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Research paper

Artificial intelligence in physical rehabilitation: A systematic review

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ABSTRACT

Background: Physical disabilities become more common with advancing age. Rehabilitation restores function, maintaining independence for longer. However, the poor availability and accessibility of rehabilitation limits its clinical impact. Artificial Intelligence (AI) guided interventions have improved many domains of healthcare, but whether rehabilitation can benefit from AI remains unclear.
Methods: We conducted a systematic review of AI-supported physical rehabilitation technology tested in the clinical setting to understand: 1) availability of AI-supported physical rehabilitation technology; 2) its clinical effect; 3) and the barriers and facilitators to implementation. We searched in MEDLINE, EMBASE, CINAHL, Science Citation Index (Web of Science), CIRRIE (now NARIC), and OpenGrey.
Results: We identified 9054 articles and included 28 projects. AI solutions spanned five categories: App-based systems, robotic devices that replace function, robotic devices that restore function, gaming systems and wearables. We identified five randomised controlled trials (RCTs), which evaluated outcomes relating to physical function, activity, pain, and health-related quality of life. The clinical effects were inconsistent. Implementation barriers included technology literacy, reliability, and user fatigue. Enablers included greater access to rehabilitation programmes, remote monitoring of progress, reduction in manpower requirements and lower cost.
Conclusion: Application of AI in physical rehabilitation is a growing field, but clinical effects have yet to be studied rigorously. Developers must strive to conduct robust clinical evaluations in the real-world setting and appraise post implementation experiences.

1. Introduction

Ageing populations are burdened by chronic disease and functional disabilities [1,2]. By 2050, the World Health Organization (WHO) estimates that 22 % of the world population will be aged 60 years and above [3]. Accordingly, the different needs of an aged multi-morbid population have prompted a reconsideration of health services [4]. Chronic disease or disability often requires a sustained care management approach, which requires effective self-management to maintain independence for as long as possible. When functional ability is compromised, rehabilitation (i.e., "*an intervention designed to optimise function and reduce disability*" *WHO* [5]) can restore mobility and function.

Physical rehabilitation focuses on restoring physical function and strength. Physical rehabilitation interventions come in many forms: hospital or community-based, clinician-led or self-directed, multiple- or single-component programmes. Although physical rehabilitation is widely available, it is frequently underused with poor compliance worldwide [6,7]. Poor uptake and compliance are multifaceted issues caused by low physician referral or endorsement, transportation barriers, poor perceived efficacy, and inconvenient programme timing [8].

Technological advances have overcome some barriers to rehabilitation use, in recent years. For example, telerehabilitation can improve accessibility [9] and digital technologies can improve compliance and monitoring of home exercise [10], but implementation challenges remain. More recently, technology supported rehabilitation has been enhanced by Artificial Intelligence (AI). AI refers to a specific type of technology designed to simulate human intelligence. Machine learning is a subset of AI, which automatically learns from the data and makes incremental improvements [11]. Of the many technological

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developments, AI's unique advantages include processing more complex data, faster data computation than humans, and facilitation of tailored interventions [12–14].

Although AI innovations in healthcare have shown great promise, particularly in diagnostics [12], new technologies are often resisted and underused due to usability, usefulness, and cost issues [15,16]. Thus, it is essential to understand the implementation challenges of new health technology. A systematic review of the impact of machine learning on patient care found hundreds of retrospective 'proof of concept studies' but only eight articles that prospectively evaluated machine learning algorithms in clinical practice [17]. The purpose of this review is to understand the evidence for AI-supported physical rehabilitation. The study objectives are to:

1. Identify what AI applications have been developed to support physical rehabilitation.
2. Investigate the effectiveness of AI-supported rehabilitation interventions in comparison to standard care, including clinical and non-clinical outcomes.
3. Identify the barriers and enablers of using AI-supported rehabilitation interventions.

2. Methods

The study was conducted and is reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [18]. A copy of the PRISMA checklist is included in the supplements. The systematic review protocol was prospectively registered on the PROSPERO database of systematic reviews (registration number CRD42020201553).

2.1. Literature search

MEDLINE, EMBASE, CINAHL, CIRRIE (now NARIC), Science Citation Index (Web of Science) and OpenGrey were searched in July 2020. An updated search was then conducted in October 2021. A combination of MeSH terms and keywords on the themes: AI and physical rehabilitation were used. The initial search strategy was developed in MEDLINE and revised with the help of an information specialist. The search strategy was then converted for use in the other databases. A copy of the MEDLINE search strategy is included in the supplements.

2.2. Study selection

Titles and abstracts were initially screened for inclusion by individual reviewers (JS, HWL, LSC, AB, AM, GK). Provisionally included articles were then full text screened by two independent reviewers for eligibility (JS, HWL, LSC, SB) (Table 1).

We excluded studies that only reported validation outcomes (e.g., algorithm training). Studies that did not test the intervention in its intended setting (e.g., home-based) or by the target users (i.e., patients) were also excluded, except for living lab experiments. Brain control interface interventions were excluded if the purpose was not to enable a physical function.

Disagreements were discussed and resolved with a third reviewer if required. When the eligibility of a study was unclear from the publication, we attempted to contact the author(s) via email to clarify eligibility.

2.3. Data extraction and management

Data extraction was undertaken by one researcher (LSC, AB or HWL) and checked for consistency by a second independent researcher (HWL or JS). Extracted data items included: study and population characteristics; intervention details including algorithm accuracy if reported; measures of clinical and non-clinical effectiveness (i.e., adherence, acceptability); barriers and enablers of technology implementation; and any cost-related measures. The extraction sheet was piloted on a sample of papers and refined before full data extraction.

Table 1
PICOS eligibility criteria.

