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Dr. Jose Luis Contreras-Vidal
University of Houston
Gregory Brusola
University of Texas Medical Branch
Muhammad Mansoor Mughal
mmughal@cougarnet.uh.edu
University of Houston

Systematic Review

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Posted Date: April 27th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9518032/v1

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Additional Declarations: The authors declare no competing interests.

Transformative Role of Artificial Intelligence and Machine Learning in Rehabilitation Engineering; A Systematic Review

Muhammad Mansoor Mughal[3], Gregory Brusola[2] and Jose L Contreras-Vidal[1,3,4]

[1]Department of Electrical and Computer Engineering, University of Houston, Houston, USA
[2]Department of Physical Therapy and Rehabilitation Sciences, School of Health Professions, University of Texas Medical Branch, Galveston, USA
[3]Department of Biomedical Engineering, University of Houston, Houston, USA
[4]Noninvasive Brain-Machine Interface System Laboratory, Department of Electrical and Computer Engineering, University of Houston, Houston, USA

E-mail: mmughal@cougarnet.uh.edu

July 12 2025

Abstract.

Objective: The field of rehabilitation engineering has evolved to incorporate Artificial Intelligence (AI) and Machine Learning (ML) into technologies and tools designed to assist and promote the rehabilitation of individuals suffering from stroke, paralysis, and other clinical conditions. Here, a systematic review was done to understand the opportunities, challenges, gaps, deficiencies, inconsistencies, and trends in the deployment of AI/ML in rehabilitation engineering.

Approach: A search in IEEE Xplore, Web of Science and PubMed databases for the period 2011 to 2021 resulted in 110 identified studies that met the inclusion criteria. Findings are summarized with respect to clinical population, number of participants, rehabilitation task, rehabilitation device, model inputs, duration of intervention, AI/ML algorithm, model accuracy, clinical outcome and presence of feedback.

Main Results: Most studies (63%) focused on upper limb or hand rehabilitation with 27% addressing lower-limb rehabilitation. Stroke had the largest representation (58%) among the clinical populations studied followed by spinal cord injury (20%). Classical ML algorithms accounted for 90% of the studies, followed by deep learning (DL). About half of the studies used electroencephalography (EEG) as input to the AI/ML model. The output of these models were used to control different types of virtual and physical devices. Although not all the studies reported the model accuracy, for those that reported results the accuracy ranged from 42% - 100%. Clinical outcome measures were not included in 66% of the studies. Less than one-fifth of the studies had open-loop protocols. Unfortunately, 18% of the studies were single session, with 26% reporting between 2-10 sessions.

Significance: Future studies should 1) investigate applications of DL in the rehabilitation of motor function; 2) be closed-loop and 3) include multiple sessions to understand the longitudinal effects of therapy. Moreover, studies should address model explainability, and follow standard engineering, clinical, and end-user metrics.

Keywords: artificial intelligence, machine learning, rehabilitation, stroke, electroencephalography (EEG), spinal cord injury (SCI)

Submitted to: *Journal of NeuroEngineering and Rehabilitation*

Glossory

Clinical Population

IHMA Impaired hand motor abilities
SCI Spinal cord injury
ULA Upper limb amputation
TBI Traumatic brain injury
CP Cereberal palsy
NI Neurological impairment
LLP Lower limb paralysis
FD Foot drop
PD Parkinson disease
PP Paraplegia
MCD Mild cognitive impairment
MSA Multiple systems atrophy
NS Not stated

Rehabilitation Task

UL Upper limb
LL Lower limb
HRI Human robot interaction
ED Emotion detection
UI User intent

Device

BCI Brain-computer interface
VR Virtual reality
Exo Exoskeleton
FES Functional electrical stimulation
VF Visual feedback
SMR Sensorimotor rhythm
CC Cursor control
TS Transcutaneous electrical stimulation
BMI Brain-machine interface
BOTAS BMI-based occupational therapy assist suit

MI Motor imagery
VE Virtual environment
SDAE Stacked denoising auto-encoder
IMMUs Xsens MTw2 wireless motion trackers
Rob-sim. Robotic simulator
FDS foot-drop stimulator
N/A Not addressed

Model Input

EEG Electroencephalogram
EMG Electromyography
KIN Kinematic
IMU Inertial motion unit
NMES Neuromuscular electrical stimulation
MI Motor imagery
MT Motion trajectory
MMG Mechanomyography
Physiol. Physiological
EOG Electrooculography

Algorithm

KNN K-nearest neighbors
SVM Support vector machine
LDA Linear discriminant analysis
ANN Artificial neural network
RF Random forest
REG Regression
RNN Recurrent neural network
CSP Common spatial pattern
GAAN Greedy assist as needed controller
PCA Principal component analysis
CART Classification and regression tree
TNFLD Tensor-based nearest feature line distance
EPNN Enhanced probabilistic neural network
TCNN Two-headed convolutional neural network
DPN Deep polynomial network
DBN Deep belief network
CNN Convolutional neural network
LSTM-NN Long short-term memory
BPNN Back propagation neural network
FSM Finite state machine

HMM Hidden markov model
NFS Neuro-fuzzy system
DCA Dynamic control allocation
NTSA Novel-T symmetric encryption algorithm
MKL Multiple kernel learning
GMM Gaussian mixture model
DT Decision tree
EDT Ensemble decision tree
MLP Multilayer perceptron
TDANN Time-delay artificial neural network
CRF Conditional Random Field

Clinical Outcome

VAS Visual analogue scale
MMT Manual muscle test
MAS Modified ashworth scale
WMFT Wolf motor function test
FAS Functional ability scale
MEP Motor evoked potential
F/M F-wave/M-wave amplitude ratio
ERD Event-related desynchronization
ARAT Action research arm test
GS Grip strength
MCP Movement completion percentage
FMA Fugl-meyer assessment
FAI Frenchay Activities Index
FIM Functional independence measure
RMI Rivermead mobility index.
TEMPA Upper extremity performance test for the elderly
MRC Medical research council scale
ROM Range of motion
WISCI Walking index for SCI
GS-C comfortable gait speed

1. Introduction

Over 1 billion people (about 15% of the world's population) currently live with a disability [1], which the World Health Organization (WHO), as a part of the International Classification of Functioning, Disability and Health (ICF), defines as " complementary to functioning and encompasses impairments, limitations in activities, and restrictions in participation" [2]. People with disabilities (PWDs), in many cases, may be highly dependent and rely on other individuals in the performance of activities of daily living and self-care activities, such as preparing a meal, going to the bathroom, taking medicine, or getting out of bed. Conventional rehabilitation methods have been found to be effective in improving performance of activities, participation, and quality of life in people with PWDs. However, current rehabilitation methods do have limitations that may restrict PWD to fully return to participating in their societal roles. For example, conventional powered wheelchairs can be very challenging for some PWDs to operate and PWD with powered wheelchairs may face various environmental barriers 6083565. Efficient and technologically advanced techniques such as artificial intelligence (AI) and machine learning (ML) have been proposed as ways to transform various conventional rehabilitation interventions to be more person-driven and actively engaging, as opposed to passive mechanisms, which have been shown to limit neuroplasticity and clinical effectiveness 6083565.

Recent advancements in brain-computer interfacing (BCI), virtual reality (VR), and AI are revolutionizing conventional rehabilitation approaches, offering unprecedented potential to enhance the quality of life and independence of PWDs [3]. BCI technology, in particular, has demonstrated remarkable efficacy in facilitating patient engagement by translating neural signals associated with motor intent into commands for virtual and physical systems, including robotic devices. A typical BCI system comprises several key components, including signal acquisition and pre-processing, feature engineering, pattern classification, device control, and system feedback [4]. These systems can interface with various rehabilitation devices, including BCI-augmented exoskeletons [5], VR systems [6], haptic gloves [7], and functional electrical stimulation (FES) systems. [8]. Exoskeletons augmented with intention detection and assist-as-needed control have emerged as one of the most promising applications for the restoration of motor functioning [9]. Exoskeletons are changing the paradigm of rehabilitation, by promoting a user-centric approach, i.e., assist-as-needed, that motivates users to perform motor tasks independently [10]. Exoskeletons are utilized not only for compensatory and adaptive rehabilitation strategies but also to achieve thresholds for neuroplasticity and promote therapeutic effects for motor recovery. This ability of exoskeletons to leverage compensatory and restorative approaches to rehabilitation makes exoskeletons an increasingly utilized rehabilitation tool in clinical settings.

Advances in AI and ML hold significant promise for enhancing BCI systems and rehabilitation engineering. Advances in explainable AI/ML have the potential to work as a cognitive framework for intelligent rehabilitation devices, enabling robust identification

of patterns in brain and/or body activity that are predictive of motor intent. [10] A variety of classification algorithms have been employed in BCI applications, with neural classifiers such as support vector machine (SVM) [9], linear discriminant analysis (LDA) [9], regression models [11], Bayesian's classifiers [6], and k-nearest neighbors (KNN) [9] being among the most frequently utilized. These advanced algorithms are being integrated into various rehabilitation devices and systems, including BCI-controlled exoskeletons [9], VR systems [12], and FES systems. [13] The synergistic integration of AI/ML with BCI technology is paving the way for more intuitive, adaptive, and effective top-down rehabilitation strategies, potentially revolutionizing treatment approaches for individuals with motor impairments.

This synergistic integration of BCI, VR, AI, and robotic technologies represents a significant advancement in rehabilitation engineering, offering tailored, engaging, and effective interventions that have the potential to significantly improve outcomes for individuals undergoing physical rehabilitation. In this review, the authors examined the current state of the art of AI/ML applications in rehabilitation that have emerged over the last decade. The authors analyzed the literature with respect to clinical populations, sample sizes, rehabilitation tasks and devices, model inputs, AI/ML algorithms, intervention durations, model accuracy, clinical outcomes, and feedback mechanisms. By comprehensively evaluating these factors, this review aims to provide a roadmap for the field AI/ML in rehabilitation engineering, noting both the progress made and domains requiring further research and development. Our analysis offers insights into the most promising approaches and identifies key challenges and opportunities for future work in this rapidly evolving area.

