulation of Research Questions

This research was structured according to the bibliographic review protocol based on the PRISMA statement. As an initial step, a clear and focused research question was formulated. To identify all the elements that needed to be covered in the review question, the PICO methodology was used. This model focuses on four aspects: the patient (P) or problem addressed, the intervention (I) considered, the comparison (C) of interventions or control group, and the outcomes (O) obtained. Table 1 defines the concepts under which the question guiding the bibliographic review was consolidated.

Table 1. *Definition of concepts using PICO*

Parameter	Definition
Patient	Individuals with healthy cognitive aging or cognitive issues, different age groups.
Intervention	Cognitive training programs mediated by artificial intelligence algorithms to stimulate, train, or improve cognitive functions.
Comparison/ Control Group	Computerized cognitive training programs, but without the use of artificial intelligence.
Outcomes	Characteristics of the cognitive training program, characteristics of the intelligent algorithm employed.

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Having defined the main axes of the review, the research questions presented in Table 2 were formulated.

Table 2. *Research questions for the bibliographic review*

No.	Research Question
PI1	Which cognitive domains were stimulated in intelligent cognitive training programs?
PI2	What is the age range of the population in which intelligent cognitive training programs were used?
PI3	Which intelligent algorithms were used for the stimulation of cognitive domains and for what purposes are they used?
PI4	Do the cognitive training programs include strategies to measure error and provide feedback?

2.2. Definition of Inclusion and Exclusion Criteria

The scope of this review had two main objectives: first, to identify commercially available software programs used for cognitive stimulation (CS), delving into their characteristics and determining whether they employed intelligent algorithms. The second objective was to analyze recent studies, published in the last ten years in recognized databases such as Scopus, Computer Science, Science Direct, IEEE Xplore, Public Health Database (ProQuest), PubMed, and Web of Science. This research focused on studies detailing the design and implementation of cognitive training programs that use artificial intelligence technologies, with a special emphasis on recommendation systems. The purpose of this study is to enrich the state of the art, providing a deep understanding of the applications, contexts, technologies, and innovative features of these programs.

To identify commercially available computerized cognitive training programs that use artificial intelligence, a Google search was conducted between February 20 and March 29, 2024, using the keywords "personalized cognitive training programs" and "cognitive training programs AND artificial intelligence". From the list obtained, the websites of each application were explored to identify relevant characteristics ensuring compliance with the inclusion criteria. Additionally, a review of grey literature was conducted via Google, and the bibliography in Google Scholar and Scopus was reviewed to determine whether the commercial programs originated from any research or if there were studies investigating the developed intelligent algorithms.

The inclusion criteria were: (a) comprehensive cognitive training programs and not just games or challenges without a specific purpose, (b) fully computerized cognitive training programs without the need for additional elements such as augmented reality glasses or brainwave sensors, among others, (c) commercially available programs, (d) programs that allow for the personalization of cognitive training and the tracking of results without therapist intervention, (e) programs that use intelligent algorithms as mentioned on their official websites or platforms, (f) programs focused on general CS.

For the search of scientific articles, on February 20, 2024, seven multidisciplinary databases were accessed: Scopus, Computer Science, Science Direct, IEEE Xplore, Public Health Database (ProQuest), PubMed, and Web of Science. The inclusion criteria for publications were: (1) articles published in scientific journals in the last ten years, (2) studies written in English or Spanish, (3) studies describing the development of software for cognitive training using artificial intelligence algorithms, (4) studies that require only a computer or mobile devices to use these applications, without the need for other devices. The studies excluded were those that (1) were not related to the inclusion criteria, (2) were systematic reviews, (3) were duplicates, (4) described the development of software with intelligent algorithms but that predict the occurrence of cognitive diseases or adherence, and not cognitive training itself.

2.3. Execution of the Search Strategy and Information Sources

Based on the research questions, keywords for the search were defined. To simplify the keyword selection process, eliminate ambiguities, and focus on the specific topic, thesauri were used

(Martínez, 2017). The thesauri employed were: Cognitive Psychology of Human Memory for terms related to neuropsychology and IEEE for the engineering field.

Keyword combinations were formulated in both Spanish and English: 1) cognitive training (entrenamiento cognitivo), 2) cognitive stimulation (estimulación cognitiva), 3) cognitive rehabilitation (rehabilitación cognitiva), 4) computer programs (sistemas o programas computarizados), 5) artificial intelligence (inteligencia artificial), 6) recommendation systems (sistemas de recomendación), 7) machine learning (aprendizaje automático). To create the search query scripts executed in each database, the aforementioned keywords were combined with logical operators and filters to refine the searches. The final result is presented in Table 3.

Table 3. *Search strategy for Google search engine and scientific databases*

Source or Database (total records)	Search Algorithm	Automatic Filters
Google (31)	“programas de estimulación cognitiva OR cognitive stimulation programs” “programas de entrenamiento cognitivo con inteligencia artificial OR cognitive training with artificial intelligence”	
Scopus (52)	(ALL (“cognitive training”) OR ALL (“cognitive rehabilitation training”) AND ALL (“recommendation system”) OR ALL (“explainable machine learning”)) AND PUBYEAR > 2014 AND PUBYEAR < 2025 AND (EXCLUDE (DOCTYPE , “re”))	Year filter applied for articles published between 2014 and 2024. ”Review” articles excluded
Computer Science (50)	Full text: "cognitive training" OR Full text: "cognitive rehabilitation training" AND Full text: "recommendation system" OR Full text: "explainable machine learning"	Date filter applied for "Publication Date" January 01, 2014 - February 20, 2024 For "Document Type" filter, "Article" was selected Academic Publications reviewed
Science Direct (14)	(“cognitive training” OR "cognitive stimulation") AND (“recommendation system” OR "explainable machine learning")	Years 2014 - 2024

