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TOPICAL REVIEW

# The Role of Artificial Intelligence in Future Rehabilitation Services: A Systematic Literature Review

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**ABSTRACT** Artificial intelligence technologies are considered crucial in supporting a decentralized model of care in which therapeutic interventions are provided from a distance. In the last years, various approaches have been proposed to support remote monitoring and smart assistance in rehabilitation services. Comprehensive state-of-the-art of machine learning methods and applications is presented in this review. Following PRISMA guidelines, a systematic literature search strategy was led in PubMed, Scopus, and IEEE Xplore databases. The search yielded 519 records, resulting in 35 articles included in this study. Supervised and unsupervised machine learning algorithms were identified. Unobtrusive capture motion technologies have been identified as strategic applications to support remote and smart monitoring. The main tasks addressed by algorithms were activity recognition, movement classification, and clinical status prediction. Some authors evidenced drawbacks concerning the low generalizability of the results retrieved. Artificial intelligence-based applications are likely to impact the delivery of decentralized rehabilitation services by providing broad access to sustained and high-quality therapy. Future efforts are needed to validate artificial intelligence technologies in specific clinical populations and evaluate results reliability in remote conditions and home-based settings.

**INDEX TERMS** Digital therapeutics, e-health, remote monitoring, intelligent systems, deep learning, machine learning.

## I. INTRODUCTION

The current model of care is resource-demanding and already faces major challenges in coping with an increasing number of patients due to demographic change, the paucity of skilled healthcare professionals and economic pressure to minimize healthcare costs [1].

Traditional rehabilitation services strongly rely on physical therapy sessions, which are based on one-to-one interactions with healthcare practitioners during a hospital stay (above all during the acute and sub-acute phase of the disease) or as part of periodic visits to specialized clinics (mostly during the chronic phase). Despite the clinical-centered model allowing healthcare professionals to closely monitor and support patients and their families physically and emotionally, it presents some limitations. A clinical-centered model that heavily relies on physical access to medical facilities and prolonged interactions with trained specialists makes events such as the coronavirus pandemic (COVID-19) and the increased demand for assistance to chronic patients challenging to manage [2], [3]. Distancing measures necessary during a pandemic phase and the increasing management issues avoiding the overload of the healthcare system could lead to a reduction in rehabilitation visits. Moreover, the lack of human resources could affect the dose and quality of therapy patients receive, limiting rehabilitation to relatively short periods that might be insufficient to achieve functional recovery [4], [5].

Despite the growing evidence that intensive high-dose rehabilitation positively impacts functional recovery even long after the disease, therapy dose is typically rather low

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at all stages of the continuum of care. In fact, after clinic discharge, there is limited support for ongoing rehabilitation management at home, which is necessary for the maintenance of functional outcomes in physical activities [6], [7]. To this end, there is a need for a sustainable approach that facilitates patients' long-term management more efficiently [8], [9], [10]. Many efforts are needed to shift care services toward a decentralized model opposite the conventional therapy approach.

New developments are emerging as possible answers to rehabilitation service limitations related to time, distance, difficult terrains, costs, and limited access to clinical facilities [11]. Some proposed solutions span from a live communication stream in which rehabilitation professionals guide and encourage patients while monitoring their progress to more advanced solutions involving various sensor and information and communication technologies (ICTs), sometimes coupled with artificial intelligence (AI) algorithms to support the monitoring and assistance in remote contexts [12], [13].

AI applications are considered to play a key role in further establishing and supporting a decentralized rehabilitation model in which intelligent connected tools will be employed to assist clinical decision-making, and health outcomes monitoring [14], [15]. Many AI-based methods and solutions have been proposed in recent years to support the future challenge of enabling assisted physical therapy and assessments in a minimally supervised and decentralized manner, ideally at the patient's home. However, to the best of the authors' knowledge, no published works provided a comprehensive review of machine learning methods and applications used for remote monitoring and assistance in the rehabilitation context. Some existing works in literature have provided an overview of the role of machine learning algorithms combined with specific technologies used for rehabilitation issues, such as wearable sensors [16], [17] and vision-based motion capture technologies [18]. More specifically, a recent work emphasized machine learning methods for movement evaluation in rehabilitation programs using motion capture systems [19]. Other works highlighted the progress in machine learning for automated evaluation of patient performance and recovery, introducing data analytics to improve the effectiveness and efficiency of care for physical rehabilitation [20].