2. Method

2.1. Search strategy

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method was used for study identification [14]. The search was conducted on IEEE Xplore, Web of Science and PubMed databases on September 29, 2021, January 25, 2022 and May 18, 2023, respectively. The syntax used for the search was: *((ARTIFICIAL INTELLIGENCE) OR (NEURAL NETWORKS) OR (BRAIN MACHINE INTERFACE) OR (BRAIN COMPUTER INTERFACE) OR (NEUROPROSTHESIS) OR (MACHINE LEARNING) OR (DEEP LEARNING)) AND (((REHABILITATION) OR (PMR)) NOT (DIABETES)) AND ((VIRTUAL REALITY) OR (FES) OR (FUNCTIONAL ELECTRICAL STIMULATION) OR (EXOSKELETON) OR (WEARABLE ROBOTIC DEVICE)).*

2.1.1. Eligibility criteria This systematic review focused on studies published between 2011 to 2021. This review includes only quantitative peer-reviewed journal articles and conference publications to ensure scientific rigor. The primary inclusion criterion was the

deployment of AI/ML methods, such as classical machine learning and deep learning algorithms, in the design and performance of rehabilitation systems. To be eligible, studies needed to include at least one participant (e.g., a case study) from a clinical population with a movement impairment, such as spinal cord injury or stroke. We defined movement impairment as any condition affecting motor skills that could benefit from rehabilitation interventions. Therefore, studies that only had healthy subjects or no subjects were excluded from this review. Given the frequent integration of AI/ML algorithms in brain-computer/machine interfaces (BCI/BMI) and neuroprostheses, this review included studies involving these devices granted they included at least one participant with a movement impairment. Lastly, the focus of this review extended to studies that included rehabilitation applications incorporating VR, FES, exoskeletons, or other wearable robotic devices.

The exclusion criteria omitted review articles, studies performed on animals, and studies that used invasive approaches such as deep brain stimulation or implanted BCIs. Since this review was only concerned with the rehabilitation of patients with motor skills impairment, studies focusing on conditions without primary motor involvement, such as diabetes, were not considered.

2.1.2. Data extraction The extracted data were converted into tabular form. We used the following categories for organizing data from selected articles:

- **Rehabilitation task**: Tasks included upper limb (UL) or lower limb (LL) movements. Rehabilitation tasks for the hand were analyzed separately from the UL. There were some other tasks that could not be placed in any of the above categories and are referred to as 'other' and analyzed in general.
- **Clinical population**: Clinical populations included people who were diagnosed with a condition with movement impairment. This includes conditions like spinal cord injury and stroke.
- **Model input**: Model input refers to the modality of signals measured from the subject to analyze either brain dynamics, motor behavior, motor intent, or movement tendencies of a subject. Some of these signals are typically pre-processed or converted to a form that can be processed by a BCI device. The types of model inputs identified in the review include electroencephalography (EEG), electromyography (EMG), kinematics, finger pressure, and others.
- **AI/ ML algorithm**: Artificial Intelligence (AI) is a term that generally describes the use of computers and technology to simulate intelligent behavior and critical thinking comparable to a human being [15]. The algorithms included in this systematic review ranged from classical machine learning algorithms such as SVM, LDA, and Bayesian algorithms, as well as deep learning (DL) algorithms, such as recurrent neural networks (RNN) and convolutional neural networks (CNN).
- **Number of sessions**: This review assessed the number of sessions included in the experimental protocol for each study.

- **AI/ML model accuracy**: When available, the classification rate for the AI/ML algorithms was analyzed in this review.
- **Clinical outcomes**: Primary clinical outcomes were recorded to examine the clinical effectiveness or efficacy of the proposed intervention experienced by participants in each study.

2.2. Quality assessment

The Quality Assessment Tool for Quantitative Studies as developed by the Effective Public Health Practice Project (EPHPP) was used to methodologically evaluate the quality of each included study. [16]. The quality of each study was analyzed in regard to selection bias, study design, confounding variables, blinding, and data collection methods. Each domain was rated as *strong*, *moderate*, or *weak*. Two raters independently rated each study and any discrepancy was resolved by consensus and a third independent rater.

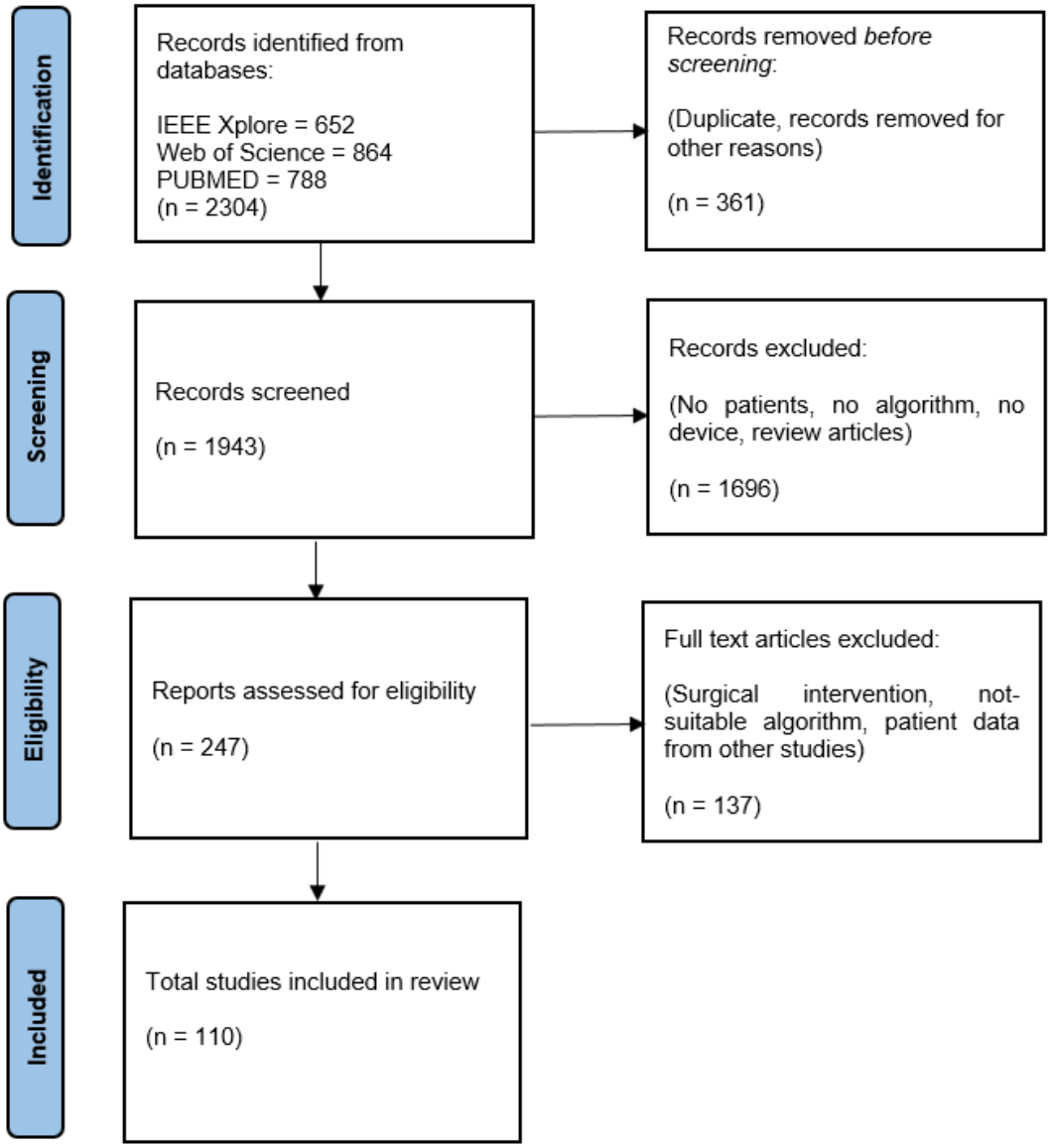


Figure 1. PRISMA flow diagram for selecting studies. The selection procedure moved through four main processes: identification, screening, and eligibility, and included a total of 110 studies were selected out of 2304.

3. Results

Using the inclusion and exclusion criteria defined in section 2.1, a total of 652 articles were identified in IEEE Xplore, 864 articles in Web of Science and 788 articles in PubMed. Articles were separately screened by two authors and a third author resolved any conflicts. After screening 2304 articles, only 247 (53 from IEEE Xplore, 102 from Web of Science and 92 from PubMed) articles were accepted for full-text review based on the inclusion criteria (see figure 1). Upon full-text review of the 247 articles, 137 of them were further excluded based on eligibility criteria. In total, 110 (47 from IEEE Xplore, 49 from Web of Science database, and 14 from PubMed) articles were included

in the final analysis of this systematic review.

3.1. Rehabilitation tasks

The analysis of rehabilitation tasks across the selected studies revealed a clear emphasis on UL rehabilitation. Most studies focused on UL rehabilitation tasks, which comprised 39% of all studies. Hand rehabilitation, analyzed separately from general UL tasks, comprised 24% of the studies. Collectively, UL and hand rehabilitation studies constituted a significant 63% of the total research focus. In contrast, LL studies comprised only 27% of the studies in this review, suggesting a potential area for future research expansion. The remaining 10% of studies were categorized as "Other" in Figure 2, encompassing a divsere range of rehabilitation tasks and body systems and tasks, such as balance [17], tremor management [18], assessment of participation levels [19], combined UL and LL tasks [20], combined UL and hand tasks [21], emotion detection (ED) [12], swallowing [22], user intent (UI) [23], VR, and human-robot interaction (HRI) [24].