Table 3. *Search strategy for Google search engine and scientific databases*

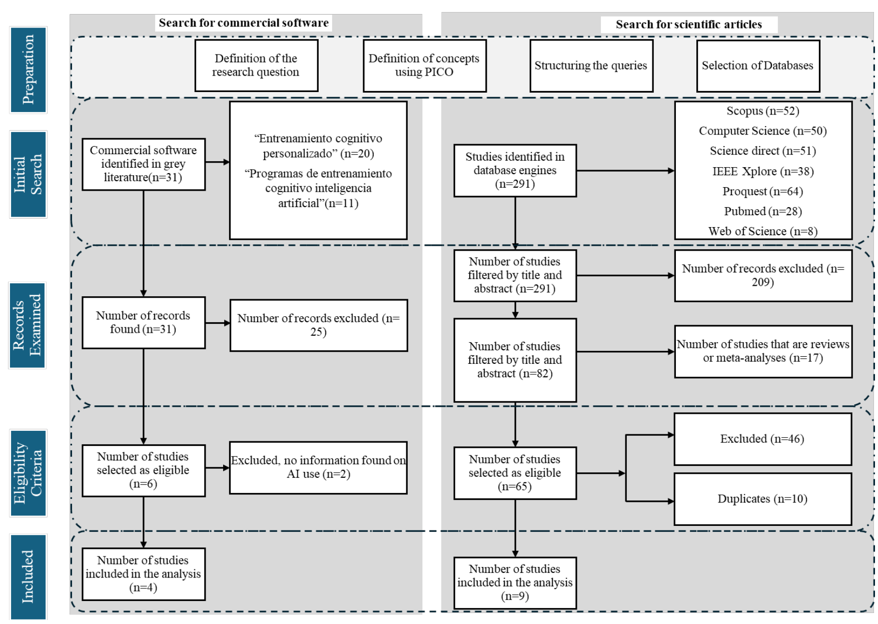
Source or Database (total records)	Search Algorithm	Automatic Filters
IEEE Xplore (38)	(("Abstract":"cognitive training") OR ("Abstract":"cognitive rehabilitation") AND ("Abstract":"recommendation system") OR ("Abstract":"explainable machine learning"))	"Publication year" filter selected for the period 2014 to 2024 "Journals" selected
Proquest (64)	"cognitive training" and "serious game" and "artificial intelligence"	Filters applied: "Scholarly Journals" "2014-01-01 - 2024-02-20", "Main article", "Article", "artificial intelligence". Excluded: "virtual reality", "robots", "literature reviews", "biomarkers", "sensors", "robotics", "systematic review", "electroencephalography", and "internet of things"
Pubmed (28)	"cognitive training" or "cognitive rehabilitation" and "recommendation system" or "explainable machine learning"	Filter applied for the period 2014 to 2024
Web of Science (8)	#cognitive training OR #cognitive rehabilitation training AND #recommendation system OR #explainable machine learning	Years 2014 - 2024

2.4 Evaluation of Articles: Selection and Application of Filters

The search for advanced commercially available software through Google identified a total of 31 programs. Of these, 20 were “cognitive stimulation programs” and 11 were “cognitive training programs with artificial intelligence.” A total of 25 programs were discarded for various reasons: two were simply games or challenges, eight were used as supplements to conventional therapies requiring pencil and paper or additional devices such as augmented reality glasses, brainwave sensors, and headphones; three were no longer available; nine did not offer autonomous personalization of the training sessions but relied on therapist intervention; and three were exclusively focused on cognitive pathologies. The main challenge encountered was the lack of information on the implementation of intelligent algorithms. For this reason, two mobile device programs were excluded because, despite showing adaptability and personalization, they did not clearly demonstrate the use of such algorithms in the available documentation.

For the second strategy, the search queries were structured according to the specific requirements of each database, as detailed in Table 3. This action generated a total of 291 records. Once the search was completed, the articles were reviewed according to the pre-established inclusion criteria, filtering by title, abstract, and full text. In the final stage of the review, nine articles were selected for detailed analysis. The PRISMA flow diagram, illustrated in Figure 1, describes the procedure carried out through the different phases of the bibliographic review.

Figure 1. *Flow diagram of the bibliographic review*



3. Results

In the current landscape of commercially available cognitive training applications and platforms, several options stand out. This review specifically selected Lumosity, CogniFit, BrainHQ, and NeuroNation, which met the inclusion criteria. These applications share the common goal of enhancing users' cognitive abilities and utilize intelligent algorithms, specifically supervised learning, to adjust game difficulty levels based on participant performance and classify final results compared to population groups of similar ages and preferences.

Studies focusing on the development of intelligent applications for cognitive stimulation (CS) make greater use of collaborative filtering recommendation systems and K-means algorithms, allowing for more accurate exercise suggestions based on patient categorization. Additionally, they employ other intelligent strategies to dynamically modify difficulty during exercise performance.

PI1: Which cognitive domains were stimulated in the intelligent cognitive training programs?

Cognitive training platforms such as Lumosity, CogniFit, and BrainHQ share the goal of improving cognitive domains like memory, attention, and processing speed. Each of these applications offers additional features that distinguish them from one another; for instance, Lumosity stimulates mental flexibility, while CogniFit includes exercises to enhance visual and auditory skills. NeuroNation addresses a broader range of cognitive areas, including critical thinking, mental speed, concentration, and language skills.

In the review of scientific literature on the development of intelligent applications for cognitive training, there is a trend to focus training programs primarily on memory and attention stimulation, followed by executive functions, language, logic, and processing speed. Less emphasis is placed on orientation and visoconstructive or visuospatial skills, while cognitive domains such as gnosis, self-regulation, and visual processing receive even less attention. This trend is illustrated in Figure 2.

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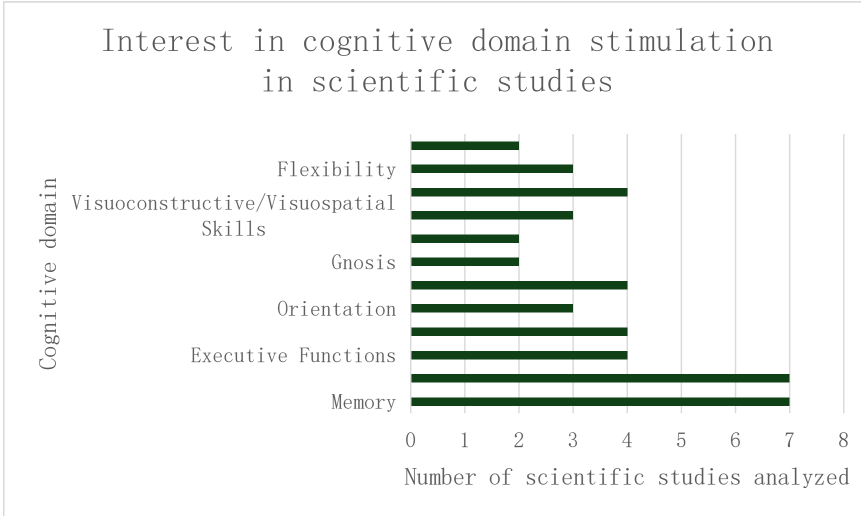
***Figure 2.** Interest in the stimulation of cognitive domains in scientific studies*

