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Artificial Intelligence in Physical Therapy for Neurological Rehabilitation: A Systematic Mapping Study

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ABSTRACT Neurological diseases represent a major global health burden, with stroke alone ranking as the second leading cause of mortality and disability. Physical rehabilitation is essential for minimizing impairments and improving quality of life for neurological patients. However, traditional rehabilitation faces significant challenges including high costs, and limited access to specialized staff. Information Technology (IT) systems, particularly those incorporating Artificial Intelligence (AI), have emerged as promising solutions to address these rehabilitation challenges. We present a Systematic Mapping Study (SMS) that analyses studies addressing the challenges of physical rehabilitation for neurological diseases through AI applications. There have been similar SMSs analysing AI on physical rehabilitation, but none were focused on neurological diseases, which require special attention due to their socioeconomic impact. 53 primary studies from the literature were included and analysed in our study. The results indicate that AI has been used to effectively support the rehabilitation of neurological diseases. Machine Learning (ML) techniques, and in particular Convolutional Neural Networks (CNNs), are the most frequently employed approaches. We also identify that most studies lack disease-specific adaptations, representing a major opportunity for improvement. Additionally, we applied the knowledge acquired in this study to our own line of research on the topic, which uses fuzzy logic to adjust rehabilitation routines automatically.

INDEX TERMS physical rehabilitation, mapping study, artificial intelligence, neurological diseases

I. INTRODUCTION

Neurological diseases are one of the major causes of death and disability around the world. Stroke, the most prevalent neurological disease, contributes to approximately 116 million disability-adjusted life years globally, and ranks as the second leading cause of mortality and disability [1]. Parkinson's Disease (PD) patients also suffer from a serious deterioration of their physical abilities, and in particular of gait impairment [2]. Furthermore, the impact of neurological diseases is set to increase in the next decade [3]. The effect will be particularly pronounced in low-income countries, where access to adequate care is limited. [4].

In order to minimize the physical impairments of neurological diseases, and increase the quality of life of patients, it is important that they take part in consistent physical rehabilitation under the supervision of a therapist. However, physical rehabilitation is expensive, and not accessible to many sectors of the population. One of the major reasons for the high cost of rehabilitation is the relative shortage of trained physicians to execute the rehabilitation [1]. Additionally, many patients must travel to specialized centers or hospitals to receive such care, which increments the financial burden. Finally, even in the cases where physical rehabilitation is accessible, physical rehabilitation is provided at a reduced proportion once the acute and sub-acute phases end. This happens despite the persistence of motor deficits in patients. Progressive deconditioning and learned non-use further drive functional decline in motor capabilities [5].

Following these obstacles, a fundamental challenge found within the rehabilitation itself is the task challenge, which is a poorly understood concept. The ambiguity of this term, which lacks a clear definition, leads to inconsistent clinical practices and risks overlooking the patient's subjective experience. The consequences of a non-optimal challenge level are severe. When a task is too easy, it results in minimal learning and can lead to patient boredom and disengagement. Conversely, if the challenge is too high, it can make recovery unrealistic, causing frustration, anxiety, safety risks, and ultimately, the abandonment of rehabilitation. Therefore, a clear and shared understanding of task challenge is critical to provide effective, consistent, and patient-centered care. [6].

As a response to these challenges, many studies in the literature proposed to alleviate the burden of neurological diseases with the support of IT systems [7]. The desired results of these proposals are diverse. Many studies were focused on automating parts of the rehabilitation process to reduce the workload of therapists [8], [9]. By reducing the workload of therapists, they can decrease the costs and increase the effectiveness of rehabilitation. One task that is commonly automated in the literature is the automatic evaluation of the performance of patients as they execute the rehabilitation exercises [10], [11].

Some studies in the literature were based on immersive technologies such as Augmented Reality (AR) [12], [13] and Virtual Reality (VR) [14], as well as robotic-based rehabilitation [15], [16], which aim to increase the consistency of patients by making rehabilitation more motivating. Other studies seek to facilitate the implementation of home rehabilitation [17], [18], which greatly reduces the costs by eliminating the need for transportation. Additionally, it can make rehabilitation available in areas with lower resources and increase adherence to the rehabilitation by reducing friction barriers.

In many of the studies applying IT to rehabilitation, AI is an essential aspect of the proposed system. AI can help implement many of the automations that are required for the achieving the desired goals. Many AI technologies have been tested, with the main focus being on ML techniques that benefit from high availability of data collected from sensors. In particular, Artificial Neural Networks (ANNs) and CNNs are used fairly often in the literature.

In this study we present a SMS of the most relevant papers that have addressed the challenges of physical rehabilitation of neurological diseases specifically through the application of AI techniques. The selected works were analysed based on the AI techniques used, and the way the proposed system supports rehabilitation. It is the right time for performing a SMS on this topic, as there is a growing interest in the application of AI to physical rehabilitation. This is evident in the increasing number of studies that are focused on this theme. Additionally, our line of work, which falls within the scope of this SMS, will benefit from its findings. It enables us to identify the most commonly used approaches and techniques in the literature, and detect unexplored lines of work to advance our research.

There have been other reviews addressing topics similar to this SMS. However, their scope and their Research Questions (RQs) differ enough to justify this review. Sardari et al. [19] evaluated the application of AI exclusively for the evaluation of rehabilitation performance. While a significant portion of studies were focused on evaluating the performance of patients, this scope neglects other applications of AI and limits applicability to broader rehabilitation systems. Mennella et al. [20] considered only home-based rehabilitation and omitted proposals that could be employed in a rehabilitation centre. The topic of the survey is significant, as home rehabilitation is a promising alternative to traditional rehabilitation. However, that scope misses a significant portion of the literature that is only viable in specialized rehabilitation centres. Gupta [21] focused on cognitive rehabilitation of neurological disorders, rather than physical therapy. The scope of this survey tackles another significant issue for neurological diseases, which is the effect they have on cognitive function. Nevertheless, there is small overlap between the studies being surveyed by this review and our SMS. Sumner et al. [22] only included studies that assessed the clinical effectiveness of their proposals, excluding developmental work. Additionally, their review included studies that were not focused on neurological diseases. Including only studies that assess clinical effectiveness ensures the rigor of the results, but such an strict inclusion criterion excludes developmental work, potentially overlooking emerging techniques and proposals. Our SMS focuses on neurological diseases due to their global socioeconomic impact, and the expected rise in this impact in the coming years.

The remainder of the article is structured as follows. Section II presents the methodology followed in our study, and analyses the threats to validity. Next, Section III offers an overview the selected studies. Then, Section IV presents the results of our study and answers the RQs. After that, Section V analyses our own proposal with the knowledge obtained in this work. Section VI discusses the limitations of our study. Finally, Section VII draws the conclusions of this paper, and propose future lines of work.

II. RESEARCH METHODOLOGY

In this section, the employed methodology for the SMS will be detailed. It is based on common guidelines for SMSs in the domain of software engineering [23], [24]. The design of the methodology was an iterative process; it was improved and refined with the results of preliminary executions. The methodology consists of 5 phases, with each phase described in the corresponding subsection: (1) definition of the research questions, (2) definition of the search strategy, (3) study selection, (4) data extraction, and (5) validity evaluation. Next, each one of these phases is presented.