Studies focusing on UL rehabilitaiton utilized a variety of techniques, including BCI-based exoskeletons [25–28], which were frequently used to enhance motor function and assist with UL tasks. FES-based devices [13, 29–34] were also prevalent in UL studies. Additionally, VR-based motor imagery movements [35–38] and BCI-based occupational therapy assistance suit (BOTAS) [11] were explored for their potential to improve patient outcomes. For hand rehabilitation, the included studies utilized BCI-based exoskeleton, VR-based imagery hand movements, BCI-based visual feedback (VF), and movements through hand gloves.

Lower limb tasks included motor imagery of LL through BCI-based VR systems, movements through BCI-based exoskeletons, LL prostheses, BCI-based FES systems, and robotic systems for LL rehabilitation. FES systems were deployed often in both UL and LL rehabilitation tasks possibly due to their ease of use, affordability, and positive outcomes. For hand tasks, exoskeletons were deployed most frequently and had an overall high success rate. However, their complexity, strict inclusion and exclusion criteria, and high cost were likely reasons for their limited usage in lower-limb tasks.

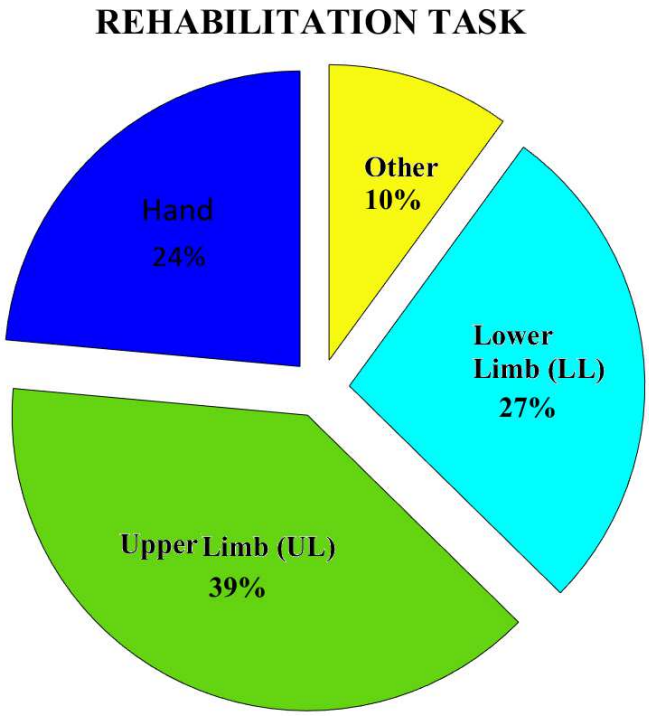


Figure 2. Type of task most often used in rehabilitation engineering studies. Approximately 63% of reviewed studies focused on UL rehabilitation, with one-third specifically focusing on hand rehabilitation. About one-fourth of studies investigated LL rehabilitation. Other types of tasks comprised one-tenth of the total number of examined studies.

3.2. Clinical populations

More than half of the studies included in this review included individuals with stroke (58%) (Figure 3), with spinal cord injury being the second most common clinical population, comprising 20% of the studies included. Stroke affects younger and older individuals [9], with risk factors such as obesity and hypertension contibuting to its occurrence. Unfortunately, many people affected by stroke experience some form of disability, [10] complicating their recovery process. Spinal cord injury also presents challenging conditions for neurorecovery, especially in chronic stages [39]. Other clinical populations reported in the selected studies included participants with paraplegia [40], lower limb paralysis [6, 41], traumatic brain injury [25, 42, 43], cerebral palsy [44, 45], Parkinson disease [17,22,46], tremor [18,47], foot drop [48], neurological impairment [49], impaired hand motor abilities [3], Alzheimer disease [12], dystonia [50], multiple systems atrophy [23] and upper limb amputation [51, 52]. These "other" clinical conditions accounted for 22% of the included studies. This variety highlights the broad applicability of AI/ML-driven rehabilitation technologies across different conditions. Each condition presents unique challenges and opportunities for intervention, underscoring the need for tailored approaches in rehabilitation engineering.

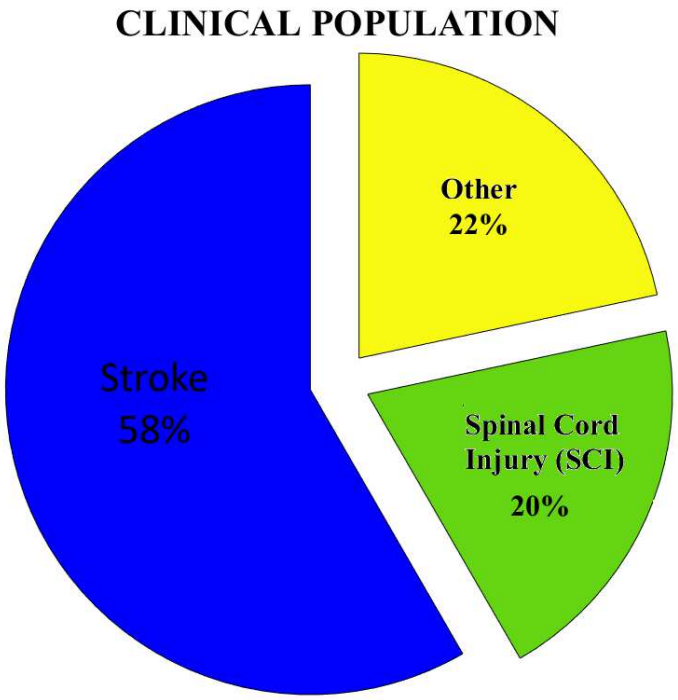


Figure 3. Clinical population. Different types of clinical populations were identified in selected studies. More than half of them were identified as stroke (58%). Participants with SCI made up one-fifth of the overall clinical population. Various other clinical populations were also identified, which combined made more than one-fifth of the total count.

3.3. Model inputs

This review identified five different types of input signal combinations (see Figure 4) to interface with devices for rehabilitation tasks. The most frequently used signal was EEG (55%) [25, 43, 45]; see Figure 4. Most studies included in this review used EEG as an input signal for BCI systems, making EEG the preferred signal choice to be used with BCI systems. The second most frequently used type of signal was EMG, with 12% of studies deploying EMG as the input for BCI devices. Additionally, 9% of studies used a combination of EEG and EMG [8,11,21]. Other EEG combinations [53–55] were used in 4% of the studies. The remaining studies, about 20%, used other types of input signals categorized as "Other" in Figure 4, including physiological signals [19], patient movement [17], engineered signals from a clinical robot [56], visual signals [35,36], foot pressure [57], kinematic [58], force [59], magnetic [60], mechanomyogram [61], angle and amplitude [44], and finger pressure [38].

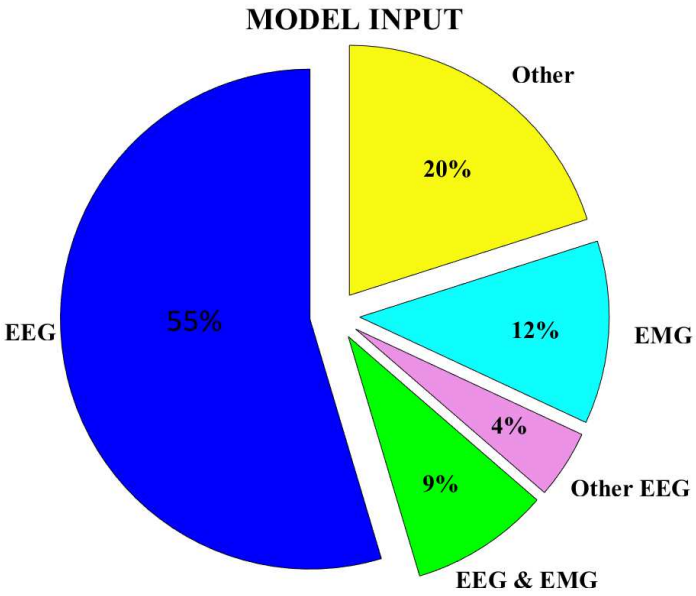


Figure 4. Types of Inputs to AI/ML Models. More than two-thirds of studies used EEG as an input to AI/ML models, either independently or in combination with other signals. EMG was identified in around one-fourth of studies. Other studies made up almost one-fifth of the total number of studies.

3.4. AI / ML algorithm

The selection of an AI model is crucial for controlling rehabilitation devices, with choices typically between classical machine learning and deep learning algorithms. Each type has its advantages and disadvantages, influenced by the specific application and dataset size. In rehabilitation engineering, patient safety is of paramount importance, making it essential to select the most suitable AI model for each rehabilitation task. The types of task and size of dataset are two primary factors for selecting the AI model.

Classical machine learning algorithms are often favored due to their effectiveness with smaller datasets, which are common in rehabilitation settings. These algorithms also offer better interpretability, an important factor when ensuring patient safety and understanding decision-making processes. [62] Another important aspect for selecting the model for rehabilitation device is their effectiveness for real time performance [63]. In this review, almost all the studies that implemented closed loop control, e.g. devices used BCI for controlling exoskeletons, FES or VR systems, were based on classical machine learning algorithms, which reinforce the preference for classical machine learning algorithms for rehabilitation devices.

In contrast, deep learning algorithms excel at feature extraction without the need for labeled data, making them promising for future autonomous rehabilitation devices. [64]. As the eventual goal of rehabilitation devices is to become more autonomous or user-driven, deep learning algorithms can offer more practical solutions toward this end. Though self-capable for extracting features, the devices based on DNN are more capable of independent learning from real environments, as compared to classical machine

learning algorithms, that require programming and appropriate data labeling.