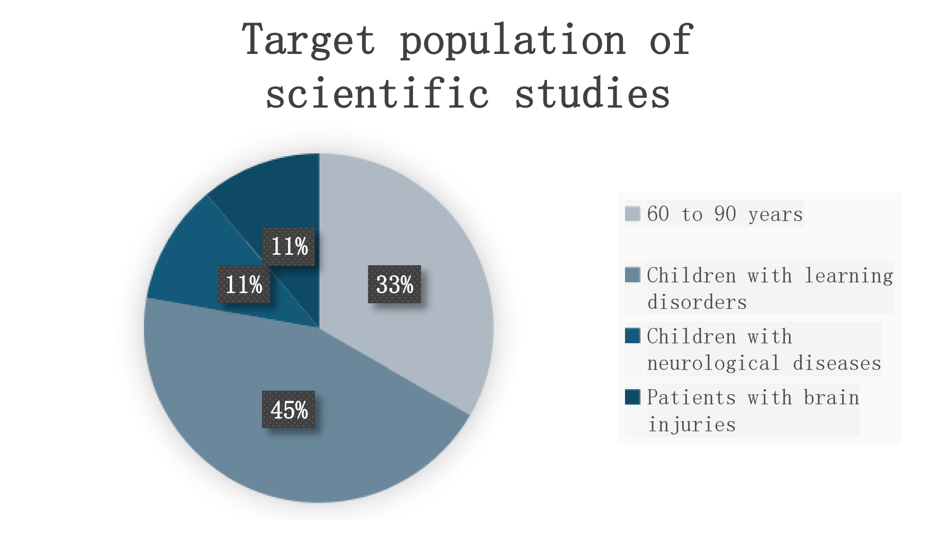


These findings suggest that the design of cognitive training programs prioritizes certain cognitive domains, likely reflecting the perception that these have greater relevance to daily life skills and are most affected by neurocognitive diseases. The diversity of approaches in commercial platforms and scientific studies highlights the complexity of the field of cognitive stimulation (CS) and underscores the need to offer personalized solutions that address users' specific needs.

PI2: What is the age range of the population in which intelligent cognitive training programs were used?

Regarding the target audience of commercially available applications, these are designed to be used by young adults, middle-aged adults, and seniors; however, specific age ranges are not clearly defined. CogniFit stands out for its inclusive approach, covering a broader audience that includes individuals with cognitive disorders, as well as children and adolescents. In contrast, scientific studies on cognitive training focus on two population groups. As shown in Figure 3, through a pie chart, 45% of the research targets overcoming diseases or disorders affecting cognition in childhood. Eleven percent of the studies are designed as therapies for children with neurological conditions, such as autism spectrum disorders or attention deficit disorder. Thirty-three percent of the studies focus on mitigating the effects of age-related diseases in older adults, aged 60 to 90, addressing conditions like cognitive decline, Alzheimer's, or dementia. Finally, 11% of the research is dedicated to treating patients of any age suffering from diseases caused by brain injuries.

Figure 3. *Population distribution in scientific studies*



The results suggest that age is a determining factor in the development of cognitive training programs. Different stages of human development present specific cognitive needs, which directly influence the exercises and cognitive domains to be stimulated. During childhood, CS focuses on improving learning processes and acquiring new skills, thus strengthening continuous and academic development. In adulthood, training aims at stabilizing, maintaining, and enhancing cognitive abilities. In contrast, during old age, the main objective is to slow down prevalent degenerative processes that affect cognitive functions.

Furthermore, the need to personalize and adapt training becomes evident to maximize its effectiveness and meet the specific needs of each age group. These programs must be based on individuals' current capabilities to effectively enhance them. Age also influences users' levels of engagement and motivation: training programs designed for children tend to be more playful and visual, while in older adults, the emphasis is on the utility of the exercise and its applicability to daily activities. In summary, age-based personalization and adaptation not only optimize the effectiveness of cognitive training but also improve user experience, increasing their motivation and engagement.

PI3: What are the intelligent algorithms used to stimulate cognitive domains and what are they used for?

The use of intelligent algorithms in cognitive training systems represents a significant advancement compared to traditional programs for cognitive stimulation (CS). These advances allow users, both patients and healthy individuals, to engage in cognitive training activities from home, accessing customizable tools that adapt to their needs without requiring the presence of a therapist or traveling to a physical space. These programs are supported by technologies based on recommendation systems, neural networks, fuzzy logic, and machine learning algorithms.

One of the biggest challenges in finding commercial platforms that use intelligent algorithms for cognitive training was finding detailed documentation on their implementation and specific use of these algorithms. To overcome this obstacle, a thorough review was conducted on official websites, and direct contact was established with the developers of each platform. This inquiry into the grey literature revealed that these platforms use various artificial intelligence approaches to personalize and optimize the user experience. Specifically, these platforms combine recommendation systems and machine learning, primarily to dynamically adjust the difficulty of games and make cognitive training recommendations based on user behavior patterns.

Lumosity stands out for its ability to adaptively personalize training using machine learning algorithms. These algorithms analyze user performance and progress in different cognitive areas, dynamically adjusting the difficulty of games and exercises. This adaptive personalization ensures that users face challenges appropriate to their current abilities, improving training effectiveness and maintaining motivation over time (Lumos Labs, 2017). Additionally, data analysis performed by these algorithms helps identify usage patterns, exercise preferences, and areas for improvement, which are used to personalize training and enhance recommendations based on each user's needs.

CogniFit relies on automated cognitive assessments to compare user results with similar profiles to maximize improvement in specific areas. The Individualized Training System (ITS) facilitates the personalization of cognitive training, allowing for the design of specific routines tailored to the individual needs of each user. The ITS has two main components: the first uses an initial diagnostic assessment to rank the user's abilities from best to worst, based on comparative performance with other users of similar characteristics. From this ranking, specific routines are designed to strengthen both the most prominent and the weakest abilities identified. The second component, using machine learning algorithms, adjusts task difficulty levels in real-time as the user progresses in training. According to the platform, "The program constantly monitors task performance, adjusting the difficulty so users can move up or down within the system according to their performance level" (CogniFit, n.d.). This methodology ensures that exercises are always presented at an appropriate level for the user, optimizing the challenge and fostering effective cognitive development.

BrainHQ uses recommendation systems based on collaborative filtering, along with a dynamic adaptation system that adjusts exercise difficulty based on real-time user performance. To personalize the experience, BrainHQ has a program known as Personal Trainer, developed with machine learning algorithms. In the paid version, this program offers six levels and sets an exercise schedule. The free version is more limited, allowing access to one daily exercise that stimulates a specific cognitive skill. The Personal Trainer continuously analyzes user performance at each level and exercise, using this information to design subsequent training sessions. According to Cala (2024), this personal trainer adjusts proposed levels to maximize the user's improvement potential, offering a variety of exercises within a single session and prioritizing those in which the user has the most potential for progress. This

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approach can vary from session to session, eliminating exercises where performance goals have been met or repeating them if necessary. As users perform activities, exercise difficulty increases based on correct responses, either by presenting more stimuli to memorize or increasing the time objects remain hidden on the screen. If users make mistakes, difficulty decreases by reducing the frequency, speed, or number of presented elements. Additionally, as an extra challenge, stars are accumulated for consecutive correct answers, granting access to restricted content in the free version. Accessing this content requires a subscription payment.

Finally, the recommendation systems based on collaborative filtering of NeuroNation work together with machine learning algorithms to suggest personalized exercises, analyzing user performance and preferences. The application requires initial registration, where users can enter an email and password or log in through Facebook, Google, or Apple. In the first interaction, an initial training session is required where exercise difficulty increases as users correctly follow instructions. This way, memory demands increase for participants. Conversely, if mistakes are made, difficulty decreases by reducing the number of stimuli and distractions on the screen, changing the color of appearing elements, or putting them in motion to require increased attention from participants.