Due to the growing importance of AI-based applications to support remote rehabilitation procedures, with the present work, for the first time, the authors aim to provide succinctly state-of-the-art about AI-based machine learning solutions supporting the promotion and delivery of physical therapy from a distance. This paper is targeted at researchers and technical developers in the field of intelligent systems for smart monitoring and assessment in rehabilitation. The goal is to highlight key aspects where emerging AI-based machine learning approaches may help solve peculiar clinical practice issues. Both advantages and drawbacks of existing approaches and future implications of AI-based solutions supporting decentralized rehabilitation services are pertinently discussed by the authors. The review and recommendations provided in this paper aim to guide the design of the next generation of AI applications in rehabilitation.

The paper is organized as follows. Section II describes the review methods and article selection procedure. Section III presents the results achieved and surveys of machine learning methods and applications proposed in recent years. Section IV provides a discussion about the potential direction of future research avenues. Section V concludes the work.

## II. MATERIALS & METHODS

### A. STUDY DESIGN AND CONTRIBUTION

This work aims to provide general and comprehensive content with the scope to better understand the recent field development.

Considering the aim of this study, a systematic literature review is an appropriate research design and strategy accordingly to Snyder guidelines [21]. Therefore, the results are synthesized and discussed according to a qualitative research approach that entails undertaking a thorough critique of each piece of text and identifying recurring themes from different works, which finally contribute to forming the basis for the critical conclusions of analyzed studies [22].

To the authors' knowledge, this article would be the first review to discuss the challenges, opportunities, and solutions of AI applications for rehabilitation services provided in remote and decentralized conditions. Most of the current literature addressing AI technologies and methods in rehabilitation is focused on specific applications or a specific area of research. This work offers a broader overview of different research areas and applications. Table 1 highlights the major differences between this review article with other articles published in the rehabilitation field. In addition, this work highlights the richness and complexity of each application domain to guide future research and developments.

The main contribution of the article is outlined as follows:

- AI-based systems and technologies for monitoring and assistance in rehabilitation are identified and discussed along with their practical implications;
- machine learning algorithms that find their application in rehabilitation are classified and discussed according to the state-of-art literature;
- machine learning methods and approaches are outlined and discussed according to the clinical application scopes from a practical point of view;
- challenges and future trends of AI applications for rehabilitation services provided at a distance are outlined.

### B. LITERATURE SEARCH STRATEGY

A literature search was conducted in PubMed, IEEE Xplore, and Scopus databases by covering the period from 2010 to May 2022. A structured search strategy was performed in each electronic database concerning AI-based machine learning methods and applications supporting remote monitoring and assistance in the rehabilitation context. The same search

**TABLE 1. Key differences between this review and existing literature.**

| Paper | Key differences |
|---|---|
| [17] | The objective of the study was to survey exercise evaluation in post-stroke rehabilitation by means of wearable devices and machine learning algorithms. |
| [18] | The study reviewed the evolution of RGB-D sensors for musculoskeletal health monitoring, also evidencing computational algorithms based on machine learning. |
| [19] | The study reviewed computational approaches for evaluating patient performance in rehabilitation programs using motion capture systems. |
| [20] | The study provided a non-systematic brief overview of big data analysis to optimize outpatient rehabilitation. |