In this review, 90% of the studies utilized classical machine learning algorithms. Support Vector Machines (SVM) were the most common AI model, appearing in 26% of the studies, with decoding accuracy ranging from 60% to 99% with a median of 79%. SVMs are preferred for their efficiency in handling non-linear data [65] and robustness in capturing different patterns within BCI data and against noise, as compared to Bayesian models. [66]. Moreover, the parameters of SVM can be tuned to achieve classification optimization [67] and can achieve higher efficiency even with a limited number of training samples. [68]

Linear Discriminant Analysis (LDA), which was used in 20% of studies, with a decoding accuracy between 57% to 95% with median results near 79%. Using LDA holds a variety of advantages in rehabilitation engineering. Most importantly, its capability for dimension reduction of feature space can greatly improve signal-to-noise ratio [69]. Moreover, LDA's statistical discrimination can maximize ratio between class variance to optimally discriminate between different classes [70]. LDA models are usually interpretable, which improves the understanding of underlying feature being used for classification and controlling devices [71].

Deep neural network (DNN) accounted for 10% of the models used in the incldued studies. The range of DNN-based algorithms was found between 48% to 90%, with a median of 86%. Bayesian (9%) was also identified with accuracy between 42% to 100%, with a median of 81%. Interestingly, the highest (100%) and lowest (42%) reported decoding accuracies were associated with Bayesian classifiers. The highest accuracy achieved by Bayesian models was associated with real-time control of BCI systems, which could be due to its ability to handle continuous data and process it at a higher rate, making Bayesian suitable for real-time BCI systems [40]. The lowest reported accuracy was related to movement prediction from patients experiencing tremors, which may be related to uncertainty background knowledge of the Bayesian algorithm, along with high computational cost [47].

Other models made up the other 35%, including Regression [11, 60, 72], common spatial pattern (CSP) [34, 73], artificial neural network (ANN) [9, 61], KNN [3], tensor-based nearest feature line distance algorithm (TNFLD) [13], random forest (RF) [9, 74], enhanced probabilistic neural network (EPNN) [35], classification and regression tree (CART) [37], and neuro-fuzzy systems (NFS) [56] (see Figure 5 and Figure 6).

Notably, one-third of the studies did not report model decoding accuracy, particularly those focused on hand rehabilitation. This review found that almost half of the studies focusing on hand rehabilitation did not report model accuracy. Similarly, one-third of UL studies and more than one-third of LL studies did not report model accuracy. This lack of reporting limits the evaluation of AI/ML model performance across these studies.

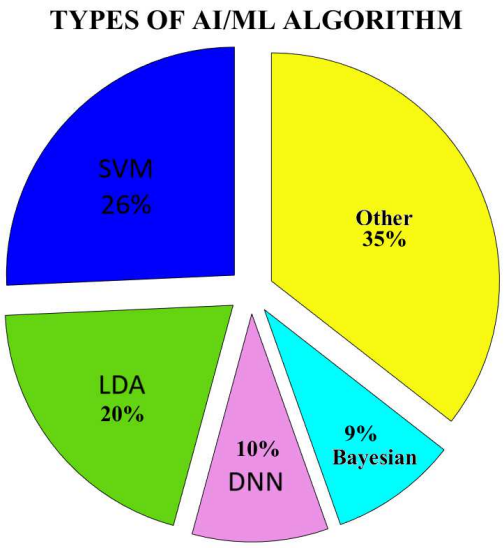


Figure 5. Type of AI/ML algorithm. Most (90%) studies deployed classical machine learning algorithms. SVM and LDA, collectively, made up almost half of all studies. Deep networks were deployed in about one-tenth of the studies.

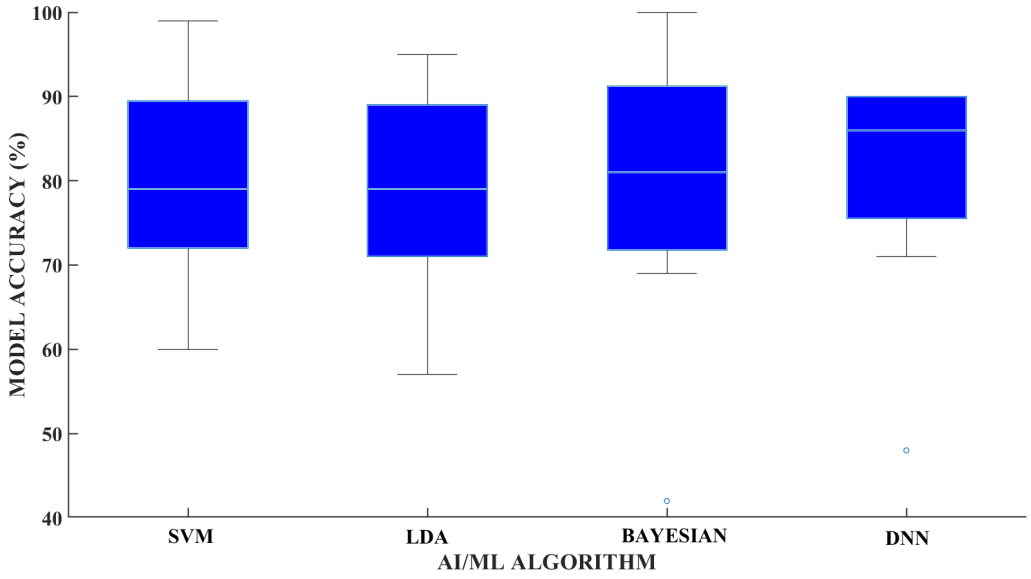


Figure 6. Percentage decoding accuracy as a function of type of AI/ML Model.

3.5. Clinical outcomes

An important finding of this review was that 66% of the included studies did not report any clinical outcomes, highlighting a gap in the literature. (see Figure 7). Among those that reported a clinical measure, the Fugl-Meyer Assessment was the most frequent method of assessment appearing in 18% of the included studies. The Fugl-Meyer Assessment assesses functional ability, including balance, sensation, and range of motion

for patients with stroke. [42, 75, 76] Approximately 23% of the studies that reported clinical outcomes included assessments like the Action Research Arm Test to assess UL dexterity and changes [13,42]; Modified Ashworth Scale to assesses spasticity in patients with stroke [42,77]; Wolf Motor Function Test to quantify upper extremity performance, including dexterity, strength, and other motor functions; [35, 37] grip strength [78], and range of motion [79, 80]. The immediate lack of clinical outcome assessment in most of the included studies underscores a critical area for further growth and improvement in AI/ML in rehabilitation research. Comprehensive reporting of clinical outcomes is necessary for evaluating the effectiveness and value of AI/ML-driven rehabilitation technologies. Additionally, incorporating clinical outcomes assessments in future AI/ML rehabilitation research will help to guide future research and clinical practice.

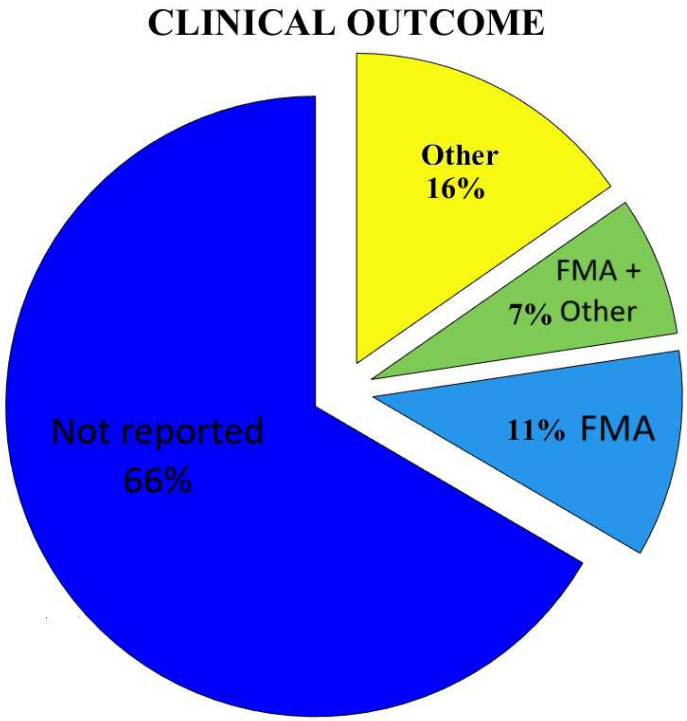


Figure 7. Clinical outcomes. Around 66% of the studies did not report any type of clinical outcome, among those which reported, FMA was identified as the most preferred method of assessment, used in 18% of studies. Other types of clinical assessment methods collectively made up 23%.

3.6. Open-loop vs. closed-loop operation

This review assessed the use of a feedback system, crucial for neurorecovery. Closed-loop systems, which provide real-time feedback appeared in 85% of the studies. These systems can enhance rehabilitation interventions by continuously updating device performance based on user responses (see Figure 8). Some examples of feedback systems utilized in the included studies include proprioceptive feedback [34], angular feedback from joints [11], visual biofeedback [51], pressure feedback, [57] and muscular torque feedback [61].