In the analyzed studies, two investigations were identified that used recommendation systems with collaborative filtering and K-means algorithms to personalize training and adjust exercise difficulty levels. Kim et al. (2018) developed a cognitive training system that collects patients' personal information and results from the Mini-Mental State Examination (MMSE) diagnostic test, used to measure cognitive decline. This data is processed using big data algorithms, and the resulting information is sent to a recommendation system that proposes personalized cognitive training sessions adapted to the difficulty level each patient can handle. This system aims to give patients autonomy to conduct their training at home and monitor results without therapist dependence. Additionally, this approach allows for the detection of early stages of mild cognitive impairment and offers training alternatives designed to keep patients motivated and mitigate disease progression (Kim et al., 2018).

On the other hand, Shen & Xu (2021) developed a collaborative filtering recommendation system on an existing platform called CogDaily, aimed at helping children select the most suitable cognitive training exercises. This research proposes an improved method for evaluating cognitive domains using K-means algorithms, which group evaluation results to map cognitive levels. This allows children to better understand their strengths and weaknesses (Shen & Xu, 2021).

One study, in addition to using collaborative filtering recommendation systems and K-means algorithms, implemented a fuzzy logic system. Navarro et al. (2018) present an adaptive system for CS activities, based on analyzing the performance of dementia patients during interactive games. This software proposes personalized stimulation therapies adapted to the changes patients experience throughout their disease. This proposal arises from the need to self-adapt the type and level of activities in an existing platform called Mente Activa, which requires constant therapist supervision to be used and evaluate user interactions. Mente Activa conducts cognitive training through games designed by psychologists, executed on touch-screen computers with multimedia resources, such as audio instructions and interactive images (Navarro et al., 2018).

The platform is modified through two main functionalities: the first determines the classification of patients' interactions with the software to evaluate their performance in completed activities; the second adapts the stimulation plans similarly to how a therapist would, using knowledge about each patient. Initially, patients register in the system, providing information such as years of schooling, age, and clinical diagnosis, then perform tests like the Mini-Mental (MM) and Neuropsi, with results stored along with medication data. The system uses a Fuzzy Logic System (FLS), MIMO, and the Mamdani inference method, applying singleton fuzzy sets and the centroid defuzzification method. Each of the seven cognitive domains has a dedicated FLS to generate an initial stimulation plan. FLS rules take input from the MM test results according to the Global Deterioration Scale (GDS), Neuropsi test results applied to patients aged 66 to 85, and schooling level. The initial stimulation plans, which later adapt based on patient interaction with the application, combine activities designed to improve cognitive performance. Performance

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is evaluated using the K-means algorithm to identify three significant performance clusters, classifying each activity based on errors made and time taken, thus allowing future performance classification in an unsupervised manner. Each data point is assigned to the nearest centroid based on Euclidean distance.

The study by Kotyrba et al. (2022) describes the development of an expert system for cognitive rehabilitation that uses fuzzy logic to personalize rehabilitation plans based on intelligence models. This system proposes a controller based on IF-THEN linguistic rules that model the semantics of natural language. Evaluative expressions like “very small,” “more or less medium,” and “quite large” are used to describe and evaluate conditions and actions in the context of cognitive training. Patients perform an ACE-R test, whose results are used to determine the domains to stimulate based on the CHC (Cattell-Horn-Carroll) intelligence model. Subsequently, fuzzy rule bases containing these linguistic expressions for each cognitive domain of the CHC model are created, determining the most suitable profile for the patient, personalizing cognitive training, and adapting the difficulty level, proposing six distinct levels.

The proposal by Antunes & Madeira (2021) presents the PLAY platform, which implements an advanced recommendation system to personalize and optimize user experience by adapting games to the individual needs of children, aiming to enhance their engagement and therapy outcomes. The PLAY model is structured in levels and sequences, with each action configured using parameters that define its behavior during execution. The recommendation system dynamically adjusts exercise suggestions based on the patient’s profile, detailed usage history, medical condition, and biometric data. Additionally, it allows the therapist to modify certain parameters if necessary. The system architecture includes a user profile where personal information and biometric data are stored, and changes in emotional or motivational state are recorded.

In the analyzed investigations, Tsiakas et al. (2020) propose a combined system of collaborative filtering recommendation systems and explainable AI. The game is designed considering several parameters: (a) number of available target/player positions, (b) types of targets, (c) player color, and (d) task rules. Each configuration of these parameters results in a task that requires specific skills. For each exercise, activity, difficulty, and speed are considered, and specific rules are established for each category. These include moving and shooting, avoiding birds, remembering target positions, and shooting targets based on player color. Additionally, three difficulty levels are established: easy, medium, and fast, varying according to the number of locations and available targets or players. The system stores a user profile that includes information on user performance, preferences, training time, number of responses, and response time. It also maintains a persuasive profile based on user susceptibilities or preferences regarding the explanations presented by the platform, in addition to storing additional demographic and educational information. The Open Learner Model (OLM) shows information for each individual skill and their average scores, as well as the best scores of previous rounds. If a round is not completely successful, meaning some rules are violated, some skill bars may increase while others remain the same. The recommendation system has two main functions: recommending a target score at the beginning of the session and suggesting appropriate task configurations for the next round. This system considers user preferences based on previous selections, user capabilities based on past task performance, and other contextual user information such as time of day and mood (Tsiakas et al., 2020). At the start of a new session, the child can set their own goal in the form of a total score. The recommendation system evaluates previously selected target scores, both from the child and other similar users in the database. After each round, it suggests possible adjustments to the task configuration, such as reducing difficulty or eliminating a rule, based on the child's goal and performance.

The proposed system focuses on developing Self-Regulated Learning Skills (SRL) through cognitive training directed at children. This component includes goal-setting functions, such as defining a target score for each session; self-efficacy, through accurate self-assessments of game skills; and task selection strategies that ensure alignment with set goals. Additionally, a persuasive explanations model is implemented, responsible for presenting recommendation results comprehensibly and convincingly. This system personalizes recommendations considering the user's persuasion profile, personal information, and training frequency and duration. Data from previous sessions and other users are also used to develop personalized persuasion profiles linking persuasion and explanation strategies, such as authority, reward, and social comparison, with user performance and preferences.

The study conducted by Baldisseri et al. (2022) implements a classification system based on neural networks that integrates music and artificial intelligence to support neurological rehabilitation for children with neurocognitive diseases or injuries. This system uses neural network algorithms to adjust game difficulty. It combines factors such as age, pathology, number of errors, last game's difficulty, number of obstacles overcome, repetitions, and total games played to determine the appropriate difficulty level for the next game. This adjustment is based on the child's previous performance and may involve increasing, maintaining, or reducing difficulty. The neural network is trained using supervised learning, with labels provided by doctors and psychologists who identify the most relevant variables. The study faced limitations in the available data for training, so they used a behavior cloning technique to generate synthetic data. This allowed training the neural network on tasks that mimicked human behavior, increasing the available dataset.