A. DEFINITION OF THE RESEARCH QUESTIONS

The main objective of this SMS is to study the applications of AI-based systems to the physical rehabilitation of neurological disease patients. The main objective of the SMS has been divided into multiple RQs. These are concerned with the techniques and purpose of the studies. Regarding the techniques used, our interest lies in AI techniques, and the approach taken by the authors for supporting rehabilitation. In relation to the purpose of the studies, our interest revolves around the neurological diseases and the parts of the body that are supported by the proposals. Additionally, the degree of validation of the studies has also been considered. All the research questions are listed in Table 1, along with their specific motivation.

B. SEARCH STRATEGY

The goal of this phase is to define the strategy that will be followed for discovering studies that may address the RQs of this work. It consists in the definition of the search string, and the selection of the academic databases where the search string was used. The search string was defined by employing a systematic approach. Search terms related to the goal of the SMS were selected, and each term was given alternative definitions to ensure that studies with different wordings were included. These are shown in Table 2, along with the assembled search string. There is a risk of scope drift, where non-rehabilitation AI topics may be included accidentally. To mitigate it, all candidate studies were reviewed manually to ensure that the paper fits the scope of the study. This was in addition to requiring that candidate studies include an alternative search term related to physical rehabilitation. To mitigate it, in addition to requiring an alternative search term.

The search string was applied to the title, the abstract, and the keywords of the candidate studies. Additionally, the definition of the search string was an iterative process. After being defined, the search string was tested, and the results were used to improve the search string. This procedure was repeated multiple times to ensure that the maximum number of relevant studies to the SMS were included.

After defining the search string, the selected academic databases were Scopus and PubMed. Both were selected because they are among the largest digital libraries for academic articles. Scopus indexes a large number of articles from multiple disciplines, while PubMed is specialized in healthcare studies, which are partially related to the topic of this work. IEEE Xplore and Web of Science were discarded as academic databases due to the large overlap of results with Scopus and PubMed. Google Scholar was not used because the number of results not matching the selection criteria was excessive. These issues were detected in the first iterations of the search strategy definition.

C. SELECTION CRITERIA

In this phase, our goal is to select the relevant studies from the search results. The first step was the elimination of duplicate studies that were found in both academic databases. Then, each primary study was reviewed, and the inclusion and exclusion criteria were applied in two steps. All the criteria except for the quality assessment were applied, and the studies that did not meet the criteria were marked as *Excluded*. The remaining studies went through an exhaustive review process, where the quality was assessed. The inclusion and exclusion criteria are shown in Table 3. To assess the quality, a questionnaire based on a Likert scale has been defined. Each question can be answered with *Strongly disagree* (-2), *Disagree* (-1), *Neither agree nor disagree* (0), *Agree* (1), or *Strongly agree* (2). A study needed to achieve a total score of at least 1 in order to be included. The questionnaire is as follows:

- Does study report clear, unambiguous findings based on evidence?
- Is the sample size of the study adequate?
- Does the study clearly describe the proposed system?
- Were the limitations of the study detected and addressed?
- Is the study reproducible/replicable?

A total of 231 studies were identified in the literature as candidate studies. Then, 24 studies were removed for being duplicates. Next, 113 studies were removed for not meeting the inclusion and exclusion criteria, with the exception of the quality assessment. Finally, the remaining 94 studies underwent the quality assessment process, and out of those, 53 were included in the SMS. Studies excluded at this stage were generally relevant to the scope of the SMS, but did not satisfy enough of the quality criteria.

TABLE 1: Research Questions and their motivation

ID	Question	Motivation
RQ1	Which AI techniques are used?	Analyse the techniques used in the literature and discover unexplored lines of work.
RQ2	Which neurological diseases are supported?	Determine which diseases are supported by the prototypes in the literature.
RQ3	To which extent has the effectiveness of systems been tested with patients?	Determine the extent to which the state of the art has been validated.
RQ4	What aspects of physical rehabilitation are supported by the system?	Study the body parts whose rehabilitation is supported with AI.
RQ5	What type of system are proposed?	Know different approaches to supporting physical rehabilitation using AI.

TABLE 2: Systematic definition of the search string

Main Search Term	Alternative Search Terms
Artificial Intelligence	artificial intelligence OR machine learning OR artificial neural network OR convolutional neural network OR recurrent neural network OR expert system OR fuzzy logic OR LLM OR large language model OR generative ai
Neurological Disease	neurological disease OR neurological disorders OR ALS OR Parkinson OR muscular dystrophy OR stroke OR Cerebrovascular accident OR brain attack OR ischemic attack
Physical Rehabilitation	physical rehabilitation OR physical therapy OR virtual rehabilitation OR functional therapy
Assembled Search String	
(artificial intelligence OR machine learning OR artificial neural networks OR convolutional neural network OR recurrent neural network OR expert system OR fuzzy logic OR LLM OR large language model OR generative ai) AND (neurological disease OR neurological disorder OR Parkinson OR muscular dystrophy OR stroke OR Cerebrovascular accident OR brain attack OR ischemic attack) AND (physical rehabilitation OR physical therapy OR virtual rehabilitation OR functional therapy)	

This was most commonly due to small sample sizes or a lack of discussion of study limitations. As seen on Figure 1, the number of publications in this area has increased significantly over time, reflecting a growing research interest.. The selection process is summarized by Figure 2.

D. DATA EXTRACTION

This phase is focused on the extraction of the data required to answer our RQs from the included studies. The data was extracted using the template defined on Table 4. This template includes the questions that are asked about each study, and possible answers that may be given to each question. The list of answers is not an exhaustive list. In addition, some questions may have multiple answers, depending on the study. Each question is associated with the RQ that it contributes to answer. To answer RQ5, two Data Extraction (DE) questions were defined.

E. THREATS TO VALIDITY

In this final step we detail the possible threats to validity of this SMS. Our analysis of the threats is based on the classification of the validity types suggested by Petersen et al. [25].

- **Descriptive validity**. It represents the degree to which observations are described precisely and objectively. We mitigated this threat by defining the data collection form during the definition of the research methodology.
- **Theoretical validity**. It consists in our ability to capture what we intend to capture. It can be divided into study identification and data extraction. To mitigate these threats, the research methodology was defined using an iterative approach. By adapting the methodology based on the preliminary results, we ensure that the studies omitted in the review are minimal, and that most of the relevant data for the RQs is extracted from the studies. However, the threats to data

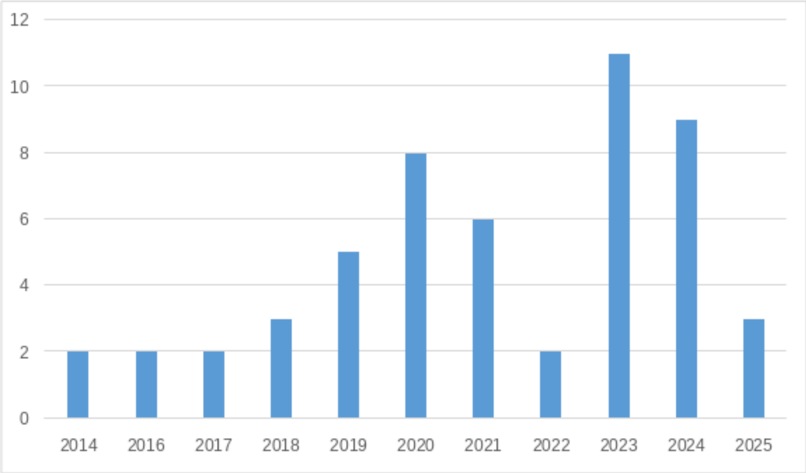

FIGURE 1: Overview of the publication year of the primary studies.