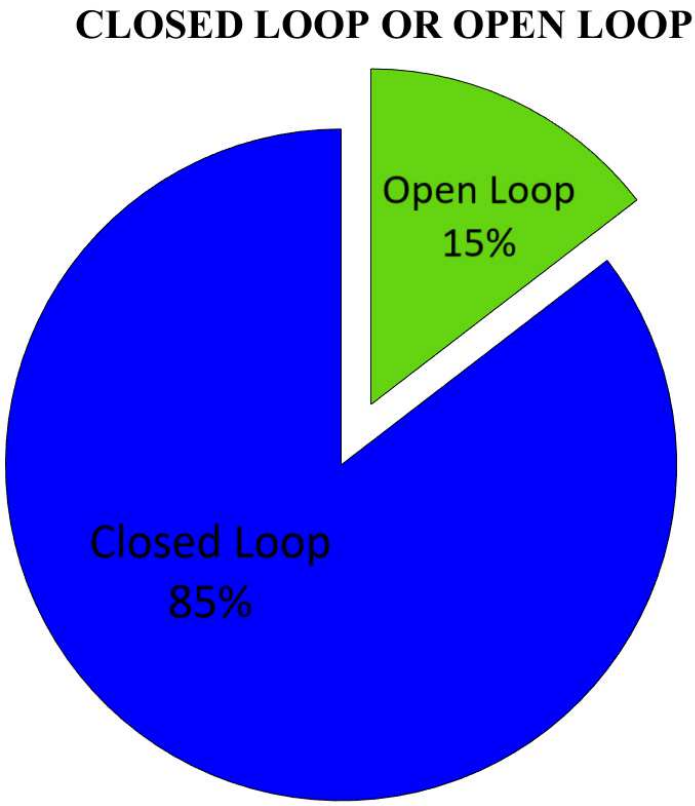


Figure 8. Closed loop vs. open loop operational modes in rehabilitation engineering.

4. Discussion

This systematic review assessed the state of the art, in the last decade, in the use of AI/ML tools in rehabilitation engineering. The findings have revealed considerable methodological gaps and heterogeneity in the studies that have applied AI/ML tools in rehabilitation, which makes interpretation challenging. This suggests that the evolution of AI/ML in rehabilitation is multi-dimensional and still in its early stage of development. Nevertheless, some developmental trends during the last ten years show future dimensions of growth for research in rehabilitation engineering based on AI/ML approaches.

Over the last decade, most rehabilitation studies that have deployed AI/ML methods have been focused on upper limb rehabilitation, with one-third of them specifically focusing on hand rehabilitation. In contrast, AI/ML for lower limb rehabilitation was studied in about one-quarter of the studies. The predominance of UL and hand rehabilitation studies may reflect the complexity and importance of fine motor skills in daily activities, the challenges in developing effective interventions for these tasks, patient preference, and the cost of end-effector devices. However, the underrepresentation of LL rehabilitation warrants further attention, given the critical role of lower limb function in mobility and independence. Future research directions could aim to bridge this gap in knowledge, potentially increasing focus of

AI/ML methods on LL rehabilitation and further exploring the innovative approaches categorized under "Other" to provide a more comprehensive coverage of rehabilitation needs.

Another important factor is reaching to the point where study is being conducted. As most of the studies are conducted at research centers, it is more challenging for people with lower limb weakness to reach there, especially for multi-session studies. Most of the time, they depend on someone to get to the desired point. To provide equal participation opportunity, new AI based intelligent and portable systems should be design which shall require minimum user input, these devices should be installed at the residence of participants where they will be able to use device, independently. Such devices can make use of DNN based adaptive model, which shall not require data labeling, and will be capable of improving the device performance with higher usage. This will also help in increasing the number of sessions of the specific study, which will eventually lead to more realistic findings.

In general, in the selected studies, stroke has been the most studied clinical population over the last decade followed by SCI. Indeed, Stroke is among the leading cause of disability, however, there are other major causes of disabilities as well, including mental illness, which has not been identified in any selected study in the review. This indicates concentration of clinical studies on specific medical conditions, while overlooking others. Also, as identified in a review, considerable number of populations of SCI participated for studies, The injury to the spinal cord can be very serious, especially in the chronic phase. It can cause loss of sensory and motor function, lack of coordination in movements, and can affect spinal reflexes, along with weakness in the limbs [81]. Another reason for focusing more on SCI is its highly challenging nature of SCI recovery [39]. However, no significant improvement in recovery of SCI patients has been identified during last many years. This can be connected to the fact that two-thirds of the studies did not use any clinical assessment methods to indicate percentage improvement of proposed treatment. Also, most of the SCI based studies had very few numbers of sessions, in fact, number of SCI studies were single session, which restricts to draw any significant finding to be used for designing better rehabilitation device. Future studies based on AI/ML approaches in rehabilitation engineering should investigate applications to SCI and other neurological disorders. Inclusion of all types of clinical populations who have experienced motor dysfunction will lead to designing more robust and efficient systems, which will accelerate the rehabilitation of effected populations. More research should be done on BMI-robotic systems like exoskeletons, which have been identified as highly effective for the SCI and stroke populations [82]. It is recommended that future studies should further explore the implementation of SVM, which is robust and works well with smaller datasets. However, the practical solutions lie with the implementation of DNN, which does not require any labeling of data, and works more independently.

In terms of devices, FES was identified as most the frequently used; however, most of them were BCI controlled. FES, when used with BCI can serve as an

efficient proprioceptive feedback system that can reduce muscle spasticity and promote neurorecovery [34]. For example, BCI-FES systems have been used for controlling muscles of patients with stroke, through motor imagery, which helped in recognizing patterns in EEG signals related to movement intent that were used for brain-computer interfacing. This was found very effective for promoting neuroplasticity and improving rehabilitation efficacy of the stroke population [34]. Approaches based on exoskeletons were identified for hand, upper and lower-limb rehabilitation. Exoskeletons are a good choice for therapeutic purpose, as it motivates the user to perform motor tasks independently, through assist-as-needed control mode [10]. Moreover, it was reported that BCI-based exoskeletons performed significantly better than non-BCI exoskeletons for motor recovery, as continuous feedback in BCI systems can modify device parameters, which can improve an individual's performance, along with device [11]. In spite of having a strong capability for providing effective therapeutic recovery methods, exoskeletons are comparatively bulky, complex to operate in a safe manner, and expensive, which likely limits their general usage. Soft robots can possibly come over this problem. Some studies have proposed new lightweight designs of exoskeletons, based on nylon, for example, which have been helpful for overcoming some of the challenges of rigid systems albeit, with lesser output capabilities [10].

Another important development made in rehabilitation engineering is AI-based VR systems. AI-based VR systems are being used for motor retraining and for functional evaluation [37]. These motor imagery-based systems have the potential to improve neuroplasticity through passive training [3]. One major advantage of AI-based VR systems is that they can make the training process more engaging and entertaining, eventually helping in reducing psychological burden and keeping the patient motivated during rehabilitation training [37]. In spite of its effective nature and comparatively low cost, BCI-based VR systems for rehabilitation have not been studied in depth. A recent study combining BCI and VR, while implementing AI algorithm, has shown potential for improving neuroplasticity [3], and thus, the deployment of AI-based BCI-VR systems is highly recommended for upcoming studies.

Most of the BCI devices implemented classical machine learning algorithms, used EEG as model input and were closed loop. This combination reinforces the idea that classical machine learning algorithms are preferred choice for BCI systems. Due to their robustness, dimensionality reduction and higher performance with smaller dataset, SVM and LDA took the lead. Implementation of EEG as model input in most of the BCI based studies shows the suitability of EEG signals for real time decoding of brain signals. Also, almost all the studies that reported clinical outcome, were BCI based. This indicates that performance monitoring and parameter adjustment for achieving higher efficiency is comparatively handier in BCI based systems. Hence, future studies should more emphasize on BCI based rehabilitation systems, as real time feedback present in BCI based systems helps in engaging the patients and keep them motivated.

Physiological and non-physiological signals collected from users have significant importance for controlling rehabilitation devices. Although signals collected through

invasive methods may carry more information, at the same time they possess a much higher risk of clinical complications and other challenges. This makes non-invasive methods a safer choice. Different types of noninvasive signals collected have been used as model input for controlling different rehabilitation devices in the examined studies. Among them, EEG was the most frequently used in the selected studies. However, variation in EEG methodology can greatly impact signal quality and therefore, AI/ML performance. For example, the number of studies using EEG as a model input was limited to using sixteen or fewer electrodes. Hence, a higher number of electrode systems for EEG data collection is highly recommended. Secondly, EEG systems are highly sensitive to artifacts, even minor movements can generate motion artifacts in EEG signals. New robust EEG de-noising algorithms can help overcome this challenge. EMG source signals remained the second best choice as the input signal. As compared to EEG, EMG was used in less than half of the studies; however, the incorporation of EMG signals was spread throughout and implemented in almost all major types of rehabilitation devices. It can be inferred that the potential of EMG is still unexplored. A combination of EEG and EMG was already identified in a few studies, and overall, they have performed significantly well [53]. Future studies shall further explore this combination for promising results. Like EEG, the problem identified related to EMG signals was background noise. EMG signals recorded through the skin surface can carry a considerable amount of background noise. Like EEG, best practices for EMG data recording should also be ensured for attaining better signals, including proper handling of equipment, data collection by trained staff, and using the latest version of software for data processing, as recommended by the provider. Other types of input signals used for controlling rehabilitation devices were mostly mechanical in nature, including pressure, force, and MMG; however, the accuracy of a device controlled through such signals was mostly unreported. Serious analysis of these signals is likely to bring significantly important results. It is also suggested that upcoming studies should provide multiple sensory data as an input for AI based devices, which will help intelligent algorithms to make better decisions. A combination of multiple sensory data can help AI models in generating big data which will significantly improve the model's performance and will make the control of device more intelligent, robust and independent.

AI/ML can play a crucial role in the interpretation of biological signals for controlling rehabilitation devices, and hence, the selection of AI/ML model and type of model inputs are important for designing an intelligent, safe, and effective rehabilitation device. One finding of this review is that most approaches are based on classical machine learning algorithms and thus the use of DNN in rehabilitation engineering remains largely unexplored. In this review, the small number of studies that deployed DNNs were analyzed collectively and they outperformed classical algorithms. On the other hand, most studies that employed DNNs reported findings with small cohorts of participants, often less than five subjects. Moreover, the number of sessions was often unreported raising some questions about the reliability of DNNs in rehabilitation applications. In addition, model explainability would be very useful to help analyze the

findings; however, interpretability and explainability of AI/ML models have been rarely discussed.