Finally, the model proposed by Eun et al. (2022) uses machine learning algorithms to develop an easily accessible web application for serious games with playful elements, designed to keep users motivated. This system adjusts difficulty levels using artificial intelligence (AI) to prevent early game dropout, allowing older adults to voluntarily engage and remain entertained and immersed in cognitive gaming. The games mainly involve interacting with objects like symbols and numbers on a touch screen. Initially, to access the platform, users must register personal information such as gender, age, and weight, then take an initial test in each of the six games, which adapt to the user's difficulty level.

The AI-based data module adjusts game difficulty according to user performance, seeking to keep users focused on the game for extended periods and generating meaningful data results to validate cognitive effectiveness. The basic adjustment system structure was designed from pretest data. The system operates through two procedures: first, deciding if the user needs a difficulty adjustment, and second, if so, determining whether to increase or decrease difficulty. A Recurrent Neural Network (RNN) based on Long Short-Term Memory (LSTM) is used to decide difficulty adjustments. This dataset consists of fifty user records used for testing, divided into two groups: one requiring level adjustment and the other not. Input data includes problem-solving time, total scores, and scores for each question. The module selected with the lowest error value allows machine learning to deduce an optimal model, facilitating the AI adjustment system to decide whether the user should remain at the same level, move up to a higher level, or move down to a lower one.

PI4: Do cognitive training programs have strategies to measure errors and provide feedback?

Another noteworthy aspect of this review is the discovery that contemporary cognitive training programs not only aim to improve cognitive abilities but also integrate additional mechanisms to measure errors and, through these, offer more effective feedback to participants. These strategies are essential for personalizing and enriching the user experience, thereby optimizing the results obtained.

Lumosity before starting a game, users participate in a trial activity designed to familiarize themselves with the game without recording any measures. Once this mini-tutorial is completed, the real game begins, during which time and scores are measured. At the end of the test, the results are displayed, including the final score, the number of correct responses, accuracy, and reaction time. Additionally, information about the scientific basis of the test performed is provided.

CogniFit in the initial stage, CogniFit conducts a diagnostic evaluation to place the user at a specific cognitive level. The game instructions are described on the left side of the screen, and an instructional video can optionally be viewed. During the test, information about the average time to complete it is provided, and the cognitive skills to be evaluated are clearly specified. A practice

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mini-tutorial is also included, which cannot be skipped, notifying the user if they are performing the actions correctly or incorrectly.

BrainHQ offers personalization and long-term tracking based on user performance, providing detailed information about cognitive progress. New users are required to create an account by entering an email and password. Initially, the user is asked which cognitive domain they want to start with and what specific skill within that domain they want to strengthen. The user is also asked about the reasons for starting cognitive training, offering options such as gaining a cognitive edge, preventing age-related decline, maintaining cognitive skills, or recovering from an injury. Next, the birthdate is requested, and the training is configured based on the provided information. Depending on the selected options, games are presented, describing the type of game and the necessary instructions to perform it. BrainHQ offers effective feedback during activities as users progress through the game. This feedback is presented in both written and auditory forms, explaining what the activity entails and how to perform it. Sounds, such as a “ding,” indicate when an error is made or a correct response is achieved. At the end of the game, the platform displays a message detailing general aspects related to the stimulated cognitive domain and how this contributes to improving cognitive health. Additionally, the challenges posed in the training aim to collect stars; it is necessary to complete a certain number of these to advance to the next level or challenge. Similarly, NeuroNation highlights errors made during activities and shows a small message indicating what the specific error was.

Regarding reports, CogniFit presents detailed results at the end of sessions, standing out for its specificity in showing results in specific cognitive functions. A significant feature of CogniFit is that it allows users to compare themselves only with groups of people who share their demographic similarities, ensuring that training feedback is more reliable and accurate. BrainHQ, on the other hand, offers detailed reports that include data on training days, accumulated stars, and completed levels. The most notable feature is the percentile where the participant is placed, obtained by comparing overall performance and in each exercise with other users of the application within the same age range, measured on a scale from 1 to 99. These percentiles help identify the skills in which the user is advancing and those in which they need improvement. Additionally, the reports allow participants to compare their results with others of the same age, dynamically adjusting the age bar in the graph to reflect these comparisons in the "PERFORMANCE DETAILS" area. In the case of NeuroNation, after completing the diagnostic test, the user is asked to select the age group with which they want to compare their results. The resulting statistics are shown as percentages on the 'Unfit' and 'Fit' scales. After the test, the user is asked about the desired training frequency and is redirected to subscription plans and costs. The general report includes a summary of the training frequency in the "Training Overview" option. The "Performance" tab evaluates the performance percentage in each stimulated cognitive skill, while the "Statistics" menu provides information related to progress in each completed challenge based on previous results. Additionally, the "Achievements" section uses a motivation strategy that allows users to achieve milestones and earn medals as they progress in their training.

In the evaluation of the studies, only four identified the use of errors as a key parameter for improving patient performance measurement. According to Kim et al. (2018), errors are used to measure both accuracy and response time. Similarly, Navarro et al. (2018) determined performance using the Euclidean norm, indicating that a lower value means better performance; that is, fewer errors result in less time required to complete tasks. Additionally, both Eun et al. (2022) and Baldisseri et al. (2022) documented errors made during training sessions to adjust task difficulty in their respective investigations.

Feedback in the Kim et al. (2018) study includes detailed reports that can be filtered by date, specifying training time, the number of responses, accuracy, and response time. A significant contribution of this research is the implementation of a spiral model for recommendations, based on Csikszentmihalyi's flow theory, which aims to keep patients in an optimal state of flow by adapting training recommendations based on patient performance and interests. Tsiakas et al. (2020) provide feedback during training to refine recommendations and measure engagement. Similarly, Antunes and Madeira (2021) facilitate the visualization of results obtained by patients, which can be shared among different clinics using the platform. Finally, Baldisseri et al. (2022) present patient performance data through charts that allow both the therapist and the patient to visualize progress over time.

4. Discussion

This literature review highlights the significant impact of artificial intelligence (AI) on improving and supporting cognitive health across various population groups. The reviewed studies show that among the main benefits of AI-assisted cognitive training programs are the possibility of remote access and decentralization of therapy. This feature allows direct linkage between the clinic and the activities the patient performs at home, thereby promoting continuity and coherence of treatment. Additionally, the adaptability of these platforms to different devices significantly enhances scalability and portability, optimizing usability and allowing users greater autonomy and continuous tracking of their progress.

Interaction with these systems also promotes a more comprehensive approach to stimulating various cognitive skills. The use of mobile and computational technologies not only facilitates the inclusion of multiple activities in games that simultaneously stimulate various cognitive domains but also leads to better treatment outcomes and a more holistic understanding of the participant's capabilities. The reviewed studies also highlight that the autonomy and flexibility provided by these programs increase users' sense of freedom, enhancing their motivation and adherence to treatment. This freedom translates into tangible improvements in the stimulated cognitive skills, demonstrating the significant impact of artificial intelligence in cognitive therapy.