TABLE 3: Inclusion and exclusion criteria

Inclusion	• The search terms apply to the paper. • It is a journal article or a conference article. • It is written in English. • It was published between January 2013 and March 2025.
Exclusion	• It does not focus on AI-based systems applied to physical rehabilitation of patients with neurological diseases. • It does not focus on human patients. • It is a webpage or PowerPoint. • It is not a primary study. • It does not reach the minimum quality score required.

extraction cannot be eliminated, as they are based on human biases.

- **Generalisability**. It refers to the degree to which the findings and conclusions can be applied to contexts either covered by the primary studies (internal generalisability) or beyond the boundaries of the studies included in the review (external generalisability). This threat was minimized by selecting studies from a wide range of contexts within the scope of the SMS. However, the findings may not apply as accurately to studies that do not focus on neurological diseases.
- **Interpretive validity**. It is achieved when the results of the SMS are reasonable given the collected data. Its main threat is researcher bias. It has been reduced by involving multiple researchers in the analysis of the results.
- **Repeatability**. This threat has been mitigated by defining a research methodology based on guidelines for mapping studies [23], [24].

III. REVIEW OF SELECTED STUDIES

In this section, we will briefly review the selected studies, with similar studies will be discussed together. Studies will be grouped according to the type of system used (DE5), and the

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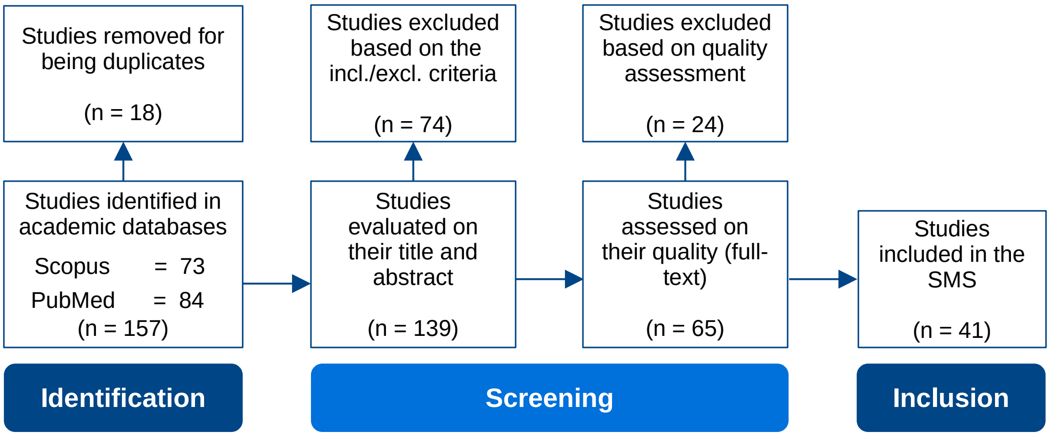

FIGURE 2: Summary diagram of the study selection process

TABLE 4: Data extraction template

RQ	DE	Question	Possible Answers
RQ1	DE1	Which AI techniques are used when implementing the system?	Rule system, Fuzzy logic, HMM, ANN, LLM...
RQ2	DE2	In which particular neurological disease is the system focused?	None, stroke, ALS, PD
RQ3	DE3	In which way was the system tested?	Synthetic data, Dataset, Tested with healthy individuals, Tested with patients...
RQ4	DE4	What aspects of physical rehabilitation are supported by the system?	UL rehabilitation, LL rehabilitation, hand rehabilitation, gait rehabilitation, ...
RQ5	DE5	What type of system was used?	AR-based system, Hand gesture recognition, rehabilitation performance evaluation, recommender system, ...
RQ5	DE6	Which sensors does the system require?	None, RGB Camera, IMU, sEMG, ...

aspect of physical rehabilitation that the system supports (DE4). Although system types are not mutually exclusive, each study will be included only once in the most relevant category. The studies have been summarized in Table 5. Additionally, the AI techniques used in the literature are shown in Figure 3. These include commonplace AI techniques such as Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN), but also less common ones, such as Gaussian Mixture Model (GMM), Linear Discriminant Analysis (LDA), Gradient Boosting Machine (GBM), Enhanced Probabilistic Neural Network (EPNN), Temporal Convolutional Neural Network (TCNN), Gated Recurrent Unit (GRU), and Mixture Density Network (MDN).

A. AUTOMATIC MOVEMENT CLASSIFICATION

A significant proportion of the selected studies implemented AI for the automatic classification of patient movements as they perform the rehabilitation routine. Here we will discuss those studies where the automatic classification of movements was the primary focus. Most proposed systems were focused on classifying upper limb movements. Chae et al. [17] classified movements using a smartwatch with a IMU for supporting home rehabilitation. David et al. [26] proposed a similar system that used an accelerometer instead. However, they found

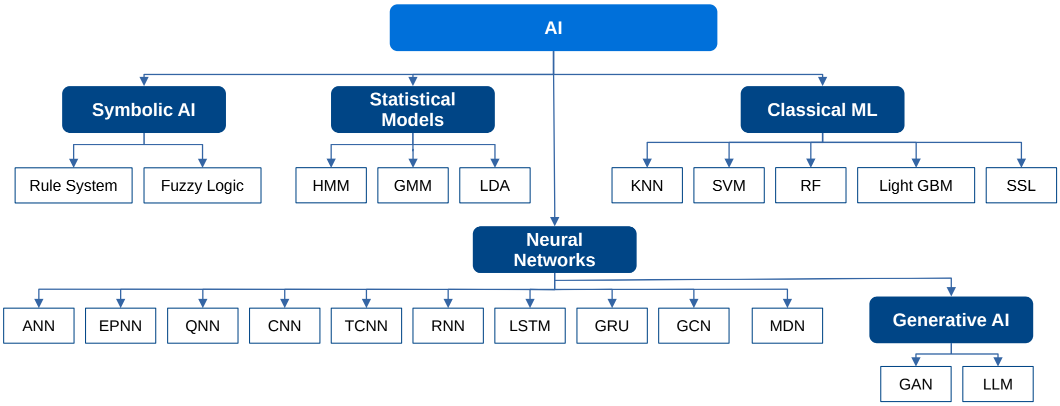

FIGURE 3: Taxonomy of the AI techniques used by the selected primary studies.

the real-time recognition accuracy to be significantly lower than the accuracy tested with their dataset. Oh et al. [27] used an IMU for tracking activities of daily living, and they observed that their model performance in the stroke patients was affected differently by movement asymmetry. Microsoft Kinect, which is composed of an RGB with Depth (RGB-D) camera, has been used extensively in the literature for supporting physical rehabilitation. Cary et al. [28] detected gestures with the Microsoft Kinect by analyzing sequences of poses. Burns et al. [29] employed an sEMG sensor with an Enhanced Probabilistic Neural Network, and they found that it outperformed other classification models using the same sEMG features. Finally, Lui et al. [30] used Infrared (IR) sensors integrated on wearable devices combined with a SVM for movement classifications