Criteria	Definition
Participants	Adult patients (≥18 years of age) undergoing formal physical rehabilitation.
Intervention	Artificial Intelligence, specifically Machine Learning applications used in physical rehabilitation programmes. These may be applications used by patients or health care providers in inpatient, outpatient, or community-based settings. Machine learning is a branch of AI designed to mimic: "a range of human intelligent actions (e.g., learning, understanding, thinking, and creating), by using data to learn and gradually improve". Physical rehabilitation programmes are defined as any healthcare-led programme to enhance and restore functional ability and quality of life. Programmes may be clinic-based or home-based, or in the community. Multi-component programmes are eligible if there is an exercise component e.g., education and exercise.
Control	For interventional studies, the control group is defined as those not receiving AI-supported physical rehabilitation. Studies without a control group were eligible for inclusion if the other criteria were met.
Outcomes	Outcome measures included: Clinical effectiveness (e.g., mobility, pain, HRQOL) and non-clinical measures (e.g., adherence, acceptability; barriers and enablers of technology implementation; and any cost-related measures).
Study types	All study types were considered (i.e., experimental or observational designs) so long as the concept was implemented and tested according to its intended purpose (i.e., intended clinical impact). Developmental work such as simulation studies, testing on healthy subjects, or validation studies (i.e., measurement accuracy) was excluded.
Other	Studies were restricted to English language only articles.

2.4. Quality assessment

For Randomised Controlled Trials (RCTs), the Cochrane Risk Of Bias tool (ROB2) was used to assess the quality of studies reporting clinical efficacy [19]. The tool asks a series of questions covering five domains where bias might occur: selection, performance, attrition, reporting, and other. Each domain is rated low, high, or unclear. Two researchers independently assessed the risk of bias, and any disagreements were discussed (JS and HWL). We did not use quality assessments to exclude papers.

2.5. Data synthesis

Results were synthesised narratively due to the heterogeneity of the study designs and outcome measures.

3. Results

We identified 9054 unique articles. After screening, sixteen projects met the eligibility criteria and were included. After updating the search strategy (re-run in October 2021), we identified twelve further projects that met the eligibility criteria (Fig. 1).

3.1. Study characteristics

Characteristics of the included projects are presented in Tables 2 and 3. Of the 28 projects (29 publications), nine were controlled cohorts, fifteen were pre-post studies, and five were RCTs. The number of participants recruited into the included studies ranged from one to four hundred and sixty-one participants. Studies were conducted in China (4), Italy (4), Germany (3), United States (3), Hong Kong (2), Taiwan (2), Ukraine (2), Belgium (1), Canada (1), Denmark (1), Japan (1), Korea (1), Netherlands (1), Romania (1) and Singapore (1).

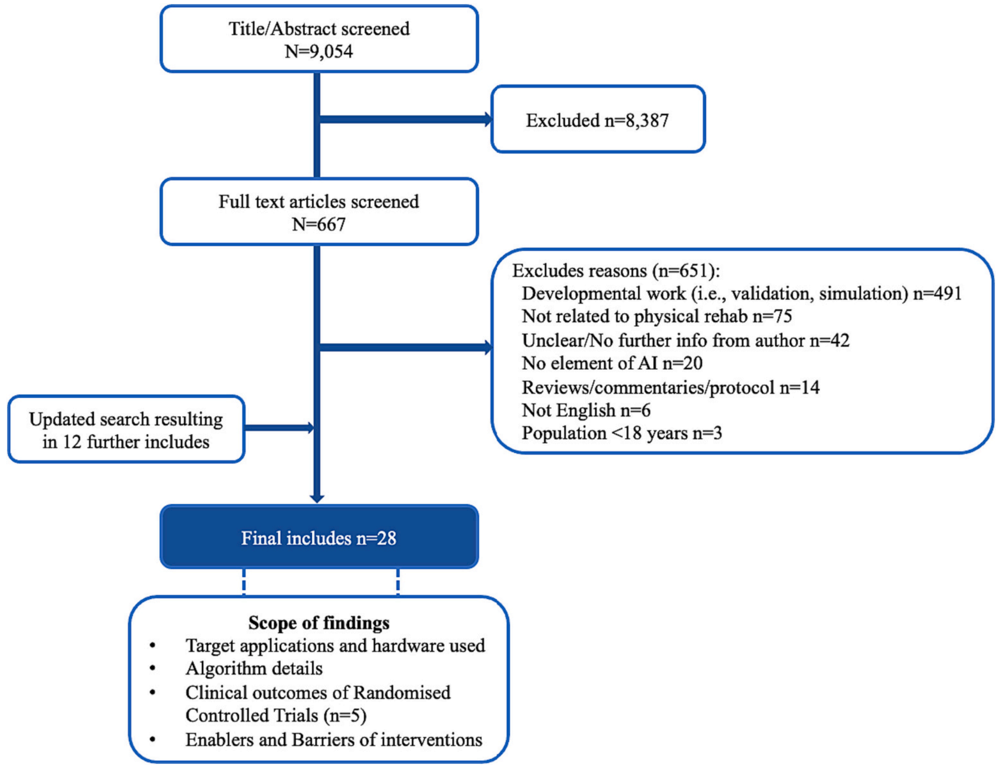

Fig. 1. PRISMA flow diagram and scope of findings.

3.2. Intervention characteristics

Interventions included two main groups: those that attempt to restore function ($n = 24$) or those that replace function (e.g., prosthetic limbs) ($n = 4$). The most treated conditions were stroke ($n = 7$), back or neck pain ($n = 6$), Parkinson's disease ($n = 3$) or limb absence ($n = 3$). Interventions were developed to improve mobility, function, balance, or pain. Solutions were home-based ($n = 14$), clinic-based ($n = 10$), or designed to be used in a mixture of settings ($n = 4$). The hardware utilised by the interventions is summarised in Table 4. While some studies used commercialised products in their system (e.g., smart watches), none reported whether their intervention was certified for clinical use.

3.3. Clinical outcomes

Clinical outcomes for the five included RCTs are reported in Table 5. Outcome measures fell into three categories: Physical function and activity, pain, and health-related quality of life (HRQOL).