As per the systematic review, no single AI/ML model can be labeled the best for rehabilitation. SVM and LDA were used most frequently and had an overall good performance; however, Bayesian models reached the highest accuracy. DNN had the best median decoding accuracies; however, they had high computational costs and require large amounts of training data. Some studies comparing SVM with DNN and other types of models, did not find any significant difference in their performance [48]. Clearly, there is a need for further investigation for finding the most suitable algorithm and model architecture for specific types of rehabilitation tasks.

Another important knowledge gap identified in this systematic review, with a few exceptions (e.g., [13], is the small number of longitudinal studies reported in the literature. Longitudinal studies are critical to assess reliability, changes in performance and brain activity as a function of the intervention, compliance, and the effects of intensity and practice in neurorecovery. Interestingly, none of the studies that reported a single experimental session, showed an improvement in clinical outcomes (if reported). However, almost all UL studies that focused on hand rehabilitation had a longitudinal experimental protocol. For other UL rehabilitation tasks, one-third of the studies were either a single session or unreported. This proportion increased for LL studies. Half of the studies targeting LL rehabilitation did not report the number of sessions or had a single session. Additionally, not any study which had a single session reported clinical outcome. By this, it can be inferred that the purpose of most single session-based studies was not to monitor any improvement in clinical populations. Also, most of the single session studies were open loop, as the presence of feedback system is very crucial for keeping the system updated, especially in real-time operations, this identifies major gap in research practices being conducted in the domain. Interestingly, Major portion of studies selected from PubMed had higher number of sessions, As PubMed database is mostly based on clinical studies hence it can be inferred that clinical settings provide better opportunities for longitudinal studies. To increase the likelihood of translation of these emergent technologies, it is imperative that future studies include a longitudinal design.

Clinical outcome is one of the most important parts of clinical research. The effectiveness of clinical trials of new or emergent AI/ML-based interventions needs to be quantified and reported. Unfortunately, with the notable exception of hand rehabilitation studies, most of the studies reviewed herein did not report primary clinical outcomes. Those studies that reported clinical outcomes used mostly the FMA for clinical assessment. The Studies that were selected from PubMed, the ratio of reported outcome was much higher, as compared to other two databases, almost two third of the studies selected from PubMed reported clinical outcome, most of them used multiple methods to monitor outcome of rehabilitation in targeted population. This reinforces the finding that clinical setting provides better research environment for conducting clinical studies and monitor changes more closely. Also, all the studies that reported

clinical outcome were closed loop, and majority of them had higher number of sessions. It can be inferred that presence of closed loop system is very important for monitoring clinical improvement, as presence of feedback can continuously adjust the parameter for providing better therapy, in real-time. It also connects with the finding that higher number of sessions leads to draw better clinical findings. Moreover, almost all studies that reported clinical outcome, implemented classical machine learning algorithms, which, again, supports the fact about better suitability of classical machine learning algorithm for rehabilitation purpose, due to their robust nature and higher performance with limited dataset. It is recommended for future studies to use standardized clinical assessment methods to quantify the effectiveness and improve the interpretability of findings across studies.

The presence of feedback is critical for rehabilitation. It enables the observation of the real-time performance of a user-device interaction, promotes plasticity, and readjusts the parameters of the rehabilitation device, e.g., change in the model input [51], in which authors used a feedback system to improve consistency and distinguishability of movements. Most of the UL rehabilitation studies were closed-loop; however, around one-fifth of all examined studies were open loop and most of them did not report clinical outcomes, which suggests a weak study design. It also implies that getting feedback from LL rehabilitation devices possess a greater challenge as compared to that of UL rehabilitation devices.

The quality assessment of quantitative studies has highlighted many shallow areas of research conducted during the last ten years in the field of rehabilitation research incorporating AI/ML. More than two-thirds of the studies did not qualify for a strong global assessment rating, indicating the unqualified quality of research in a number of areas. In sub-sections of quality assessment, most *weak* studies were found in *the blinding* section, which means in many cases, participants were aware of the research question and intervention, and outcome assessors were aware of the intervention status of participants. In order to minimize bias and generate reliable results, appropriate blinding of studies is needed.Except for studies selected from PubMed, another area with a high number of *weak* studies was *data collection methods*, which means that a considerable number of studies did not use reliable tools and methods for data collection. Acquisition of high-quality data is very crucial for reliable results. Future studies should consider better practices and data collection tools. On the other hand, *the withdrawal and dropout* section remained commendable, in which most of the studies were rated as *strong*, indicating a strong screening process for recruiting participants in the studies.

5. Conclusion and Future work

The use of AI and ML has immense potential in rehabilitation engineering. This systematic review has revealed knowledge gaps and heterogeneity in study methodology, which indicates an early developmental stage of AI/ML in rehabilitation as well as a lack of best practices; however, it also indicates its multidimensional growth. Upper limb

rehabilitation has been studied more than twice that of the LL due to the UL's more complex nature of impairment, which demands more therapeutic efforts to be made. The most studied clinical population was stroke, followed by SCI, with more work much needed in SCI and other clinical populations. Most studies implemented FES systems, followed by exoskeletons and VR. The rehabilitation devices often used EEG as model input, individually or in combination with other signals, followed by EMG. In terms of AI algorithms, SVM was preferred by researchers, followed up by LDA. Both of them showed good results. DNNs displayed the highest median accuracy but were implemented in fewer systems. More than one-fourth of the studies did not report the number of sessions, restricting any type of longitudinal analysis, e.g., to study the effects of disease progression, brain adaptation, and context. Most studies had a closed-loop protocol, which is very crucial for promoting neurorecovery and for updating the parameters of rehabilitation devices. Unfortunately, most studies did not report clinical outcomes, with the exception of studies on hand rehabilitation that reported FMA to assess clinical status.

Future studies in rehabilitation research need to incorporate different types of clinical populations experiencing motor impairment, along with stroke, including, PD, CP, and other conditions. In terms of devices, BCI-VR systems are likely to be deployed more in future studies because of their low cost, ease of use, adaptability, accessibility for home use, and possibly higher efficiency. In terms of AI/ML algorithms, the performance of DNNs remains to be explored, and future studies shall report model accuracy and shall consider longitudinal protocols. In terms of clinical assessment, it is highly recommended for all upcoming studies to incorporate standardized engineering, clinical, and end-user assessment metrics to strengthen their findings and allow comparisons with other studies. In terms of quality assessment, around two-thirds of the studies did not qualify for a strong global rating. Future studies should ensure blinding when practically feasible, and use best practices and reliable data collection methods to improve the overall quality of studies.