Additionally, a significant number of studies were centered on identifying hand movements automatically using a multitude of sensors. Chandrasekhar et al. [31] used sEMG as a sensor for hand movement identification, and they found that they needed as many electrodes as the number of hand movements that they wanted to classify. Fu et al. [32] used sEMG combined with Electroencephalography (EEG), and they found that halving the number of EEG channels did not significantly impact the performance of their AI models, while incrementing their interpretability. Xiao et al. [33] used force myography to detect hand movements when playing a virtual piano. Force myography uses force sensors rather than electrical sensors for detecting the force produced by muscles. They detected multiple limitations to this approach, such as the challenge of classifying dynamic gestures accurately. Butt et al. [34] proposed using IMU sensors, and Korti et al. [35] employed radio waves in their study. Butt et al. [34] proposed using IMU sensors, which measure the force and angular rate, and are generally used in wearable devices. Korti et al. [35] employed radio waves with extremely randomized trees in their study, and discovered that the inference times were low enough for real-time predictions. Finally, Xu et al. [8] used a regular RGB camera with an ANN for tracking hand movements during home rehabilitation.

Only a reduced number of studies focused on lower limb rehabilitation, with two studies focused on lower limb movement classification. Noor et al. [36] used sEMG sensors to analyse and classify ankle movements. However, they discovered that the accuracy of the classification decreased as the severity of the physical disability increased. Bisio et al. [18] created a prototype using multiple wireless nodes in wearable devices to recognize the exercises the patient performs and provide real-time feedback.

B. TECHNOLOGY-ENHANCED REHABILITATION

Some systems incorporate elements that enhance the rehabilitation process and make it more dynamic for the patient. These include robotic-based rehabilitation, VR systems and AR systems. Robotic-based rehabilitation utilizes robotic devices to support patients during therapeutic exercises. These devices can modify resistance levels, monitor progress, and deliver real-time feedback. Epeagba et al. [15] use ultrasound imaging to recognize motion intent in the context of a robotic based rehabilitation. Jumphoo et al. [37] process the signal of an EEG sensor to enhance rehabilitation with a robotic glove. Kumar et al. [38] detect error-related potentials from an EEG signal to implement a robotic rehabilitation system that assists patients according to their needs, and they found real-time detection of training error-related potentials to be viable with only a small delay. Jeter et al. [39] detected stroke severity when performing rehabilitation exercises with robotic gloves and shoes. Using neural networks, they achieved a high degree of accuracy.

There are few studies that focus on enhancing VR rehabilitation with AI techniques. Jacob et al. [14] employ machine learning to assess early stage Parkinson's Disease while patients perform physical rehabilitation exercises by means of a VR-based system. Saleh et al. [40] used an ANN to predict scores and facilitate remote monitoring in the context of a VR rehabilitation system.

AR-based systems have been used extensively for assisting physical rehabilitation. Kanade et al. [41] proposed an AR-based system that uses CNNs, providing live feedback to patients, and an overall performance score to physicians. Martins et al. [42] used the Microsoft Kinect to implement an AR system, and deep learning to detect the correct execution of the exercises. Martínez et al. [43] present a Decision Support System (DSS) to assist therapists by adjusting physical rehabilitation routines according to the data captured through the AR system. It is implemented using fuzzy logic Zadeh [44]. In a following paper [45], they improved their work by incrementing the Explainable AI (XAI) capabilities of their system, and by employing additional metrics. Similarly, Gmez-Portes et al. [13] used fuzzy logic to adjust the workload of a rehabilitation routine based on the data provided by the Microsoft Kinect. Zulkifley et al. [12] assess squat exercises with an RGB stream as input.

C. PATIENT PERFORMANCE ASSESSMENT

Other studies used AI to evaluate the performance of patients as they performed rehabilitation exercises and provide recommendations accordingly. Bijalwan et al. [46] used a Microsoft Kinect sensor with CNN for assessing the performance of patients, and they reported an accuracy of 98%. Murikipudi et al. [47] used a Microsoft Kinect sensor with skeleton markers and CNN to assess post-stroke exercises, and they achieved state-of-the-art results in public datasets. Fatema et al. [48] employed a pressure sensor to evaluate the accuracy of exercises involving weights. Kuang et al. [49] present a general framework for evaluating rehabilitation exercises from skeletal joint data. Wei et al. [10] propose a virtual physical therapist that evaluates exercises and provides guidance to patients using Hidden Markov Models (HMMs). Khalil et al. [50] used ML models to assess the mobility of PD patients.

Deb et al. [51] assessed performance using Graph Convolutional Networks (GCNs). Khan et al. [52] used Quantum Neural Networks (QNNs), although the execution was limited to simulated quantum circuits. Vakanski et al. [53] model human emotions during physical rehabilitation using a Recurrent Neural Network (RNN). Mazumder et al. [54] employed fuzzy logic to evaluate postural stability during the Single Limb Stance exercise. Sivarajkumar et al. [55] used Large Language Models (LLMs) to extract knowledge from physical rehabilitation notes. Rihana et al. [56] focused on assessing patient performance during Sit-To-Stand exercises using ANN, while Junkes-Cunha et al. [11] used a rule-based expert system that required manual intervention. They discovered that usability is one of the key features in an expert system for physiotherapy. Chen et al. [57] employed Generative Adversarial Networks (GANs) to automatically adjust the difficulty of rehabilitation routines, and they achieved more flexibility than other literature. Sitdhisanguan et al. [58] proposed an expert system for analyzing and customizing 3D exergames, and they found that patients stayed more time in therapy sessions. Finally, Rafiei et al. [59] created an ANN that supports assesses the likelihood of recovery in constraint-induced movement therapy.

D. GAIT AND SPASTICITY ANALYSIS

Finally, some studies were focused on evaluating the gait of patients, which is a relevant aspect of physical rehabilitation for certain neurodegenerative diseases, such as Parkinson's Disease [2]. Wei et al. [60] evaluated the balance of patients using a Microsoft Kinect sensor. Iseki et al. [61] used the iPhone's RGB-D camera, and while the processing speed is significantly slower than the Microsoft Kinect, they found in their study it was enough for physical rehabilitation. Park et al. [62] implemented ML models to identify optimal responders to Robotic-Assisted Gait Rehabilitation (RAGR). Tsakanikas et al. [63] proposed an approach for assessing gait impairment using IMU and pressure sensors, while Rezayat Sorkhabadi et al. [16] used a similar setup for controlling a robotic-based gait rehabilitation system. Kim et al. [64] identified fall-related balance predictors during RAGR. Reches et al. [9] applied machine learning to detect Freezing of Gait, a phenomenon that affects Parkinson's Disease patients. They found that the model output was positively correlated with clinical assessments and anti-parkinsonian medication withdrawal. Brand et al. [65] used wearable sensors with accelerators for detecting gait in older adults through Self-Supervised Learning (SSL). Bernad-Elazari et al. [66] employed body-fixed sensors worn for several days and machine learning methods to assess movement transitions, such as sit-to-walk and walk-to-sit. Kara et al. [67] used ANN to assess balance from tests performed by therapists.