3.4. Risk of bias summary

As assessed using the Cochrane risk of bias tool (Fig. 2), three of the studies had an overall risk of bias of 'some concerns' [22,29,45] and two studies had a high risk of bias [23,26]. Risk of bias issues related to a lack of detail on the randomisation process and participant characteristics, a lack of assessor blinding, and large proportions of missing data.

3.5. Enablers and barriers to implementation

No studies conducted a comprehensive implementation evaluation, although several included comments on the barriers and enablers associated with their interventions. Implementation experiences are summarised according to the type of technological solution. Experiences primarily focus on hardware rather than software challenges, as we did not include validation studies.

3.5.1. Standalone app-based systems

Accessibility of the system (i.e., being able to access a programme anywhere at any time) [21,22], ease of use – for those that are technology literate [20,23], and the ability to personalise treatment through the app [20] were enablers of app-based systems. In one study, participants found the app-based instructions easier to follow than traditional verbal instructions [20]. One study reported that integration with an already established messenger app facilitated the use of their intervention [23]. Apps also had the advantage of reducing manpower requirements, as the intervention could operate autonomously [20]. One paper addressed data privacy; reporting concerns could be minimised by data capture on the patients' phones [20].

Reported barriers included low technology literacy, particularly in older, less tech savvy adults [22], inability to know if an exercise has been done [23], and demands on the battery life of personnel devices [20]. Finally, one study reported that tailored exercise recommendations were of limited use when they did not consider the context (e.g., suggested exercise not appropriate for weather conditions) [20].

3.5.2. Robotics to replace function

Only one paper commented on the enablers of limb replacement robotics [26]. In this study, functional training helped users adapt to the prosthesis by teaching them the influence of weight and posture on control. Furthermore, gradually increasing the degrees of freedom enabled the transition from a direct control prosthesis to a machine learning controlled prosthesis.

Barriers are primarily related to prosthesis performance. Kristoff et al. [26] noted that the fit and choice of prosthesis material impacted electrode contact and performance (electrodes measure movement intention). The prosthetic material also had implications on durability, specifically concerning weight bearing tasks [26]. The scalability of advanced prosthetics requires reliable and robust hardware [27]. Technical difficulties, a lack of portability and independent set-up, the accuracy of the system, or devices that require ongoing calibration hindered usability and scalability [24,27,28]. Fatigue from overuse also

Table 2
Included study characteristics (restores function).

Author, date, country	Purpose of device	AI role	Algorithm details	Target condition(s) and sample characteristics	Outcome measures	Results summary
Alcaraz, 2018, Germany	To improve rehabilitation progress and quantify performance.	Analysis and interpretation of motion data	A deep Convolutional Neural Network (CNN) was trained (supervised) using data from different Inertial Measurement Units (IMUs) and kinematic signals measuring gait following hip unilateral arthroplasty surgery. Accuracy not reported.	Gait related issues. Int $n = 10$, Mean age: 63 ± 10 years. Ctrl $n = 10$, Mean age: 61 ± 8 years.	Gait metrics	Faster recovery time compared to usual care.
Anan, 2021, Japan	To improve musculoskeletal symptoms through an app-based health promotion system.	Exercise and symptom control recommendations sent through chatbot	Predictive analytics system called Secaide.me ver 0.9. created by Travoss Co, Ltd. No details on training. Accuracy was not reported.	Back and neck pain Int $n = 48$, Mean age: 41.8 ± 8.7 years. Ctrl $n = 46$, Mean age: 42.4 ± 8.0 years.	Pain and adherence	Improved neck/shoulder pain and stiffness and reduced lower back pain.
Andrei, 2015, Romania	To improve functional capacity through AI guided therapy.	Generates treatment recommendations based on medical status	A modified fuzzy inference system, using a modified Sugeno type inference system. The system was tested on data from 260 patients. System error was under 2 %.	Back pain $n = 260$. Age not reported.	Daily activities and movement	Significant improvements in functional capacity.
Ang, 2017, 2014 Singapore	To improve motor recovery through motor imagery and feedback through a haptic knob.	Motor detection and modulation of haptic knob	EEG data were recorded during a calibration session involving 80 motor imagery tasks and 80 idle state tasks. Signal processing was performed using the Filter Bank Common Spatial Pattern algorithm. For the intervention group (Brain-Computer Interface with haptic knob training) calibration accuracy averaged 79.8 %. Accuracy dropped to 69.5 % during intervention training.	Stroke Int $n = 6$, Mean age: 54.0 ± 8.9 years. Ctrl 1: $n = 8$, Mean age: 51.1 ± 6.3; Ctrl 2: $n = 7$, Mean age: 58.0 ± 19.3 years.	Motor function	Significantly larger motor gains compared to usual care.
Avola, 2013, 2018, 2019, Italy	To provide customised rehabilitation exercises using virtual reality.	Analysis and interpretation of exercise performance	A Gated Recurrent Unit Recurrent Neural Network (RNN) was used to rate how much an exercise is correctly performed compared to a reference model developed on healthy subjects. Accuracy compared to therapist was rated between 0 and 10.	Parkinson's disease $n = 92$, Mean age: 40 years.	Patient and staff experience, rehabilitation progress and leg mobility	Significant recovery of mobility. Users were motivated to exercise. Usability and customisation were rated highly.
Bockbrader, 2016, 2019, US	To restore motor function through brain-computer interface (BCI) and functional electrical stimulation (FES).	Interpretation of BCI signals and communication of movement intention	Nonlinear, Support Vector Machine (SVM) decoders were trained on different grip movements. Decoder training took 10 to 15 min, with 3 to 4 repetitions of each movement across 4 to 6 blocks. Accuracy was not reported.	Tetraplegia $n = 1$, Age: 27 years.	Motor function metrics and sensation	Participants were able to perform coordinated grasps and made significant gains in upper limb function.
Burns, 2021, Canada	To remotely monitor participation in physiotherapy using a smartwatch.	Detection of physiotherapy exercise activity	A fully convolutional neural network (FCN) classifier was trained (supervised) to detect and differentiate labelled inertial data from supervised physiotherapy activity. The last training session, per patient, was used as the test set, and prior sessions as a training set. The training data set was augmented with data from 20 healthy	Rotator cuff disorders $n = 42$, Mean age: 45 ± 13 years.	Participation in therapy, pain	Exercise participation was low. A statistically significant dose response relationship was found between physiotherapy and pain.