6. Appendix

Ref.	Clin. Pop.	# Ss	Task	Device	Model Input	AI/ML Algorithm	Sessions	Model Accuracy %	Clinical Outcome	CL
[5]	Stroke	10	Hand	BCI - Exo	EEG	SVM	NS	75.75	N/A	Y
[10]	Stroke	4	Hand	BCI - Exo	EEG	SVM	12 - 16	70-81	↑ VAS	Y
[83]	Stroke	21	Hand	BCI-Exo	EEG	LDA	multiple	56.8	↑MAS,WMFT FAS,MEP	Y
[84]	Stroke	2	Hand	BCI - Exo	EEG	LDA	1	79.38	N/A	Y
[75]	Stroke	14	Hand	BCI-Exo	EEG	Bayesian	NS	N/A	↑ FMA	Y
[85]	Stroke	1	Hand	BCI-Exo	EEG	Bayesian	10	N/A	↑ FMA	Y
[42]	Stroke,TBI	58	Hand	BCI-Exo	EEG	Bayesian	15	N/A	↑ FMA,ARAT,MAS,FAI,FIM	Y
[76]	Stroke	51	Hand	BCI-FES	EEG	LDA	25	N/A	↑ FMA	Y
[86]	Stroke	16	Hand	BCI-FES	EEG	CSP,LDA	12	72.90	↑ FMA-UE	Y
[87]	Stroke	2	Hand	BCI-FES	EEG	LDA	10	95	↑ ROM	Y
[45]	CP	32	Hand	BCI-Exo	EEG	Bayesian	10	N/A	N/A	Y
[88]	Stroke	4	Hand	BCI-Exo	EEG, EMG	SVM	multiple	77.17	↑ ARAT,GS	Y
[9]	Stroke	9	Hand	BCI - Exo	EMG	SVM,ANN,RF,KNN,LDA	1	95	N/A	N
[89]	Stroke	4	Hand	EMG-Exo	EMG	ANN	1	90	N/A	Y
[90]	SCI	1	Hand	EMG-Exo	EMG	SVM	20	NS	(↑ Grip force, box and block test ,GRASSP), PINCH force	Y
[91]	SCI	12	Hand	Exo	EMG	Bayesian (GNB), SVM	1	81 (Avg)	NS	Y
[9]	Stroke	8	Hand	BCI-Orthosis	EEG+EMG	SVM	NS	>79.94	N/A	Y
[92]	Stroke	5	Hand	N/A	EMG+Kin	LDA	NS	>90	N/A	Y
[60]	Stroke	6	Hand	Robotic	Magnetic	REG	15	N/A	↑ FMA	Y
[51]	TRA	4	Hand	BCI-VR	EMG	LDA	8	77.5 - 94.4	↑ MCP	Y
[3]	IHMA	8	Hand	BCI-VR	EEG	KNN	1	100	N/A	Y
[7]	Stroke	10	Hand	Hand glove	IMU	SVM	>50	99	N/A	N
[93]	TP	12	Hand	BCI-FES	EEG	LDA	20	N/A	↑ MMT	Y
[50]	Dystonia	1	Hand	BCI-VF	EEG	LDA	10	N/A	NA	Y
[44]	TP,CP,CM	3	Hand	Joystick	Angle, Amplitude	RNN	NS	N/A	N/A	N
[94]	TP	3	Hand	VR	Camera	RNN	NS	*	N/A	Y
[95]	Stroke	1	UL	BMI, HRI, FES	EEG	Bayesian	1	x	N/A	Y
[26]	Stroke	10	UL	BCI-Exo	EEG	SVM	12	>60	↑ FMA	Y
[27]	Stroke	3	UL	BCI-Exo	EEG,EMG	SVM, LDA	5	>46.50	N/A	Y
[25]	stroke,TBI	5	UL	BCI-Exo	EEG	SVM	NS	82.9	N/A	Y
[96]	Stroke	10	UL	BCI-Exo	EEG	SVM,CSP	12	79	(↑ARAT,FMA-UE), JTHFT,GRIP,PINCH	Y
[97]	Stroke	9	UL	BCI-Exo-FES	EEG	LDA	1	55.78–83.20	N/A	Y
[98]	Stroke,TBI	5	UL	BCI-Exo-FES	EEG	SVM	1	71.60	NS	Y
[28]	SCI	3	UL	BCI-Exo	EEG	SVM	NS	>80	N/A	Y
[99]	Stroke	4	UL	EXO	EEG	SVM	1	89.4	N/A	Y
[29]	Stroke	32	UL	BCI-FES	EEG	SVM	11	N/A	↑ MMT	Y
[30]	Stroke	7	UL	BCI-FES	EEG	SVM	24	>70	↑ FMA	Y
[31]	Stroke	5	UL	BCI-FES	EEG	LDA	10-24	87.4	↑ MRC	Y
[32]	Stroke	4	UL	BCI-FES	EEG	REG	8	>50.5	↑ FMA	Y
[13]	Stroke	8	UL	BCI-FES	EEG	TNFLD	24	>70	↑ FMA,ARAT	Y
[33]	Stroke	5	UL	BCI-FES	EEG	SVM	24	avg	N/A	N
[34]	Stroke	2	UL	BCI-FES	EEG	CSP & SVM	1	76.6	N/A	Y
[100]	Stroke	32	UL	BCI-FES	EEG	SVM,CSP	11	NS	(↑ FMA-UE,MMT), MBI	Y
[101]	Stroke	15	UL	BCI-FES	EEG	CSP, SVM	24	77	(↑ARAT),FMA	Y
[102]	Stroke	8	UL	BCI-FES	EEG	TNFLD+SVM+CSP	24	70.5 (Avg)	↑ FMA, ARAT	Y
[103]	Stroke	20	UL	BCI-CC,FES,TS	EEG	SVM	NS	92.5	N/A	Y
[104]	Stroke	16	UL	MI-BCI,FES	EEG	LDA	12	72.9	↑ FMA	Y
[105]	Stroke	10	UL	BCI, HRI, FES	EEG	LDA	>1	x	N/A	N
[43]	Stroke,TBI	8	UL	BCI/BCI-FES	EEG	SVM+LDA	5	66.575	N/A	Y
[74]	Stroke	3	UL	MI-BCI	EEG	SVM,KNN,RF	25	↑ 93	N/A	Y
[73]	Stroke	19	UL	MI-BCI,Robot	EEG	CSP	10	N/A	↑ FMA	Y
[106]	Stroke	1	UL	BCI-VR	EEG	LDA	10	60	↑ FMA	Y
[77]	Stroke	7	UL	BCI	EEG	LDA	25	78.55	↑ FMA,MAS	Y
[47]	Tremor	4	UL	N/A	EEG	Bayesian	2	>14	N/A	N
[78]	Stroke	4	UL	Exo	EEG, EMG	SVM	12	77.17	↑ ARAT,GS	Y
[72]	Stroke	1	UL	EXO	EEG, EMG	LDA/REG	NS	TPR:0.642.FPR:0.201	N/A	Y
[11]	SCI	1	UL	BOTAS	EEG, EMG	REG	NS	x	N/A	Y
[8]	Stroke	5	UL	BCI-FES	EEG, EMG	SVM	20	91.5	N/A	Y
[54]	Stroke	3	UL	EXO	MI-BCI, EEG	SVM	1	82.51	N/A	Y
[55]	Stroke	1	UL	BCI	NMES & EEG	LDA	5	N/A	↑ FMA	Y
[107]	Stroke	10	UL	Exo	EMG	RNN	NS	>98	N/A	Y
[52]	SD	1	UL	VR	EMG	LDA	NS	N/A	N/A	Y
[35]	Stroke	19	UL	VR	Visual	EPNN	4	94.5	↑ WMFT	Y
[36]	Stroke	35	UL	VR	Visual	TCNN	10	>80	N/A	Y
[37]	Stroke	22	UL	VR	MT,TP,ES	SVM,CART	6	92.72	↑ FMA, TEMPA,WMFT	Y
[38]	Stroke	2	UL	VR	KIN, finger pressure	SVM	10	71.3	N/A	N
[49]	NI	12	UL	FES	KIN, Force	GAAN	1	x	N/A	Y
[81]	SCI	6	UL	BMI	BMI	PCA	6 - 9	x	N/A	Y
[59]	Stroke	8	UL	Robot	Force	SVM	NS	>95	N/A	Y
[108]	Stroke	6	LL	BCI-Exo	EEG	Kalman	12	85	NS	Y
[109]	Stroke	8	LL	BCI	EEG	CNN	1	77.3	N/A	N
[6]	LLP	1	LL	BCI-VR	EEG	LDA+DPN	1	high	N/A	Y
[110]	SCI	1	LL	BCI-Exo	EEG	MKL	Multiple	74.5	N/A	Y
[111]	SCI	2	LL	BCI-FES	EEG	CSP,LDA	22	78.55 (Avg)	†WISCI II, LEMS	Y
[39]	SCI	2	LL	BCI-FES	EEG	LDA	25	>73.9	↑ WISCI II	Y
[112]	SCI	1	LL	BCI-FES	EEG	Bayesian	19	N/A	N/A	Y
[113]	SCI	5	LL	BCI-VR	EEG	LDA,Bayesian	19-29	N/A	N/A	Y
[114]	SCI	5	LL	BCI-VR	EEG	Bayesian , LDA	5	85.70	NS	Y
[115]	SCI	8	LL	BCI	EEG	SVM	NS	>67.82	N/A	Y
[116]	Stroke	1	LL	BCI - Exo	EEG, EMG	Kalman	1	r=[0.4,0.5]	N/A	N
[41]	LLP	1	LL	VE-SDAE	EEG	DBN,DPN,CNN	NS	90.69	N/A	Y
[48]	FD	6	LL	FES	EMG	LSTM-NN, SVM & BP	4	90.2	N/A	Y
[46]	PD	7	LL	HRI	Force	FSM, HMM	3	>95	N/A	Y
[117]	Stroke	2	LL	EXO	EEG, EMG	LDA	5	92.4	N/A	Y
[56]	Stroke	58	LL	VR	Clinical, Robotic	NFS	693	93.7	N/A	N
[118]	SCI	1	LL	Prosthesis	KIN, Force	DCA	1	x	N/A	N
[82]	SCI	4	LL	BMI	EEG	SVM	1	80	N/A	N
[79]	Stroke	3	LL	BCI-FES-VR	EEG	LDA	25	94	†ROM	Y
[40]	PP	1	LL	BCI-FES	EEG	Bayesian	>1	>avg	N/A	Y
[80]	Stroke	3	LL	BCI-FES	EEG	Bayesian	>15	50	†ROM	Y
[119]	Pr	2	LL	BMI- Exo	EEG	NTSA	1	87	N/A	Y
[120]	NS	3	LL	FES	EMG	ANN & REG	1	>95	N/A	N
[58]	Stroke	11	LL	IMMUs	KIN	KNN	NS	x	N/A	N
[61]	SCI	8	LL	BCI-FES	MMG	ANN	2	>64 , >74	N/A	Y
[121]	Stroke	10	LL	VR-Exo	VR	NNs	NS	<7(RMSE)	N/A	Y
[122]	SCI	4	LL	Goniometer	EMG	BPNN	NS	N/A	N/A	Y
[123]	CI	1	LL	Rob-sim.	EMG	BPNN	NS	N/A	N/A	Y
[57]	stroke	99	LL	FDS,FES	Pressure	REG	8	N/A	↑ GS-C	Y
[124]	SCI	3	LL	FES	EMG	RNN,Kalman	Multiple	>93,>85	N/A	Y
[20]	Stroke	4	UL / LL	BCI-FES	EEG	GMM	24	>avg	N/A	Y
[21]	Stroke	37	UL & Hand	BMI-Robot	EEG,EMG	SVM	↑ 8	60	N/A	Y
[17]	PD	35	Balance	VR	KIN	SVM	2-4	>86.3	N/A	Y
[24]	SCI	3	VR & HRI	VR, HRI	EEG	LDA	NS	>avg	N/A	Y
[18]	Tremor	5	Tremor Mng	HRI	EEG, EMG	Bayesian	1	High	N/A	N
[19]	MCD	31	Part. Level	EXO	Physiol.	ML, DT,EDT,SVM	2	81 - 91.0	N/A	N
[12]	AD	30	Emotion	BCI-VR	EEG	MLP,SVM,RNN	NS	70.97	N/A	Y
[22]	PD	7	Swallow	EMG-FES	EMG	TDANN	6	96,93	N/A	Y
[23]	SCI, Stroke, Atrophy	8	User Intent	BCI-VR	EEG+EOG	CRF	2	87	N/A	Y
[125]	SCI, Stroke, Atrpohy	8	Whole body	BCI-VR	EEG+EOG	CRF	2	87	NS	Y
[126]	Visually impaired	12	Vission correction	Augmented Cane	Camera	CNN, REG	NS	NS	↑ walking speed	Y