Finally, a single study was focused on spasticity, which is the abnormal muscle contraction for prolonged periods of time. Kim et al. [68] assessed the severity of elbow spasticity using wearable inertial sensors, and they showed this approach to be effective for patients with a high Modified Ashworth Scale (MAS) score.

IV. DISCUSSION

The aim of this systematic mapping study is to analyse the state of the art in the application of Artificial Intelligence in the context of physical rehabilitation for patients of neurological diseases. In particular, the study should give knowledge of the types of AI techniques employed, the aspects of rehabilitation that are being supported, and the sensors that are employed in combination with AI. In this section, we present a discussion of the results obtained after executing the systematic mapping plan, discussing the main findings in each RQ. Each RQ corresponds with a DE question, except for RQ5, that has DE5 and DE6.

TABLE 5: Summary table of all the selected studies.

Paper	DE1	DE2	DE3	DE4	DE5	DE6
S01 [31]	SVM	stroke	Case study	Upper-limb	Hand gesture recognition	sEMG
S02 [41]	CNN,LSTM	stroke	Dataset	Upper-limb	AR,Performance eval.	RGB Camera,Kinect
S03 [46]	CNN,LSTM,GRU	stroke	Patients	Upper-limb	Performance eval.	Kinect
S04 [32]	CNN,GCN,LSTM	stroke	Dataset	Hand	Hand gesture recognition	sEMG,EEG
S05 [56]	ANN	None	Healthy indiv.	Full-body	Performance eval.	IMU
S06 [43]	Rule system,Fuzzy	stroke	Synthetic data	Upper-limb	AR,Performance eval.,RecSys	RGB Camera
S07 [10]	SVM,HMM	PD	Patients	Full-body	Performance eval.,RecSys	Kinect
S08 [11]	Rule system	None	Questionnaire	Full-body	Performance eval.,RecSys	None
S09 [68]	RF, SVM, ANN	None	Patients	Upper-limb	Spasticity evaluation	IMU
S10 [34]	SVM, ANN	stroke	Patients	Hand	Hand gesture recognition	IMU, SensHand
S11 [30]	SVM	stroke	Healthy indiv.	Upper-limb	UL movement classif.	IMU, IR sensors
S12 [35]	CNN	stroke	Dataset	Hand	Hand gesture recognition	IR-UWB
S13 [14]	ANN	PD	Patients	Full-body	VR,Performance eval.	sEMG,Heart,Pressure
S14 [15]	RNN,LSTM	stroke	Healthy indiv.	Upper-limb	UL movement classif.,Robotic	Ultrasound
S15 [48]	ANN	stroke	Dataset	Upper-limb	Performance eval.	Pressure
S16 [28]	ANN	stroke	Healthy indiv.	Upper-limb	UL movement classif.	Kinect
S17 [51]	GCN	None	Dataset	Full-body	Performance eval.	RGB-D Camera
S18 [58]	Rule system	stroke	Questionnaire	Upper-limb	RecSys	IR sensors
S19 [36]	ANN	stroke	Patients	Lower-limb	LL movement classif.	sEMG
S20 [60]	CNN	PD	Patients	Full-body	Gait Assessment	Kinect
S21 [37]	ANN	stroke, ALS	Healthy indiv.	Hand	Robotic	EEG
S22 [12]	TCNN	stroke	Healthy indiv.	Full-body	AR	RGB Camera
S23 [38]	SVM,CNN	stroke	Patients	Upper-limb	UL movement classif.,Robotic	EEG
S24 [17]	CNN	stroke	Patients	Upper-limb	UL movement classif.	IMU
S25 [8]	ANN	stroke	Dataset	Hand	Hand gesture recognition	RGB Camera
S26 [18]	RF	stroke	Patients	Lower-limb	LL movement classif.	IMU, Pressure
S27 [26]	RNN,LSTM	stroke	Patients	Upper-limb	UL movement classif.	IMU

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Table 5 (continued)

Paper	DE1	DE2	DE3	DE4	DE5	DE6
S28 [16]	GMM	stroke	Patients	Lower-limb	Gait Assessment,Robotic	IMU, Pressure
S29 [33]	ANN,KNN,LDA	None	Healthy indiv.	Hand	Hand gesture recognition	Force Myography
S30 [63]	SVM	PD	Patients	Lower-limb	Gait Assessment	IMU, Pressure
S31 [52]	QNN	stroke	Dataset	Full-body	Performance eval.	Kinect
S32 [61]	Light GBM	None	Patients	Lower-limb	Gait Assessment	RGB-D Camera
S33 [67]	ANN	None	Patients	Lower-limb	Gait Assessment	None
S34 [9]	SVM	PD	Patients	Lower-limb	Gait Assessment	IMU
S35 [29]	EPNN	stroke	Dataset	Upper-limb	UL movement classif.	sEMG
S36 [53]	MDN,RNN,LSTM	None	Dataset	Full-body	Performance eval.	Kinect
S37 [27]	CNN	stroke	Patients	Upper-limb	UL movement classif.	IMU
S38 [59]	EPNN	stroke	Patients	Upper-limb	Performance eval.	None
S39 [66]	SVM	PD	Patients	Lower-limb	Gait Assessment	IMU
S40 [13]	Rule system,Fuzzy	stroke	Case study	Upper-limb	AR,Performance eval.,RecSys	Kinect
S41 [54]	Rule system,Fuzzy	stroke	Patients	Full-body	Performance eval.	Kinect
S42 [39]	ANN,Light GBM	stroke	Patients	Full-body	Performance eval.,Robotic	IMU sensors,Pressure
S43 [42]	ANN	None	Questionnaire	Upper-limb	AR,UL movement classif.	Kinect
S44 [47]	CNN,LSTM	stroke	Dataset	Full-body	Performance eval.	Kinect
S45 [40]	ANN	None	Patients	Upper-limb	VR,Performance eval.	IMU sensors
S46 [49]	ANN	None	Dataset	Full-body	Performance eval.	None
S47 [45]	Rule system,Fuzzy	stroke	Patients	Upper-limb	AR,Performance eval,RecSys	RGB Camera
S48 [55]	Rule system,SVM,LLM	None	Dataset	Full-body	RecSys	None
S49 [57]	GAN	stroke	Synthetic data	Upper-limb	RecSys	IMU sensors
S50 [62]	RF,Light GBM	stroke	Patients	Lower-limb	Gait Assessment,Robotic	IMU sensors
S51 [65]	SSL	None	Patients	Lower-limb	Gait Assessment	IMU sensors
S52 [50]	RF	PD	Patients	Lower-limb	Performance eval.	IMU sensors
S53 [64]	SVM,RF	stroke	Patients	Lower-limb	Gait Assessment,Robotic	None

RQ1: Which AI techniques are used? Most studies incorporate ML approaches, with ANN and their variants emerging as the most popular (see Figure 4). The usage of ML techniques can be explained due to the high availability of data with which to train models, whether it is an ad-hoc dataset created by the researchers, or standard datasets used in the context of physical rehabilitation. One of the most popular datasets is the KIMORE dataset[69], which consists of RGB-D data of rehabilitation exercises. Additionally, the studies that analyse the effects on physical tests such as Fugl-Meyer Assessment exhibit significant improvements [17].