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Table 2 (*continued*)

Author, date, country	Purpose of device	AI role	Algorithm details	Target condition(s) and sample characteristics	Outcome measures	Results summary
			volunteers. Algorithm accuracy between 0.90 and 0.95.			
Chae, 2020, Korea	To remotely monitor rehabilitation exercises using a smartwatch and smartphone app.	Detection of physiotherapy exercise activity	A CNN algorithm was used for detecting home exercises. Training data were collected from patients performing four types of exercises. The data was divided into one test dataset and four training datasets, to build and establish model accuracy. Accuracy between 95.8 % and 99.9 % depending on data input.	Stroke Int $n = 17$, Mean age: 58.3 ± 9.3 years. Ctrl $n = 6$, Mean age: 64.5 ± 9.6 years.	Functional assessment, range of motion and depression	The system facilitated home-based rehabilitation and significantly improved motor function and range of motion.
De Cannière, 2020, Belgium	To interpret functional capacity using a wearable sensor for the longitudinal follow-up of cardiac rehabilitation (CR) patients.	Prediction of 6-minute walk distance data to determine functional capacity	The performance of different SVM regression models was compared. Eighty percent of the participant's data were used to train (unsupervised) the model, while the remaining 20 % validated the model. A 20-fold-validation was performed to measure prediction error. Mean error in 6-min walking test was 42.5 m.	Heart failure $n = 89$, Mean age: 63 ± 1 years.	Functional capacity	The technology successfully facilitated objective tracking of clinical progression in CR.
Donisi, 2021, Italy	To assess rehabilitation outcomes through gait analysis using a wearable inertial system.	Analysis of motion data to determine clinical improvement	Four tree-based algorithms compared differences in admission and discharge parameters: Random Forest, Rotation Forest, Ada-Boost of Decision Stumps, and Gradient Boost tree. A synthetic minority oversampling technique was used–to perform a reliable analysis. Accuracy 0.94, 0.79, 0.94 and 0.90 respectively.	Parkinson's disease $n = 12$, Age range: 51–77 years.	Gait and posture metrics, anticipatory postural adjustment, turning, balance, functional independence, and disease impairment	The system corroborated clinicians' evaluations of rehabilitation assessment. Significant improvements in gait were found.
Hospodarskyy, 2020, and Tsvyakh, 2021, Ukraine	To deliver a tailored rehabilitation plan through a telemedicine system.	Monitoring of exercise time, local temperature, the frequency of injured limb activity	Machine learning was developed in the Ternopil Medical University. No further information reported.	Lower extremity injury Study 1: Int $n = 96$. Ctrl $n = 52$. Age not reported. Study 2: Int $n = 32$, Mean age: 44.7 (5.4) years. Ctrl $n = 16$, Mean age: 48.6 years.	Study 1: Exercise time, temperature, and patient satisfaction Study 2: Pain, functional status, consultation time, patient satisfaction	Subjects reported higher satisfaction with tailored telerehabilitation than with traditional orthopaedic rehabilitation.
Jezernik, 2003, Switzerland	Automated treadmill training for rehabilitation.	Analysis and interpretation of motion data to automatically correct gait pattern	A RNN model was able to generate hip and knee trajectories. The gait-pattern adaptation algorithms were tested and compared in closed-loop simulations in several pilot experiments with healthy subjects and four pilot experiments with patients. Accuracy not reported.	Spinal cord injury, stroke $n = 10$, Age not reported.	Body loading	Overall, the Lokomat was shown to be an important robotic rehabilitation device. Patients' mobility improved with time.
Lee, 2021, Taiwan	To rehabilitate upper-limb motor function using a virtual reality training system and automatic assessment of motor function.	Classification of stroke recovery	Multilayer Perceptron, Radial Basis Function Network, Classification and Regression Tree and SVM were used to classify exercise indicators. The exercise indicator data and the relevant recovery level serve as training sets (supervised). Accuracy	Stroke $n = 22$, Age not reported.	Motor function metrics	The virtual reality motor training system effectively improved upper limb motor training, significantly improving motor function.

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Table 2 (*continued*)