Table 4. *General characteristics of applications meeting the inclusion criteria*

<table>
<tr><th>Characteristic</th><th>Lumosity</th><th>CogniFit</th><th>BrainHQ</th><th>NeuroNation</th></tr>
<tr><td>Cognitive Domains</td><td>Speed, memory, attention, flexibility, and problem-solving</td><td>Attention, memory, visual and spatial perception, processing speed, executive functions, language, motor coordination, and reasoning</td><td>Memory, attention, brain speed, interpersonal skills, navigation, and intelligence</td><td>Memory, logic, attention, and verbal skills</td></tr>
<tr><td>Target Population Age Range</td><td>No specific audience</td><td>Young and middle-aged adults, people with cognitive disorders. Children and adolescents</td><td colspan="2">Adults of all ages</td></tr>
<tr><td>Use of Intelligent Algorithms</td><td>Recommendation system with collaborative filtering and machine learning</td><td>Recommendation system with collaborative filtering and automated evaluations</td><td>Recommendation system with collaborative filtering and dynamic adaptation systems</td><td>Recommendation system with collaborative filtering and machine learning</td></tr>
<tr><td rowspan="5">Actions Controlled by Intelligent Algorithms</td><td>Recommendation of exercises for each training session based on the user's individual performance</td><td colspan="2">Recommendation of exercises for each training session based on usage history and cognitive needs</td><td>Recommendation of exercises for each training session based on usage history and cognitive goals</td></tr>
<tr><td>Uses algorithms to adapt games and exercises according to the user's individual performance.</td><td colspan="2">Uses algorithms to personalize training according to the user's needs and progress in specific areas.</td><td>Uses algorithms to adapt the difficulty of exercises and maximize the user's cognitive progress.</td></tr>
<tr><td colspan="4">Prediction of future performance and probability of achieving cognitive goals.</td></tr>
<tr><td colspan="4">Manages exercise difficulty according to the user's performance, increasing or decreasing the difficulty level.</td></tr>
<tr><td>User classification based on demographic characteristics, skill levels, and usage patterns.</td><td>Grouping users by age for effective personalization.</td><td colspan="2">Classification of users into different groups based on demographic characteristics for report visualization.</td></tr>
<tr><td>Feedback/Error Management</td><td>During the test: yes, indicates with an x when an error occurs.

Provides general information about the skill being stimulated at the beginning of the exercise.</td><td>Indicates with an x when there are errors.

No feedback about the test or the importance of stimulating it.</td><td colspan="2">Indicates with an auditory stimulus when correct or incorrect.

Explains in writing and sound which skill is being stimulated with the exercise, and how stimulating that cognitive domain is useful in real life.</td></tr>
</table>

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Table 5 summarizes the characteristics identified in the studies collected from various scientific databases. There is a predominant preference for commercial software that mainly stimulates memory, attention, and executive functions. These studies are specific and focus on presenting cognitive rehabilitation platforms to support treatments for diseases that impact cognitive function, with a focus on specific populations such as older adults and children.

Regarding intelligent algorithms, the frequent use of recommendation systems with collaborative filtering combined with K-means to group patients and make more accurate predictions about the necessary exercises in each training session is evident. Some studies incorporate fuzzy logic systems to dynamically and in real-time adjust game difficulty, as well as other machine learning strategies and neural networks.

A notable contribution is the development of a feedback system based on explainable artificial intelligence (XAI), which, according to Tsiakas et al. (2020), has interesting applicability in cognitive stimulation, allowing “to promote self-regulated learning skills in children, taking into account individual differences in skills, preferences, and learning needs” (p. 2). Additionally, the spiral model proposed by Kim et al. (2018) aims to improve exercise performance by increasing patient interest and adapting to their capacity. This model employs “Csikszentmihalyi’s flow theory to induce a state of immersion through motivation and interest, as well as using Jesse’s fractal pattern to model the training process with an appropriate difficulty level” (p. 39), aiming to challenge patients and offer a space for relaxation and mental tranquility that favors the continuity of treatment.

Table 5. *Summary of General Characteristics of Scientific Studies*

Study Title	Authors	Year	Domains	Target Population Age Range	Use of Intelligent Algorithms	Actions Controlled by Intelligent Algorithms	Feedback and Error Management
Personalized recommendation system for efficient integrated cognitive rehabilitation training based on bigdata	Kim et al. (2018)	2018	Memory, Executive Function, Concentration, Activities of Daily Living (ADL), Attention, and Orientation	60 to 90 years with mild cognitive impairment	Collaborative filtering system, K-means algorithm	Personalized cognitive training, Difficulty levels	Uses errors to measure accuracy and response time, Detailed reports, Spiral model
Fuzzy adaptive cognitive stimulation therapy generation for Alzheimer's sufferers: Towards a pervasive dementia care monitoring platform	Navarro, et al., (2018)	2018	Memory, Attention, Language, Gnosis, Executive Functions, Calculation, and Orientation	66 to 85 years with cognitive impairment	K-means algorithm, Recommendation system, Fuzzy Logic	Personalized cognitive training, Session difficulty	Uses error count to measure performance
BrainHood: Towards an explainable recommendation system for self-regulated cognitive training in children y BrainHood: Designing a cognitive training system that supports self-regulated learning skills in children	Tsiakas, et al., (2020)	2020	Executive functions, self-regulation, and metacognition	Children with learning disorders	Collaborative filtering recommendation system, Explainable AI	Target score, Task selection, Success probability/ selection	Uses comments during training to refine recommendations and measure engagement
An Integrated Music and Artificial Intelligence System in Support of Pediatric Neurorehabilitation	Baldisseri, et al., (2022)	2020	Memory, motor coordination, language, memory, attention, and processing speed	Children with neurological diseases	Neural networks	Real-time difficulty level depending on player's abilities	Uses error frequency as another parameter to adjust difficulty, Performance data visualized through graphs
Research on children's cognitive development for learning disabilities using recommendation method	Shen & Xu, (2021)	2020	Memory, attention, speed, flexibility, and logic	Children with learning problems	Collaborative filtering recommendation systems, K-means algorithm	Target score, Recommend cognitive training elements	
PLAY - Model-based Platform to Support Therapeutic Serious Games Design	Antunes & Madeira, (2021)	2021	General cognitive and emotional domains	Children with learning problems	Recommendation system	Suggests games	Allows visualization of results, which can be shared among different clinics using the platform
Development and Evaluation of an Artificial Intelligence–Based Cognitive Exercise Game: A Pilot Study	Eun, Kim, & Kim, (2022)	2021	Memory, attention, logic, processing speed, visual processing	60 to 80 years with cognitive impairment	Machine learning models	Difficulty level	Uses error frequency as another parameter to adjust difficulty
Expert System for Neurocognitive Rehabilitation Based on the Transfer of the ACE-R to CHC Model Factors	Kotyrba, et al., (2022)	2022	Memory, attention, language, visuospatial skills	Patients with brain injuries	Fuzzy logic	Personalized cognitive training sessions	

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5. Conclusion

This literature review highlights the significant research potential of artificial intelligence (AI) in supporting and enhancing cognitive health across a wide range of population groups. The analyzed studies demonstrate that one of the most relevant benefits of AI-assisted cognitive training programs is their ability to integrate and adapt multiple activities that simultaneously stimulate various cognitive domains. This not only optimizes treatment outcomes but also provides a more comprehensive understanding of the participant's capabilities.