In particular, CNN and Long Short-Term Memory (LSTM) are the most used ANN models, often in combination. LSTM have been used in combination with other models because their capacity to model time series. Among ML methods distinct from ANNs, SVMs are frequently utilized, namely due to their effectiveness in high-dimensional datasets and their aptitude for non-linear data. In studies where multiple techniques are compared, CNN and SVM generally show the greatest accuracy, which accounts for their high usage in the literature.

Non-ML methods employed for physical rehabilitation include rule-based systems modelled using expert knowledge, predominantly implemented using fuzzy logic, as well as HMMs. HMMs are used for their flexibility and their ability to model sequential data, which is important when making inferences on rehabilitation data [10]. Fuzzy logic is used for its capacity to deal with uncertainty and sensor imprecision, as well as for their interpretability [43]. Additionally, Generative AI techniques such as GANs and LLMs have been employed as part of physical rehabilitation systems, but their usage remains limited. This is because these techniques represent recent developments, and the application of Generative AI in physical rehabilitation is not straightforward. In conclusion, while ML techniques are the AI methods most commonly used to support physical rehabilitation for their effectiveness, non-ML techniques are a promising line of work due to their interpretable nature that remains largely unexplored. In this regard, recent progress in areas like fuzzy logic highlights how non-ML AI can be used to supplement existing approaches to support physiotherapy [70], [71].

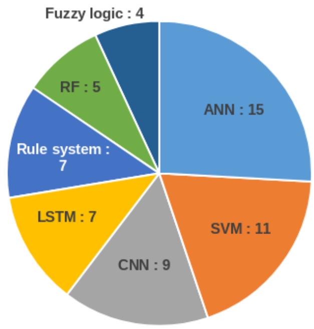

FIGURE 4: Overview of the AI techniques employed.

RQ2: Which neurological diseases are supported? The systematic review reveals that the vast majority of systems focus on stroke (see Figure 5). This trend can be explained not only due to the current incidence of stroke in the population [1], but also in its forecasted incidence [3]. PD also receives notable attention, particularly with lower limb rehabilitation. This is due to the impact that PD has on lower limb mobility, and conditions such as freezing of gait [2]. Other conditions, such as ALS, appear in only isolated studies. This can be explained by the lower incidence of other neurological diseases that affect motor function on the population. [72]. ALS has a significantly lower impact worldwide than stroke or PD [73]. This gap in the literature represents a major opportunity for future research on the field.

It is important to note that most systems presented in the studies focus on a disease superficially. There are few examples of studies fully incorporating knowledge about the neurological disease they are supporting. Butt et al. [34]

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include knowledge about hemiparesis, which is the incomplete loss of strength on one side of the body affecting stroke patients. Reches et al. [9] incorporate knowledge about freeze of gait, a common symptom of PD. Incorporating disease-specific knowledge into the proposed systems requires acquiring detailed knowledge about the disease and integrating the knowledge in the system, which is out of scope for many studies. Considering all this, disease-specific adaptations studies, as well as studies focused on less prevalent neurological diseases represent a significant area for future research.

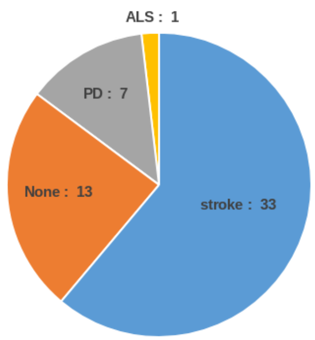

FIGURE 5: Overview of the diseases specifically supported.

RQ3: To which extent has the effectiveness systems been tested with patients? Nearly half of the studies tested their systems with actual patients (see Figure 6). The high percentage of studies validating their proposals with patients of neurological diseases reinforces the clinical relevance and rigour of the research area. However, it is worth noting that the clinical scale used to evaluate the improvement of patients varies significantly between studies. This reveals a major area of improvement for future research on the field. Details of the studies that conducted patient-based evaluations, including sample size, demographics, and clinical scales employed, are summarized in Table 6. The remaining studies relied on alternative evaluation methods, such as experiments with healthy individuals and datasets. While these validation techniques are popular due to their reduced cost and easier execution, they are less rigorous and the derived results are not as reliable. Datasets are used in certain applications where datasets are readily available, such as rehabilitation assessment [69]. Others used synthetic data and case studies, to a lesser extent, to validate the AI models that support the systems. In conclusion, this shows that AI application in physical rehabilitation systems has undergone significant validation with neurological disease patients.

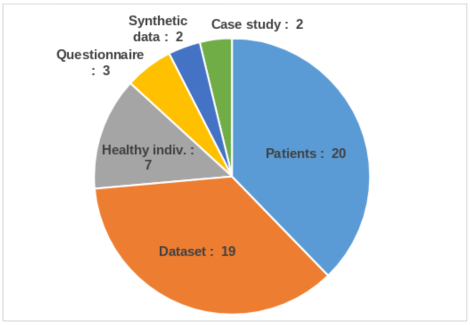

FIGURE 6: Overview of the validation methods employed.

RQ4: What aspects of physical rehabilitation are supported by the system? The findings indicate that upper-limb rehabilitation is the most commonly supported body part, appearing in 21 studies, followed by full-body rehabilitation and lower-limb rehabilitation (see Figure 7). Additionally, a smaller number of studies specifically target hand rehabilitation. These trends align with the importance of upper-limb functionality in activities of daily living and overall quality of life for neurological disease patients. Also, upper-limb rehabilitation occurs later in the rehabilitation process, which means that more efforts are required to achieve the same results [74], [75]. Although gross motor function has been widely explored, support for fine motor function, including hand rehabilitation, remains as one of the most relevant gaps in the literature.

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TABLE 6: Summary of studies that validated physical rehabilitation systems with patients

Study ID	Sample Size	Age (range or mean)	Clinical Scales Used
ID03	25 (15M, 10F)	20–60	–
ID07	35 (22M, 13F)	56–89	Hoehn & Yahr
ID09	48 (26M, 22F)	47–87	MMSE
ID10	22 (12M, 10F)	31–60	FM-UE, RLCFS, Ashworth
ID13	57 (29M, 28F)	50–74	–
ID19	11 (11M)	48–61	MMSE, Fugl-Meyer Assessment
ID20	41 (26M, 15F)	23–81	–
ID23	15 (10M, 5F)	46–69	–
ID24	23 (11M, 12F)	40–70	K-MMSE
ID26	–	–	–
ID27	38 (18M, 20F)	24 (avg.)	–
ID28	4 (4F)	27–68	MMT, Ashworth
ID30	19 (14M, 5F)	29–76	MDS-UPDRS
ID32	192	67–82	–
ID33	66 (43M, 23F)	35–65	AMTS, BESTest
ID34	71 (57M, 14F)	62–78	MMSE, NFOGQ
ID37	15 (11M, 4F)	34–86	FMA-UE, K-MMSE, EHI
ID38	47 (35M, 12F)	24–84	Motor Activity Log (MAL)
ID39	99	–	MMSE, Hoehn & Yahr, TUG, DGI, BBS
ID41	46 (21M, 25F)	61–78	BBS, Johns Hopkins Fall Assessment
ID42	33	–	–
ID45	50 (22M, 28F)	41.2 (avg.)	–
ID47	6	14–48	–
ID50	187 (111M, 76F)	51–77	–
ID51	83	71.9 (avg.)	–
ID52	368	54–76	Hoehn & Yahr, UKPDSBB
ID53	105	59.1 (avg.)	BBS, FAC

This is despite the importance of fine dexterity in the activities of daily living [76]. Consequently, we encourage researchers to investigate ways of supporting functional rehabilitation of patients, narrowing this research gap in the field.