Author, date, country	Purpose of device	AI role	Algorithm details	Target condition(s) and sample characteristics	Outcome measures	Results summary
			rates of 92.72, 88.87, 63.7 and 74.9 % respectively.			
Lo, 2018, China	To assist people using an app to self-manage chronic neck and back pain.	Generation of exercise recommendations based on symptoms	A multilayered perceptron artificial neural network was used to generate recommendations. Computer-simulated data ($n = 300$ sets) were reviewed by experts to ensure exercises were appropriate. Once the initial algorithm was trained, a back-propagation algorithm was used to continue the training until an accuracy of at least 80 % was achieved.	Back and neck pain $n = 158$, Age range: 18 to >60 years.	Pain, perceived improvement, usability, time spent exercising or reading educational material	Users reported exercising more with the intervention and pain was reduced.
Pirovano, 2014, 2016, Italy	An exergame system which facilitates remotely monitored home rehabilitation.	Measurement of exercise performance with autonomous feedback	Fuzzy systems are used to monitor exercise performance. Exercise parameters were tuned during exercise to the patient's performance through a Bayesian framework that also takes into account input from the therapist (Quest method). Accuracy not reported.	Posture and balance $n = 7$, Age range: 68–82 years.	Patient experience, game success rate	The system integrated the functionalities to support autonomous rehabilitation.
Pogrzeba, 2018, Germany	To record, auto-calibrate, and analyse repetitive motion to objectively assess long-term rehabilitation performance.	Tracking of motor function progression	A probabilistic model, trained (supervised) from a dataset of "healthy" and "impaired" motion, was used to monitor recovery of motion. Classification accuracy up to 0.88, depending on the feature selection.	Stroke or Parkinson's disease Int $n = 20$, Mean age: Not reported. Ctrl 1: $n = 10$, Mean age: 31.4 ± 2.54 years; Ctrl 2: $n = 1$, age: 31 years.	Motor function	The model assisted therapists in the objective assessment of therapy success and encouraged changes in treatment if used concomitantly to the therapy.
Rabbi, 2018, US	MyBehaviorCBP is a mobile phone app that generates physical activity recommendations similar to existing behaviours.	Generation of exercise recommendations based on physical activity behaviours	Developed using data from a healthy population. A Gaussian Mixture Model was used to identify common daily physical activities (unsupervised). A multi-armed bandit algorithm was then used to generate personalized suggestions based on past behaviour. Accuracy not reported.	Back pain $n = 10$, Age range: 31–60 years.	App usage, physical activity, patient experience	Physical activity recommendations were actualised more with the app, and instructions were easier to follow than generic advice.
Sandal, 2021, Denmark	To facilitate and improve self-management of lower back pain through the selfBACK app.	Tailored self-management recommendations based on the participant's characteristics, symptoms, and progression	Recommendations were generated using a case-based reasoning approach i.e., data from successful previous cases are used to suggest the most suitable self-management plan for a current user. Accuracy not reported.	Back pain Int $n = 232$, Mean age: 48.3 ± 15.0 years. Ctrl $n = 229$, Mean age: 46.7 ± 14.4 years.	Disability, pain, self-efficacy, fear-avoidance, illness perception, health-related quality of life, physical activity, and perceived effect	Adults with lower back pain who received the AI intervention had less back pain disability at three months than usual care.
Song, 2005, Hong Kong	An Electromyography (EMG) controlled robotic system to improve upper limb function.	Interpretation of EMG signals into robotic arm control	A RNN was trained (supervised) using healthy and stroke patient data. The first batch of testing (3 × 2 movements) was used as training data, and the second batch of testing was used as the test data. Accuracy in stroke patients: training model relative error 7.59 %; test data 10.82 %.	Stroke $n = 3$, Age range: 39–57 years.	Arm function (strength, extension, tone, control), patient experience	Functional improvements were observed in all three subjects after a four-week training protocol.
Thiengwittayaporn, 2021, Germany	To assess the stage of knee osteoarthritis, personnel treatment and	Tailored exercise recommendations	An adaptive assessment, based on a decision tree algorithm, was used to	Knee osteoarthritis Int $n = 42$, Mean age: 62.2 ± 6.8	Range of motion, symptoms, pain, physical activity,	Patients saw significant improvements in quality

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Table 2 (*continued*)

Author, date, country	Purpose of device	AI role	Algorithm details	Target condition(s) and sample characteristics	Outcome measures	Results summary
	promote rehabilitation exercise using an app.		determine the disease stage. No further training or accuracy information reported.	years. Ctrl $n = 40$, Mean age: 63.0 ± 9.7 years.	quality of life, patient experience	of life, pain, and physical function.
Wang, 2021, China	To analyse motion using IMUs to evaluate gait and rehabilitation progress.	Quantifying gait deviations based on IMU data	A principal component analysis method was used to calculate the gait normalcy index, which was compared to normal gait ranges in healthy subjects. The approach was first validated in seven inpatients each performing six walking trials. Accuracy not reported.	Gait related issues Int $n = 8$, Mean age: 40 ± 8 years. Ctrl $n = 10$, Mean age: 40 ± 11 years.	Gait metrics	An improvement in the IMU-based gait normalcy index (INI) was demonstrated during the rehabilitation process.
Ye, 2021, Hong Kong	To provide robotic assisted upper limb rehabilitation and automatic detection of rehabilitation progress.	Interpretation of EMG signals to determine clinical status	A backpropagation neural network was trained (supervised) using 80 % of the EMG epochs data. The remaining 20 % were testing data. AI scores and manual clinical assessment scores were highly correlated >0.9 ($p <$ 0.001).	Stroke $n = 29$, Mean age: 58.7 ± 8.3 years.	Motor function	The system successfully evaluated motor function. Significant improvements in function were observed.
Yeh, 2014, Taiwan	An interactive virtual reality rehabilitation game with sensors to improve balance.	Interpretation of balance indices to determine clinical status	A SVM was trained (supervised) on participant data. The dataset was separated into a training and testing dataset, following the methods of 10-folds cross-validation. Classification accuracy between 65 and 75 %.	Vertigo Int $n = 48$, Age: 64 ± 16 years. Ctrl $n = 36$, Mean age: 22 ± 4 years.	Balance metrics	The proposed interactive VR rehabilitation system effectively helped patients with vestibular dysfunction improve their balance scores.
Zhou, 2021, China	To evaluate lower back pain and the effect of rehabilitation using surface EMG.	Interpretation of EMG signals during rehabilitation	The ARAN algorithm, built with a time-varying parameter AR model and ANN, was trained (supervised) using the Ninapro database in a simulation study. ARAN was compared to the autoregressive moving average algorithm and the CNN algorithm. Accuracy 96.31 %, 85.16 % and 83.35 % respectively.	Back pain $n = 106$, Mean age: 18–50 years.	Perceived disability and mobility	Surface EMG effectively evaluated the golfer's lower back pain and the effect of rehabilitation.

Abbreviations: Intervention (Int); Control (Ctrl); Brain-Computer Interface (BCI); Convolutional Neural Network (CNN); Fully Convolutional Network (FCN); Functional Electrical Stimulation (FES); Cardiac Rehabilitation CR; Electromyography (EMG); Inertial Measurement Units (IMUs); Inertial Normalcy Index (INI); Recurrent Neural Network (RNN); Support Vector Machine (SVM).

limited the use of advanced prosthetics [24].