In particular, recommendation systems using collaborative filtering combined with K-means algorithms have proven effective in personalizing and adjusting the difficulty of exercises in these therapies. These systems facilitate more precise interventions tailored to the individual needs of users, thereby improving treatment efficacy. Additionally, the implementation of explainable artificial intelligence (XAI) in this field represents an innovative advancement offering considerable opportunities. XAI significantly enhances the quality of feedback provided to users, making it more detailed and comprehensible. This clarity not only allows users to identify areas for improvement but also helps them understand the cognitive processes they are working on, boosting their self-efficacy and motivation.

References

Antunes, A., & Madeira, R. (2021). PLAY - Model-based Platform to Support Therapeutic Serious Games Design. Procedia Computer Science, 198, pp. 211-218. doi: https://doi.org/10.1016/j.procs.2021.12.230

Bainbridge , K., & Mayer, R. (2017). Shining the Light of Research on Lumosity. Journal of Cognitive Enhancement, 2, pp. 43-62. doi: https://doi.org/10.1007/s41465-017-0040-5

Baldisseri, F., Maiani, A., Montecchiani, E., Delli Priscoli, F., Giuseppi, A., Menegatti, D., & Fogliati, V. (2022). An Integrated Music and Artificial Intelligence System in Support of Pediatric Neurorehabilitation. Healthcare, 10(10), pp. 1-11. doi: https://doi.org/10.3390/healthcare10102014

Barocas, S., Hardt, M., & Narayanan, A. (2023). Classification. Fairness and machine learning Limitations and Opportunities. London: The MIT Press, pp. 49-80.

Barranco, M., Pérez , L., & Martinez, L. (2006). Un Sistema de Recomendación Basado en Conocimiento con Información Lingüística Multigranular. In Proceedings of the SIGEF XIII: Optimization techniques: Fuzziness and nonlinearity for management and economy, pp. 645-664.

Berrío, A. (2020). Sistemas de Recomendación, tesis (Grado en Estadística), Valladolid. Universidad de Valladolid, España, p. 4. http://uvadoc.uva.es/handle/10324/43778.

Bhareti, K., Perera, S., Jamal, S., Pallege, M. H., Akash, V., & Wiieweera, S. (2020). A Literature Review of Recommendation Systems. 2020 IEEE International Conference for Innovation in Technology (INOCON). Bangluru, India, pp. 1-7. doi: https://doi.org/10.1109/INOCON50539.2020.9298450

BrainHQ. (23 de 11 de 2015). Posit Science lanza programa de entrenamiento cerebral en español. Obtenido de https://www.brainhq.com/news/latest-news/posit-science-lanza-programa-de-entrenamiento-cerebral-en-espanol/

BrainHQ. (08 de 04 de 2024). BrainHQ: Personalized Training. Obtenido de https://support.brainhq.com/hc/en-us/articles/360033432171-How-the-Personal-Trainer-picks-exercises

Budianto, I., Yusrotis, A., & Sari, A. (s.f.). Web Based Video Games Recommendation System Using Collaborative Filtering Method. 2023 International Conference on Informatics, Multimedia, Cyber and Information Systems (ICIMCIS), pp. 549-554. doi: https://doi.org/10.1109/ICIMCIS60089.2023.10348983

CogniFit. (s.f.). Evaluaciones cognitivas. Recuperado el 28 de 02 de 2024, de https://www.cognifit.com/ec/test-cognitivo#:~:text=La%20Evaluaci%C3%B3n%20Cognitiva%20para%20conductores,visual%20y%20tiempo%20de%20respuesta

CogniFit. (s.f.). Individualized Training System™ (ITS): Personalized Brain Fitness Programs. Recuperado el 02 de 28 de 2024, de https://www.cognifit.com/cognifit-individualized-training-system

Cortés Luque, E. (s.f.). Sincrolab: Inteligencia artificial para entrenar el cerebro. Recuperado el 24 de 02 de 2024, de https://blogthinkbig.com/peoplefirst/sincrolab-inteligencia-artificial

Eun, S., Kim, E., & Kim , J. (2022). Development and Evaluation of an Artificial Intelligence–Based Cognitive Exercise Game: A Pilot Study. Journal of Enviromental and Public Health, pp. 1-15. doi: https://doi.org/10.1155/2022/4403976

Fajardo Cuéllar, A., & Wobbeking Sánchez, M. (2020). Programa de intervención para estimular la reserva cognitiva en el enjecimiento activo. Studia Zamorensia, XIX, 19, pp. 91-101.

González-González , C., Toledo-Delgado, P., Muñoz-Cruz, V., & Torres-Carrión, P. (2019). Serious games for rehabilitation: Gestural interaction in personalized gamified exercises through a recommender system. Journal of Biomedical Informatics, 97, pp. 1-19. doi: https://doi.org/10.1016/j.jbi.2019.103266

Hardy, J., & Scanlon, M. (2009). The sciencia behind Lumosity. Obtenido de https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=17e03b5d406520ea079533c30f4fbbbb72bb7178

Herpich, M., Rist, T., Seiderer, A., & Andre, E. (s.f.). Towards a Gamified Recommender System for the Elderly. DH '17: Proceedings of the 2017 International Conference on Digital Health. London, United Kingdom, New York: United States, pp. 211-215. doi: https://doi.org/10.1145/3079452.3079500

Hyman, K. (2017). Is Lumosity an effective brain training program?: A meta-analysis of the existing research. Carolina del Norte: Western Carolina University. Obtenido de https://api.semanticscholar.org/CorpusID:149209529

Imbeault, F., Bouchard, B., & Bouzouane, A. (2011). Serious Games in Cognitive Training for Alzheimer's Patients. 2011 IEEE 1st International Conference on Serious Games and Applications for Health (SeGAH), Braga, Portugal, pp. 1-8. doi: https://doi.org/10.1109/SeGAH.2011.6165447

Jara Madrigal, M. (2008). Estimulación cognitiva en personas adultas mayores. Revista Cúpula, 22(2), pp. 4-14.

Kim, J. J., Kim, Y.-J., Lee, H.-M., Lee, S.-H., & Chung, S.-T. (2018). Personalized Recommendation System for Efficient Integrated Cognitive Rehabilitation Training Based on Bigdata, Stephanidis, C. (eds) HCI International 2018 – Posters' Extended Abstracts. HCI 2018. Communications in Computer and Information Science, vol 851, Cham: Springer, pp. 32-39. doi: https://doi.org/10.1007/978-3-319-92279-9_4

Kotyrba, M., Habiballa, H., Volná, E., Jarušek, R., Smolka, P., Prášek, M., . . . Kulišťák, P. (2022). Expert System for Neurocognitive Rehabilitation Based on the Transfer of the ACE-R to CHC Model Factors. Expert System for Neurocognitive Rehabilitation Based on the Transfer of the ACE-R to CHC Model Factors, 11(1), pp. 1-19. doi: https://doi.org/10.3390/math11010007

Kpolovie, P. (2012). Lumosity training and brain-boosting food effects on learning. Education Research Journal , 2(6), pp. 217-230.