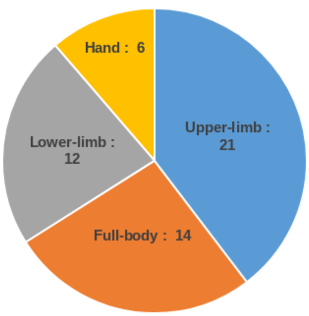

FIGURE 7: Distribution of the aspects of rehabilitation supported.

RQ5: What type of system are proposed? According to their purpose, they show a high level of diversity, with many addressing multiple rehabilitation goals simultaneously. Common objectives include evaluating the performance of patients, classifying their movements as they perform the rehabilitation exercises, and providing recommendations that support the role of therapists (see Figure 8). These goals are generally pursued by the studies because they can potentially reduce the workload of therapists, increasing the capacity for dealing with neurological diseases. Additionally, some studies integrate immersive technologies like VR and AR or employ robotic-assisted rehabilitation. As mentioned above, these technologies make the rehabilitation more dynamic for the patients and encourage them to be consistent in their recovery, which is why they are proposed for physical therapy. These findings show that multiple approaches for physical rehabilitation have been explored, but with uneven level of focus. A majority of studies focused on a reduced number of ways to support physical rehabilitation with AI. This tendency can be explained by the challenge of discovering alternative ap-

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proaches to support rehabilitation in contrast with perfecting goals that have already been explored in the literature. Despite this diversity, there is an observable imbalance: the literature concentrates on measurement and assessment, rather than on recommender systems and AI-driven therapeutic interventions. To advance the field, we suggest putting the focus on AI-driven interventions, where AI systems play a larger role in the rehabilitation process. By tailoring therapy to the needs of patients, studies would be able to increase their effectiveness.

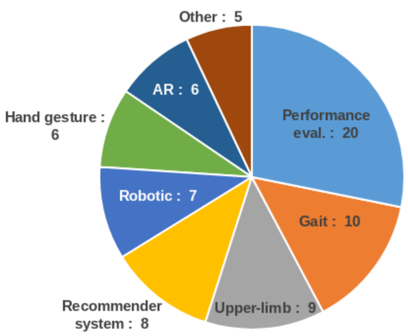

FIGURE 8: Overview of the type of systems proposed.

Regarding the use of sensors, most studies incorporate AI in combination with sensors, particularly IMU sensors and cameras (see Figure 9). Camera sensors, such as Microsoft Kinect, often include a depth channel for more accurate readings. These have been chosen by the studies due to their low cost, and their ease of use. The preference for cost-effective, easily deployable sensors suggests an emphasis on home-based rehabilitation applications. However, the predominance of gross-motor sensors also limits the kinds of impairments that can be addressed. Spasticity, muscle activation patterns, and fine-motor function are difficult to track reliably from IMUs or RGB-D alone. We therefore encourage greater use of specialized and multimodal sensing, such as sEMG, FMG, and other physiological channels, as they can increase clinical relevance by distinguishing compensatory movement from true recovery.

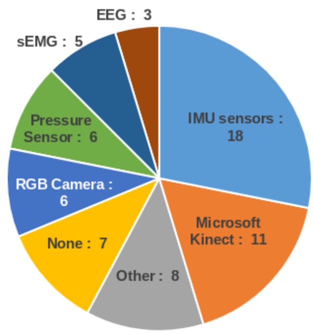

FIGURE 9: Distribution of the sensors utilized by the systems.

V. OUR PROPOSED SOLUTION

Having reviewed the state of the art for the application of AI in physical rehabilitation, the knowledge obtained as a result will be used to improve a prototype developed by the authors of this manuscript [13], [43], [45], [77]. Its objective is to support physical rehabilitation therapists by automatically adjusting physical rehabilitation routines.

In this section, the technical details of our proposed solution will be summarized to provide the necessary context. Then, the knowledge obtained in the review process will be used to compare the state of the art with our prototype, detect its strong features, and suggest possible lines of work to further improve it.

A. DESCRIPTION OF OUR PROPOSAL

Our proposal is a home rehabilitation system composed of three subsystems: a client application for patients, a client application for therapists and a server which connects both applications. This rehabilitation system is based on a cloud architecture, which offers multiple advantages in the context of remote rehabilitation [7]. It facilitates data collection, which can not only be used by physicians and caretakers, but also can be employed for additional purposes, such as the personalization of the rehabilitation process. Additionally, it can reduce costs, which facilitates its implementation in areas with low resources.

The applications used by patients and therapists are shown in Figure 10. The patient application is an AR system that guides the movements of patients as they perform the exercises. Firstly, the patient's pose is calibrated, as graphically depicted in Figure 10.a. Then, in the main screen, the virtual circles shown in Figure 10.b describe the trajectory that the joints involved in the exercise must follow to be executed correctly. The patient application captures metrics of the execution to be used by the DSS, such as the presence of compensatory movements, or the level of fatigue. The therapist application allows therapists to adjust the rehabilitation routine of their patients. This process can either be done manually, or the therapist can invoke a DSS that automatically adjusts the rehabilitation routine based on the patient's historical data. Unlike all the proposals seen during the review, the adjustment is not done to a particular exercise, but to the complete routine (see Figure 10.c). The therapist is then shown the adjusted routine with an explanation of the decisions it took before the therapist decides whether to accept the proposed adjustment (see Figure 10.d).

The platform has been developed based on web technologies. This decision was taken because it facilitates the deployment process of the system, as no installation is required. It can be used on any commercially available laptop, which in turn encourages the adaptation of the system. The sensor used by the client application is a regular RGB webcam. It was chosen because it is inexpensive, widely available, and can be set up easily. For the pose detection, a pre-existing model was used: the MediaPipe Pose Landmarker[1], developed by Google. It is a lightweight model, which means that it can be executed on a wide range of devices. Finally, the DSS has been implemented using fuzzy logic due to its ability to handle uncertainty, which is important when using data from sensors. This is particularly important in home rehabilitation systems, as the sensors that are employed often lack precision.

B. IMPROVEMENTS OF OUR PROTOTYPE

Based on the conclusions reached in the review, desirable features of our system are as follows:

- **Explainability**. In contrast with most AI methods used, our prototype employs fuzzy logic to make decisions. This alternative AI method constitutes a line of research that has not been explored by many studies. One of the main advantages of fuzzy logic with respect to ML models is the interpretability of the models, since they are inherently interpretable.
- **Ease of use**. As discussed in Subsection V-A, our prototype uses a webcam because it is easy to set up. This is in contrast to some of the reviewed studies, where sensors such as sEMG, EEG or IMU wearables are employed. These sensors are either more expensive, less readily available, or require more effort to set up.
- **Immersive technologies**. Some of the reviewed systems employed immersive technologies or robotic devices to make the rehabilitation process more dynamic, enhancing the interactivity and engagement of the therapy process. In our proposal, AR is used to guide the movements of patients, providing real-time visual feedback for improved rehabilitation.
- **Full-body rehab**. Upper-limb rehabilitation is most common, while lower-limb, full-body, and even hand-specific rehabilitation are less explored. Currently, our prototype is focused on upper-limb rehabilitation, but addressing these underrepresented areas could help improve the quality of life of patients.