Ref #	*SELECTION BIAS*	*STUDY DESIGN*	*CONFOUNDERS*	*BLINDING*	*DATA COLLECTION METHOD*	*WITHDRAWALS AND DROPOUTS*	*GLOBAL RATING*
[5]	Weak	Moderate	Weak	Moderate	Strong	Weak	Weak
[10]	Moderate	Strong	Weak	Moderate	Strong	Strong	Moderate
[83]	Strong	Moderate	Weak	Moderate	Strong	Strong	Moderate
[84]	Moderate	Moderate	Moderate	Moderate	Strong	Weak	Moderate
[75]	Moderate	Moderate	Strong	Moderate	Strong	Strong	Strong
[85]	Weak	Weak	Strong	Weak	Strong	Strong	Weak
[42]	Moderate	Moderate	Strong	Weak	Strong	Weak	Weak
[76]	Strong	Moderate	Strong	Moderate	Strong	Strong	Strong
[45]	Moderate	Strong	Strong	Weak	Weak	Weak	Weak
[88]	Moderate	Moderate	Strong	Moderate	Strong	Strong	Strong
[9]	Weak	Moderate	Strong	Weak	Weak	Moderate	Weak
[89]	Moderate	Weak	Weak	Moderate	Weak	Strong	Weak
[53]	Moderate	Moderate	Moderate	Moderate	Moderate	Strong	Strong
[92]	Moderate	Moderate	Moderate	Moderate	Strong	Strong	Strong
[60]	Moderate	Moderate	Strong	Moderate	Weak	Strong	Moderate
[51]	Weak	Moderate	Strong	Weak	Weak	Weak	Weak
[3]	Moderate	Strong	Strong	Moderate	Moderate	Strong	Strong
[7]	Strong	Moderate	Strong	Moderate	Moderate	Strong	Strong
[93]	Strong	Strong	Strong	Moderate	Strong	Strong	Strong
[50]	Weak	Weak	Strong	Weak	Weak	Strong	Weak
[44]	Moderate	Moderate	Weak	Moderate	Moderate	Weak	Weak
[94]	Moderate	Moderate	Strong	Moderate	Moderate	Weak	Moderate
[95]	Moderate	Moderate	Strong	Weak	Strong	Strong	Moderate
[26]	Strong	Moderate	Strong	Weak	Strong	Strong	Moderate
[27]	Moderate	Moderate	Strong	Moderate	Strong	Strong	Strong
[25]	Moderate	Moderate	Weak	Moderate	Strong	Strong	Moderate
[97]	Moderate	Moderate	Strong	Weak	Strong	Strong	Moderate
[28]	Moderate	Moderate	Weak	Moderate	Moderate	Strong	Moderate
[99]	Moderate	Moderate	Strong	Moderate	Moderate	Weak	Moderate
[29]	Moderate	Strong	Strong	Moderate	Strong	Strong	Strong
[30]	Moderate	Strong	Weak	Weak	Strong	Strong	Weak
[31]	Weak	Moderate	Strong	Weak	Strong	Strong	Weak
[32]	Weak	Moderate	Strong	Weak	Strong	Strong	Weak
[13]	Moderate	Strong	Strong	Moderate	Moderate	Strong	Strong
[33]	Weak	Moderate	Strong	Weak	Weak	Strong	Weak
[34]	Moderate	Moderate	Strong	Moderate	Moderate	Weak	Moderate
[103]	Strong	Strong	Strong	Moderate	Strong	Strong	Strong
[104]	Strong	Strong	Strong	Moderate	Strong	Strong	Strong
[105]	Strong	Moderate	Weak	Moderate	Strong	Strong	Moderate
[43]	Moderate	Moderate	Strong	Weak	Strong	Strong	Moderate
[74]	Moderate	Moderate	Strong	Moderate	Weak	Weak	Weak
[73]	Moderate	Moderate	Strong	Moderate	Strong	Weak	Moderate
[106]	Moderate	Moderate	Strong	Weak	Moderate	Strong	Moderate
[77]	Weak	Moderate	Strong	Weak	Strong	Strong	Weak
[47]	Moderate	Moderate	Moderate	Moderate	Moderate	Strong	Strong
[78]	Moderate	Moderate	Strong	Moderate	Moderate	Strong	Strong
[72]	Weak	Weak	Strong	Weak	Weak	Strong	Weak
[11]	Moderate	Moderate	Strong	Moderate	Strong	Strong	Strong
[8]	Moderate	Moderate	Strong	Moderate	Strong	Strong	Strong
[54]	Moderate	Moderate	Strong	Moderate	Moderate	Strong	Strong
[55]	Weak	Weak	Strong	Weak	Strong	Weak	Weak
[107]	Moderate	Moderate	Weak	Weak	Weak	Strong	Weak
[52]	Moderate	Moderate	Strong	Moderate	Strong	Strong	Strong
[35]	Moderate	Moderate	Strong	Moderate	Weak	Weak	Weak
[36]	Moderate	Moderate	Strong	Weak	Strong	Strong	Moderate
[37]	Strong	Moderate	Weak	Moderate	Weak	Strong	Weak
[38]	Moderate	Moderate	Strong	Moderate	Weak	Strong	Moderate
[49]	Strong	Moderate	Strong	Moderate	Weak	Strong	Moderate
[81]	Moderate	Moderate	Weak	Moderate	Strong	Strong	Moderate
[59]	Moderate	Moderate	Strong	Moderate	Strong	Strong	Strong
[109]	Moderate	Moderate	Weak	Moderate	Moderate	Strong	Moderate
[6]	Moderate	Moderate	Strong	Moderate	Moderate	Strong	Strong
[110]	Weak	Moderate	Weak	Weak	Weak	Strong	Weak
[39]	Weak	Moderate	Strong	Weak	Strong	Strong	Weak
[112]	Weak	Weak	Strong	Weak	Weak	Strong	Weak
[113]	Moderate	Moderate	Strong	Moderate	Strong	Strong	Strong
[115]	Moderate	Moderate	Weak	Moderate	Strong	Strong	Moderate
[116]	Weak	Moderate	Strong	Weak	Weak	Strong	Weak
[41]	Weak	Weak	Weak	Weak	Weak	Strong	Weak
[48]	Moderate	Moderate	Moderate	Moderate	Strong	Strong	Strong
[46]	Moderate	Moderate	Weak	Weak	Weak	Strong	Weak
[117]	Moderate	Moderate	Moderate	Moderate	Moderate	Strong	Strong
[56]	Strong	Moderate	Strong	Moderate	Weak	Strong	Moderate
[118]	Moderate	Moderate	Weak	Weak	Moderate	Strong	Weak
[82]	Moderate	Moderate	Strong	Moderate	Strong	Strong	Strong
[79]	Weak	Moderate	Strong	Weak	Strong	Strong	Weak
[40]	Weak	Weak	Strong	Weak	Weak	Strong	Weak
[80]	Moderate	Moderate	Strong	Moderate	Moderate	Weak	Moderate
[119]	Weak	Weak	Weak	Weak	Weak	Weak	Weak
[120]	Moderate	Moderate	Moderate	Moderate	Strong	weak	Moderate
[58]	Moderate	Moderate	Strong	Moderate	Moderate	Weak	Moderate
[61]	Moderate	Moderate	Strong	Moderate	Strong	Strong	Strong
[121]	Strong	Moderate	Moderate	Moderate	Moderate	Strong	Strong
[122]	Moderate	Moderate	Moderate	Moderate	Moderate	weak	Moderate
[123]	Weak	Weak	Strong	Weak	Weak	Strong	Weak
[57]	Strong	Moderate	Strong	Moderate	Strong	Strong	Strong
[124]	Moderate	Moderate	Weak	Moderate	Strong	Strong	Moderate
[20]	Weak	Moderate	Strong	Weak	Strong	Strong	Weak
[21]	Moderate	Strong	Weak	Moderate	Weak	Strong	Weak
[17]	Moderate	Moderate	Strong	Moderate	Weak	Strong	Moderate
[24]	Moderate	Moderate	Strong	Moderate	Moderate	Strong	Strong
[18]	Weak	Moderate	Strong	Weak	Weak	Strong	Weak
[19]	Strong	Moderate	Strong	Moderate	Strong	Strong	Strong
[12]	Moderate	Moderate	Strong	Moderate	Moderate	Strong	Strong
[22]	Moderate	Moderate	Moderate	Moderate	Strong	Strong	Strong
[23]	Weak	Moderate	Strong	Weak	Weak	Strong	Weak

Ref #	***SELECTION BIAS***	***STUDY DESIGN***	***CONFOUNDERS***	***BLINDING***	***DATA COLLECTION METHOD***	***WITHDRAWALS AND DROPOUTS***	***GLOBAL RATING***
[100]	Moderate	Strong	Strong	Moderate	Strong	Weak	Moderate
[86]	Weak	Strong	Weak	Weak	Strong	Strong	Weak
[111]	Moderate	Moderate	Strong	Weak	Strong	Strong	Moderate
[96]	Moderate	Moderate	Weak	Weak	Strong	Weak	Weak
[108]	Moderate	Moderate	Weak	Moderate	Strong	Strong	Moderate
[98]	Moderate	Weak	Weak	Weak	Strong	Strong	Weak
[87]	Moderate	Moderate	Weak	Weak	Weak	Strong	Weak
[114]	Moderate	Moderate	Weak	Weak	Strong	Strong	Weak
[125]	Weak	Moderate	Weak	Weak	Strong	Strong	Weak
[101]	Moderate	Strong	Strong	Weak	Strong	Strong	Moderate
[102]	Moderate	Strong	Strong	Weak	Strong	Strong	Moderate
[126]	Weak	Moderate	Weak	Weak	Strong	Strong	Weak
[90]	Moderate	Weak	Strong	Weak	Strong	Strong	Weak
[91]	Moderate	Moderate	Strong	Weak	Strong	Strong	Moderate

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