Laseno, F., & Hendradjaya, B. (2019). Knowledge-Based Filtering Recommender System to Propose Design Elements of Serious Game. 2019 International Conference on Electrical Engineering and Informatics (ICEEI), Bandung, pp. 158-163. doi: https://doi.org/10.1109/ICEEI47359.2019.8988797

Lumos Lab. (16 de Marzo de 2017). Meet Lumosity's Research Team. Obtenido de https://www.lumosity.com/en/blog/meet-lumositys-research-team

Mahncke, H. (2020). How can I compare my performance to others? Obtenido de https://support.brainhq.com/hc/en-us/articles/360031596611-How-can-I-compare-my-performance-to-others

Martínez Ferreras, D. (2017). . Sistemas automatizados de gestión de tesauros. Tesauros en línea. Los tesauros. Barcelona, pp. 31-34, Universidad Oberta de Cataluya. https://openaccess.uoc.edu/bitstream/10609/236/9/Fundamentos%20de%20lenguajes%20documentales_M%C3%B3dulo5_Los%20tesauros.pdf

Mateer, C. (2003). Introducción a la rehabilitación cognitiva. Avances en Psicología Clínica Latinoamericana, 21, pp. 11-20.

Navarro , J., Faiyaz , D., Zamudio, V., Iqbalc, R., Kumar Sangaiah, A., & Lino, C. (2018). Fuzzy adaptive cognitive stimulation therapy generation for Alzheimer's sufferers: Towards a pervasive dementia care monitoring platform. Future Generation Computer Systems, 88, pp. 479-490. doi: https://doi.org/10.1016/j.future.2018.06.018

O'Connor, D., Green, S., & Higgins, J. (2008). Defining the Review Question and Developing Criteria for Including Studies. En T. J. Higgins JPT, Cochrane Handbook for Systematic Reviews of Interventions. Chichester, pp. 81-94, John Wiley & Sons. doi: https://doi.org/10.1002/9780470712184.ch5

Ogata, H., Flanagan, B., Takami, K., Dai, Y., Nakamoto, R., & Takii, K. (2023). EXAIT: Educational eXplainable Artificial Intelligent Tools for personalized learning. Research and Practice in Technology Enhanced Learning, 19, pp. 1-30. doi: https://doi.org/10.58459/rptel.2024.19019

Page, M., McKenzie, J., Bossuyt, P., Boutron, I., Hoffmann 5, T., Mulrow, C., . . . Brennan, S. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ, 372(70). doi: https://doi.org/10.1136/bmj.n71

Peña, S., & Raymondi, W. (2023). Análisis de las predicciones en un filtro colaborativo basado en el algoritmo ALS para una empresa de comida rápida en la ciudad de Guayaquil. Guayaquil, pp. 16-47, Editorial Tecnocientífica Americana. doi: https://doi.org/10.51736/eta.vi.58

Prins, P. &. (2013). “Braingame Brian”: Toward an Executive Function Training Program with Game Elements for Children with ADHD and Cognitive Control Problems. Games for Health Journal, 2(1), pp. 44-49. doi: https://doi.org/10.1089/g4h.2013.0004

Rennie, J., Zhang, M., Hawkins, E., Bathelt, J., & Astle, D. (2020). Mapping differential responses to cognitive training using. Dev Sci, 23(12868), pp. 1-15. doi: https://doi.org/10.1111/desc.12868

Rocha, R., Fernandes, S., & Santos, I. (2023). The Importance of Technology in the Combined Interventions of Cognitive Stimulation and Physical Activity in Cognitive Function in the Elderly: A Systematic Review. Healthcare, 11(17), pp. 1-20. doi: https://doi.org/10.3390/healthcare11172375

Rosell, J. (2018). Estimulación cognitiva para personas mayores sanas mediante programas computarizados: una revisión de la literatura. Estudios de Psicología = Studies in Psychology, 39(2-3), pp. 421-436. doi: https://doi.org/10.1080/02109395.2018.1494678

Shahmoradi, L., Mohammed, F., & Rahmani, M. (2022). A Systematic Review on Serious Games in Attention Rehabilitation and Their Effects. Behavioural Neurology, pp. 1-32. doi: https://doi.org/10.1155/2022/2017975

Shen, X., & Xu, C. (2021). Research on children’s cognitive development for learning. Concurrency Computat Pract Exper, 33(6097). doi: https://doi.org/10.1002/cpe.6097

Synaptikon GmbH. (s.f.). Neuronation. Recuperado el 21 de 02 de 2024, de https://www.neuronation.com/science/fr/la-science-derriere-neuronation/

Tetlow, A., & Edwards, J. (2017). Systematic Literature Review and Meta-Analysis of Commercially Available Computerized Cognitive Training Among Older Adults. Journal of Cognitive Enhancement, pp. 559-575. doi: https://doi.org/10.1007/s41465-017-0051-2

Trápaga-Ortega, C., Pelayo-González, H., Sánchez-Ortiz, I., Bello-Dávila, Z., & Bautista Baños, A. (2018). De la psicología cognitiva a la neurosicología. Madrid: El manual moderno, pp. 20-83.

Tsiakas, K., Barakova, E., Khan, J.-V., & Markopoulos, P. (2020). BrainHood: Designing a cognitive training system that supports self-regulated learning skills in children. Technology and Disability, 32(4), pp. 219-228. doi: https://doi.org/10.3233/TAD-200294

Valenzuela, M., & Sachdev, P. (2005). Brain reserve and dementia: a systematic review. Psychological Medicine, 36(4), pp. 441-454. doi: https://doi.org/10.1017/S0033291705006264

Villalba Agustín, S., & Espert Tortajada, R. (2014). Estimulación cognitiva: Una revisión neuropsicológica. Therapeía, 6, pp. 73-94.

Wilms, I. (2011). Using Artificial Intelligence to Control and Adapt Level of Difficulty in Computer-Based, Cognitive Therapy – an Explorative Study. Journal of Cyber Therapy and Rehabilitation, pp. 387-396.

Yue, L., Chen, W.-g., Liu, S.-c., Chen, S.-b., & Xiao, S.-f. (2023). An explainable machine learning based prediction model for Alzheimer's disease in China longitudinal aging study. Frontiers in aging neuroscience, 15. doi: https://doi.org/10.3389/fnagi.2023.1267020

Yun, Y., Dai, H., Zhang, Y., Wei, S., & Shang, X. (2022). Interpretable Educational Recommendation: An Open Framework based on Bayesian Principal Component Analysis. Conference: 2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 3409-3414. doi: https://doi.org/10.1109/SMC53654.2022.9945498

Zamarrón, M. (2007). Envejecimiento activo: un reto indivudial y social. Sociedad y utopía: Revista de ciencias sociales, 34, pp. 449-463.