3.5.3. *Robotics to restore function*

Only two studies commented on implementation-related factors [30,31]. One study evaluated the usability of a robotic orthosis with Electromyography (EMG) sensors [31]. The study team rated the clarity of instructions, ease of use, comfort, appearance, simplicity of training, effectiveness, and overall satisfaction. The mean usability score was 29.3 (maximum score 36) [31]. Jezernik et al. [30] evaluated an intelligent treadmill training system. Patients preferred adaptive gait-pattern training over a traditional fixed gait-pattern system [30]. No barriers were reported.

3.5.4. *Gaming systems*

Gaming systems were perceived as low-cost solutions [33,36] and were rated highly for their usability [33,35]. The opinions on cost and usability are most likely due to the availability of 'off the shelf' commercial gaming hardware, e.g., Kinect (Table 4). All gaming systems used at least some commercially available hardware in their system. The flexibility of gaming systems was another perceived advantage, for instance, customising the game and exercises according to different clinical groups [33,35]. Furthermore, clinicians reportedly valued the ability to remotely manage patients and objectively assess their progress [33,35,36]. From the patient's perspective, game-based exercise was engaging, easy to do, and set at an appropriate difficulty level [35]. Patients also felt gesture and voice recognition were suitable for interacting with gaming systems [35]. Barriers included latency issues (causing motion sickness) [33], gaming fatigue [35], unclear visuals, and a preference for greater personalisation (e.g., background music, bespoke avatars) [35].

3.5.5. *Activity monitoring using wearables*

Wearable devices, including smartwatches, Inertial Measurement Units (IMUs) and accelerometers, were advantageous in terms of portability, convenience [38,40,46], comfort [38], and low cost [41,46]. One author noted that wearables facilitated the analysis and synthesis of

Table 3
Included study characteristics (replaces function).

Author, date, country	Purpose of device	AI role	Algorithm details	Target condition (s) and sample characteristics	Outcome measures	Results summary
Kristoffersen, 2021, Netherlands	To restore limb function with a robotic prosthesis.	Interpretation of EMG signals and communication of movement intention	An artificial neural network was trained (supervised) on mini batches of participant EMG data using a mean squared error regression loss and the ADAM optimizer. A validation set was created using 10 % of the entire training data. Accuracy not reported.	Limb absence Int $n = 4$, Age range: 52–59 years. Ctrl $n = 4$, Age range: 39–74 years.	Functional use	Use of serious game training achieved similar results to conventional training—no consistent improvements in EMG metrics or functional use were found in either group.
Osborn, 2021, US	To restore limb function with a robotic prosthesis.	Interpretation of EMG signals and communication of movement intention	Supervised linear discriminant analysis was trained by the participant selecting the desired prosthesis movement and attempting to perform it with the phantom hand while recording the myoelectric data. The myoelectric training data was stored for each desired movement class. Accuracy not reported.	Limb absence $n = 1$, Age: 63 years.	Prosthesis control metrics, usage, perceived workload	This work demonstrated the functional benefit of an anthropomorphic prosthetic limb.
Tang, 2018, China	A brain-actuated wheelchair and robotic arm for transportation.	A real time target detection algorithm	A pre-trained (supervised) neural network (YOLOv2) was used. A training database was built from the Common Objects in Context dataset and ImageNet. Accuracy not reported.	Severe motor-disability Int $n = 3$, Age range: 33–55 years. Ctrl $n = 4$, Age range: 25–30 years.	Navigational metrics, command performance	The results proved that the system worked smartly and efficiently.
Tombini, 2010, 2012, Italy	To restore limb function with a robotic prosthesis.	Interpretation of Electroencephalography (EEG) and electroneurographic signals and communication of movement intention	Participants' EEG data were collected while performing motor imagery tasks and classified using an SVM algorithm. Classification was then enhanced by executing the tasks with the prosthesis and analysing event-related brain waves for each motor command. Accuracy values are reported in graphical form.	Limb absence $n = 1$, Age: 26 years.	Pain, movement recognition	A clinical improvement in phantom limb pain was observed, and a progressive return to normal perception of hand motion was achieved.

Abbreviations: Intervention (Int); Control (Ctrl); Electromyography (EMG); Electroencephalography (EEG) sensors; Support Vector Machine (SVM).

more complex data. However, complex data outputs can make it harder for users to understand and execute decisions [42]. One intervention, which incorporated a wearable sensor with telerehabilitation, reported improved care satisfaction and shorter consultations, reducing healthcare costs [44].

Limitations of wearables included the type of sensors available (and what can be measured) and how many can be worn without causing inconvenience, discomfort, and reduced battery life [40,41,46]. Other barriers included issues with connectivity [40], poor compliance with wearing the devices (often due to inconvenience or battery life problems) [40,41], and the technical inability to capture if an exercise is performed accurately [41].

4. Discussion

Preserving independence is a critical goal of health systems as population's age. As the burden of disease and disability increases, rehabilitation services must innovate to improve access while optimising efficiency given limited resources [1–3]. Health technology, including AI systems, is one-way rehabilitative care can be advanced. However, it remains unclear what technology is clinically effective and what the barriers to implementation are. We undertook a systematic review of AI technologies supporting physical rehabilitation. Specifically, we searched for machine learning supported interventions tested in 'real-life' settings, which reported on their clinical effect. While novel developments were expansive, we found few high-quality evaluations measuring clinical impact. We conclude that the clinical evidence for AI technologies supporting physical rehabilitation remains inconclusive.