[1]https://ai.google.dev/edge/mediapipe/solutions/vision/pose_landmarker

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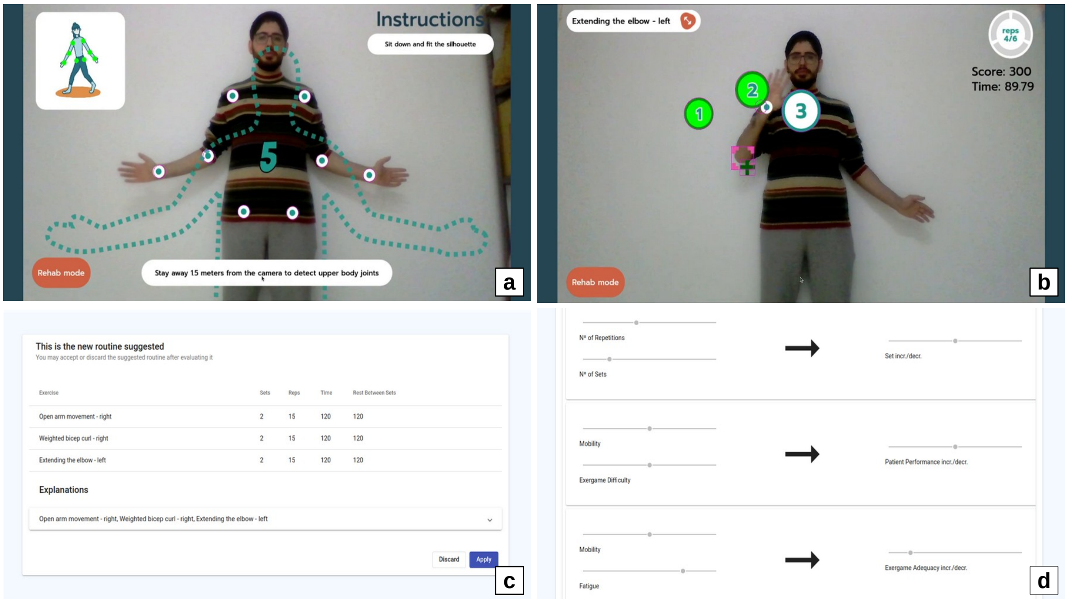

FIGURE 10: Screenshots taken from our prototype. a) Pose calibration screen. b) Main screen for performing the physical rehabilitation. c) Rehabilitation routine suggested by the DSS. d) Explanations of the decisions provided by the DSS.

- **Disease-Specific Adaptations**. Most reviewed studies focus superficially on the neurological diseases of patients. There is a significant opportunity to develop AI systems that offer tailored, disease-specific adaptations.

VI. LIMITATIONS OF THE STUDY

The methodological choices and scope of our systematic mapping study introduce several limitations that should be considered when interpreting the results.

Quality Assessment Subjectivity. The five-item Likert-type questionnaire applied for quality screening, while structured, necessarily involves subjective judgments regarding the clarity, reproducibility, and validity of each study. Despite providing guidelines, different reviewers could score differently the same paper, especially when evaluating ambiguous aspects. This inherent subjectivity may affect which studies were included and thus influence our overall outcomes.

Heterogeneity of Included Studies. Our sample of 53 primary studies exhibits considerable variety across multiple dimensions: AI techniques, study designs, types of sensors sensor, patient demographics, and outcome metrics (ML accuracy, clinical rating scales, or patient-reported satisfaction). Such diversity prevents any significant quantitative analysis from being made and complicates direct comparisons. This ultimately limits our ability to draw universally applicable conclusions regarding performance and best practices.

Disease and Population Generalizability. The majority of research efforts we identified centre on post-stroke rehabilitation, with Parkinson's disease representing a secondary focus. Few studies address other neurological populations such as multiple sclerosis or amyotrophic lateral sclerosis. Consequently, our findings may not extend to rehabilitation strategies focused on these conditions, nor capture unique challenges related to cognitive impairment, spasticity, or disease-specific progression patterns.

Quick Field Evolution:. Finally, the rapid pace of progress in AI means that methods deemed state-of-the-art at the beginning of our time window may have been replaced by newer techniques released after our cut-off. As a result, our study provides a temporal snapshot whose relevance may diminish as the field continues to evolve.

VII. CONCLUSIONS AND FUTURE WORK

This Systematic Mapping Study provides a summary of existing research in the topic of supporting physical rehabilitation of neurological patients through the application of AI. This is a field of growing interest, as it is indicated by the rising number of publications in recent years. A research methodology was defined for this review based on standard guidelines for SMSs [24]. After the application of said methodology, a total of 53 primary studies were included in this review. The primary studies were then classified according to several criteria derived from the research questions of the review. This mapping review provides a baseline for future research on this research topic.

Through our SMS, we obtained insights that contributed to answering the RQs. The results allowed us to identify prominent research trends within the literature. We recognized the most frequently addressed neurological diseases, as well as the most common AI techniques employed in the studies. Additionally, we gained a clearer understanding of the approaches used to support rehabilitation, in terms of the intended goals of the proposals, the part of the body that was involved in the rehabilitation, and the types of sensors utilized. Lastly, we analysed the quality of the experimental designs employed to validate the primary studies.

A comprehensive review of the primary studies identified the state-of-the-art research on the field, while also highlighting significant gaps in the existing literature. Future research should consider investigating less explored AI approaches such as fuzzy logic, HMMs, and the more recently introduced LLMs. Most of the literature is focused on established ML models, which have been shown to yield accurate results on a set of tasks. However, alternative models could enable different avenues for supporting physical rehabilitation that cannot be as easily exploited with ML models. Moreover, there is a notable lack of systems with disease-specific adaptations. The majority of the reviewed proposals only address neurological conditions only at a surface level. This represents a major blind spot in the field, and future studies should consider including adaptations for the disease their study tackles to increase its effectiveness.

The conclusions drawn from the mapping study have served to gain insight to further improve our own prototype within this line of work. Many elements of our proposal are consistent with established trends in the literature, while others represent more novel contributions. Similar to several other studies, our system incorporates a standard RGB camera. Likewise, we employ AR, which some of the reviewed works also employed to increase patient motivation. However, our use of fuzzy logic as a AI technique stands out, as it remains a relatively underutilized technology in the literature.

In summary, the literature demonstrates that AI can effectively alleviate the burden of physical rehabilitation for neurological conditions. It has been shown to improve the effectiveness of therapy, automate certain processes to address the shortage of specialized personnel, and enhance accessibility. These factors are essential to increasing the real-world adoption of such systems in rehabilitation settings. Ongoing development and assessment of these technologies will continue to improve patient outcomes.

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