AI-supported rehabilitation technologies were wide-ranging and added value in several ways. Firstly, AI solutions can interpret a greater volume and complexity of data than clinicians, which can help with pattern recognition, enhanced decision support and tailoring of care [12–14]. AI data analytics can also facilitate more objective assessments, improving the precision of patient evaluation - particularly over time [12–14]. Secondly, AI systems can enable autonomous remote monitoring, generating more insights on progress between visits and potentially replacing the need for physical visits entirely. Finally, AI has greatly enhanced the capabilities of prosthetic devices. By including machine learning algorithms, intended muscular movements can be better predicted, thus improving prosthetic limb control [48]. While AI

Table 4
Summary of hardware used by interventions organised by system type.

System type	Types of technology used
App-based systems	• App [20–23]
Robotics to replace function	• Motor cortex brain implant, functional electrical stimulation [24] • Longitudinal intrafascicular electrodes, Electroencephalography (EEG) sensors, robotic prosthesis [25] • Computer game, robotic prosthesis, Electromyography (EMG) sensors [26] • Robotic prosthesis, osteointegration implant, EMG sensors [27] • Wheelchair with a robotic arm (Mico, Kinova), Kinect [camera], lidar sensors, EEG sensors (Actichamp amplifier) [28]
Robotics to restore function	• EEG sensors, haptic knob robot [29] • Treadmill, robotic orthosis (Lokomat), Functional Electrical Stimulation (FES) sensors [30] • EMG sensors, robotic orthosis [31] • EMG sensors, robotic orthosis [32]
Gaming systems	• Virtual reality game, time of flight camera, infrared stereo camera, head mounted display [33] • Virtual reality game, Kinect [camera], 3D VISION stereo glasses, projector, 3D display card [34] • Computer game, TV screen, Kinect [camera], balance board (Nintendo Wii or Tyromotion Tymo therapy plate) [35] • Kinect [camera], drum kit [36] • Virtual reality game, balance board (Wii Fit), Kinect [camera] [37]
Activity monitoring using wearables	• Wearable Inertial Measurement Units (IMUs), android tablet, App and headphones (gait tracking) [38] • Computer guided rehab, Zebris motion range device (home exercise tracking) [39] • App and smartwatch (Huawei 2) [40] • App and smartwatch (LG W270) [41] • Wearable electrocardiogram and accelerometer (MUSEIC) (functional capacity assessment) [42] • Wearable inertial system (Opal) (gait analysis) [43] • Telemedicine platform, axis sensor, temperature, and volume sensor (home exercise tracking) [44] • App and step counter (MiBand 3) [45] • Wearable IMUs (gait analysis) [46] • EMG sensors (back pain monitoring) [47]

Abbreviations: Electroencephalography (EEG); Electromyography (EMG); Functional Electrical Stimulation (FES); Inertial Measurement Units (IMUs).

Table 5
Clinical outcomes of included randomised controlled trials.

Measurement category	Measurement	Between group difference
Physical function and activity		
Ang et al. [29] $n = 21$	Motor function (FMMA)	No difference (*p* value not reported)
Sandal et al. [45] $n = 461$	Disability (RMDQ) Physical activity (SGPALS)	In favour of intervention $p = 0.01$ No difference (*p* value not reported)
Theingwittayaporn et al. [22] $n = 82$	Range of motion (assessed using goniometer) Physical activity (KOOS) Activities of daily living (KOOS) Functional activity score (KSS)	No difference $p = 0.371$ In favour of intervention $p = 0.002$ In favour of intervention $p = 0.002$ No difference $p = 0.634$
Kristoffersen et al. [26] $n = 8$	Functional use (SHAP and CRT)	No difference (p value not reported)
Pain		
Sandal et al. [45] $n = 461$	Average pain intensity 0–10 (preceding week) Worst pain intensity (preceding week) Pain self-efficacy questionnaire score	All in favour of intervention $p = 0.001$
Theingwittayaporn et al. [22] $n = 82$	Pain (KOOS)	No difference $p = 0.279$
Anan et al. [23] $n = 21$	Degree of pain 1–5 Pain improvement 1–5	All in favour of intervention $p = 0.001$
HRQOL		
Sandal et al. [45] $n = 461$	Fear-avoidance (FABQ) Illness perception (BIPQ) Health-related quality of life (EQ5D) Global perceived effect scale 5–5	No difference (p value not reported) In favour of intervention p < 0.001 No difference (*p* value not reported) In favour of intervention $p < 0.001$
Theingwittayaporn et al. [22] $n = 82$	QOL (KOOS) Symptoms (KOOS) Objective knee score (KSS) Satisfaction score (KSS) Expectation score (KSS)	In favour of intervention $p = 0.009$ No difference $p = 0.100$ No difference $p = 0.657$ In favour of intervention $p = 0.001$ In favour of intervention $p = 0.005$

Abbreviations: Brief Illness Perception Questionnaire (BIPQ); Clothespin Relocation Test (CRT); Fear Avoidance Beliefs Questionnaire (FABQ); Fugl-Meyer Motor Assessment (FMMA); Knee injury and Osteoarthritis Outcome Score (KOOS); Knee Society Score (KSS); Roland-Morris Disability Questionnaire (RMDQ); Saltin-Grimby Physical Activity Level Scale (SGPALS); Southampton Hand Assessment Procedure (SHAP).

can augment and improve care in many ways, more work is needed to evaluate performance in real-world settings.

Patients with stroke or back pain were the most frequently targeted end-users, likely due to the mobility-related issues associated with these conditions. Functional disability is often associated with other health-related problems, such as pain and poor psychological health [49]. Accordingly, traditional rehabilitation programmes tend to incorporate multiple components (e.g., exercise, education, psychological support). We identified only two studies that had developed a multi-dimensional intervention. Both provided exercise recommendations with educational material, one for back pain and one for knee osteoarthritis [21,22]. Otherwise, interventions predominantly focused on improving mobility alone. Future work should look at developing multi-component interventions, which can better support self-management [50].

We included five RCTs in our study; the remaining used a pre-post study design, which ranks low in the evidence hierarchy [51]. Similar to another systematic review of machine learning tools in healthcare [17], we identified (and excluded) many studies that only explored validation metrics. Only testing the intervention in healthy subjects, using laboratory-controlled settings or simulated data, were additional exclusion reasons. Although it is essential to validate and optimise AI algorithms, developers must study the clinical effect in a real-world setting. Studies should also consider the clinical impact and implementation of interventions to advance the field. Developers can refer to the World Health Organization guidelines on evaluating digital health interventions. The guidelines emphasise studying the effects of new digital technologies in healthcare to identify whether there are advantages over traditional care [52]. Further AI-related resources can also be found in a recent review of AI guidelines, covering topics in development, evaluation and reporting [53].

Comprehensive implementation evaluations were not reported in our included studies, although barriers and enablers were discussed briefly in many articles. Improved accessibility to care, greater personalisation, and reduced costs (e.g., reducing manpower needs) were the most reported enablers. Technology literacy and accuracy or completeness of the data (to determine clinical effect) were the most frequent challenges associated with the interventions. Future studies

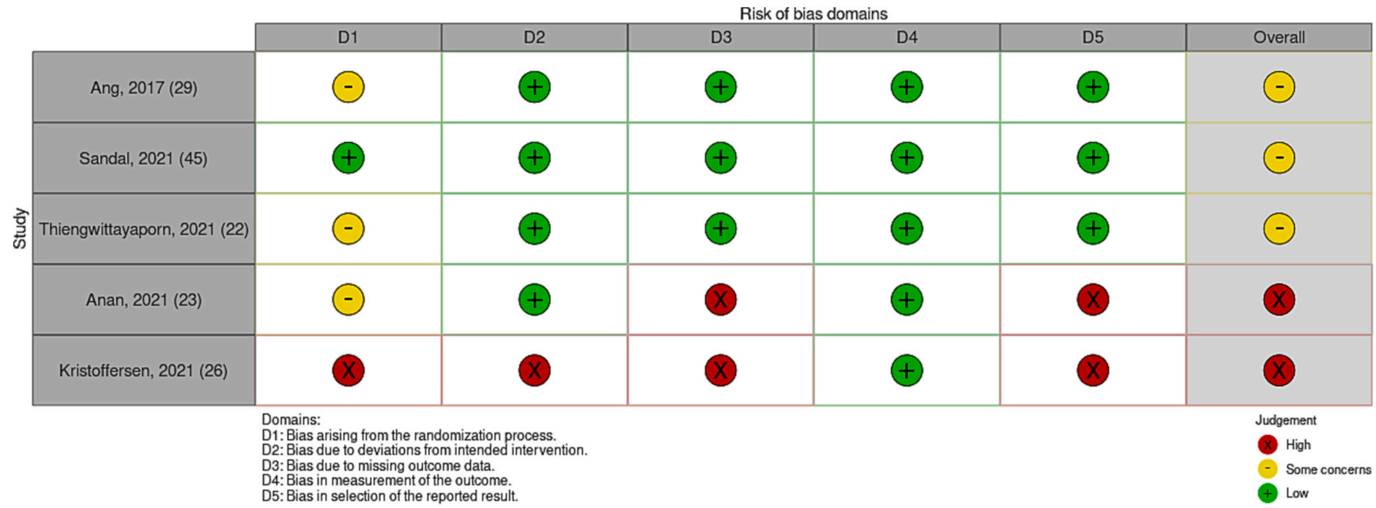

Fig. 2. Risk of bias.

should adopt framework-driven evaluation to identify factors that may help or hinder interventions' implementation and effectiveness, such as the Consolidated Framework for Implementation Research [54]. The Guidelines and Checklist for the Reporting on Digital Health Implementations (ICHECK-DH) will also help to improve reporting of digital health implementation initiatives [55].

Novel technologies are frequently hampered by poor uptake and adoption [16]. In the included papers, age was a commonly reported factor influencing uptake. For example, many of our included studies noted that older adults might be less interested in or capable of using electronic systems due to the 'technology divide'. Strategies to overcome the digital divide include identifying and designing interventions according to specific user needs, supporting users through education and engagement of carers, training healthcare providers to reject the concept of digital ageism and enabling them to support older adult's technology use, and comprehensive implementation evaluations to identify barriers to use [56–58]. Other documented obstacles to rehabilitation uptake, such as technology access, gender, ethnicity, socioeconomic status, and social support, were not mentioned, despite associations with uptake and rehabilitation compliance [8]. To improve rehabilitation, common barriers to technology-enabled care must be overcome to avoid worsening health inequalities. User-centred design methodologies are one way to identify and incorporate user needs. Participatory approaches (e.g. co-design), which involve end-users in the solution development process, are increasingly common in healthcare [59]. Studies have shown that interventions developed using a participatory approach improve the quality of care, outcomes, patient satisfaction, and cost [60]. In our study, we found no examples of participatory design approaches. To improve the acceptability and adoption of new interventions, developers should consider using participatory design approaches.

Our study has many strengths. With the help of an information specialist, we searched six databases providing a comprehensive overview of the different AI-supported physical rehabilitation applications evaluated in the rehab setting. We synthesised evidence on clinical efficacy and the barriers to using AI-supported physical rehabilitation to assess interventional impact. This review also highlights current knowledge and research gaps, guiding future investigations. However, our review may be limited by the diverse terminology used to describe AI. We tried to minimise the risk of missing relevant articles by expanding our list of search terms and working with an information specialist to develop the search strategy. In some papers, the technology was poorly described, we contacted authors in these instances, but the response rate was low; therefore, we may have excluded relevant papers. Finally, we also restricted our search to English only articles. Relevant non-English articles may have been missed.

5. Conclusions

AI-supported physical rehabilitation is a growing field that may improve services through greater accessibility, improved efficiency, and more tailored care. However, our review identified few high-quality evaluations of clinical impact. Future efforts should focus on assessing the impact of technologies in real-world settings and implementation experiences.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.artmed.2023.102693.

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