**TABLE 2. Electronic search strategy.**

| Database | Query |
|---|---|
| PubMed | ("artificial intelligence" OR "deep learning" OR "machine learning") AND ( ( tele OR remote OR home ) AND (evaluation OR monitoring OR supervision OR assessment OR interaction OR feedback OR communication ) ) AND ( "physical therapy" OR exercise OR "physical rehabilitation" ) |
| IEEE Xplore | (artificial intelligence OR deep learning OR machine learning) AND (tele OR remote OR home) AND (evaluation OR monitoring OR supervision OR assessment OR interaction OR feedback OR communication) AND (physical therapy OR exercise OR physical rehabilitation) |
| Scopus | TITLE-ABS-KEY ( ( "artificial intelligence" OR "deep learning" OR "machine learning" ) AND ( ( tele OR remote OR home ) AND ( evaluation OR monitoring OR supervision OR assessment OR interaction OR feedback OR communication ) ) AND ( "physical therapy" OR exercise OR "physical rehabilitation" ) ) AND ( LIMIT-TO ( LANGUAGE , "English" ) ) |

string was used for PubMed, IEEE Xplore, and Scopus, with the only difference due to the syntax required by the database. Performed queries are shown in Table 2.

### C. STUDY SELECTION PROCESS

This review was carried out according to the Cochrane Collaboration methodology [23]. The article selection process based on the PRISMA guidelines [24] is schematically presented in Figure 1.

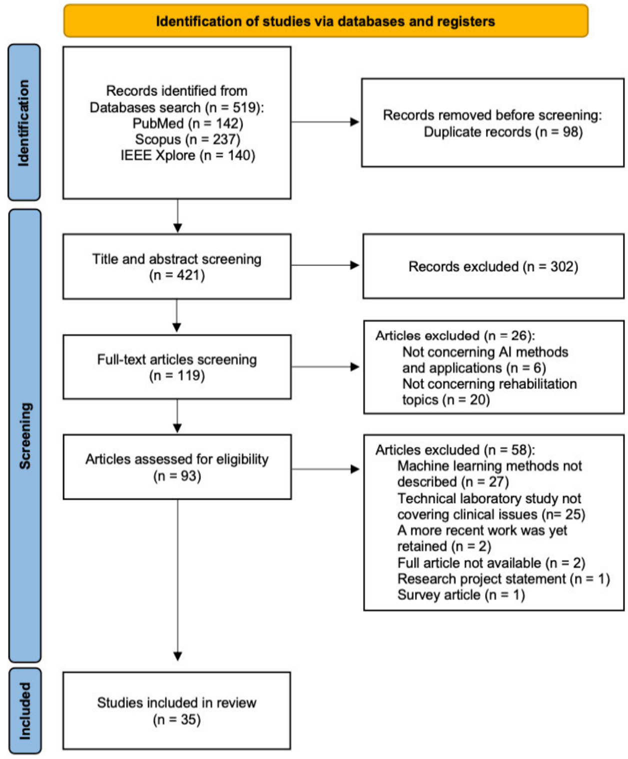


**FIGURE 1. PRISMA flowchart of the results from the literature search.**

After removing duplicated articles, titles and abstracts were explored, and then full-text screening was conducted according to inclusion and exclusion criteria for eligibility. Only the most recent study was retained when the same authors published several studies on the same research initiative.

Inclusion criteria were: (i) articles describing AI methods and applications; (ii) articles concerning both clinical and technical aspects of solving issues regarding decentralized services in rehabilitation; (iii) articles that must be written in English; (iv) articles published after 2010 (considering the recent employment of AI applications in healthcare field it would not be necessary to review older articles). Exclusion criteria were: (i) machine learning techniques not addressed by authors; (ii) technical laboratory studies describing only systems developments not covering clinical issues; (iii) only the most recent work was retained when advancements from previous research initiatives of the same author were retrieved; (v) review articles.

### D. DATA EXTRACTION PROCESS

Data extraction was performed manually. The extracted data included: (i) characteristics of the system involved in acquiring data; (ii) main features concerning the machine learning algorithms and results retrieved; (iii) information about the clinical application field evidencing rehabilitation scopes and therapy issues; (iv) the study aims and its characteristics evidencing drawbacks and advantages reported by respective authors. The "Scimago Journal & Country Rank" (SJR) database was used to extract quartile metrics to assess the quality of selected studies.

## III. RESULTS

### A. DATA SYNTHESIS

The initial paper search yielded a total of 519 results. After the preliminary screening, 93 articles were selected for eligibility. Applying the inclusion and exclusion criteria led to 35 articles related to AI-based machine learning solutions supporting the monitoring and assistance of physical therapy from a distance. Figure 1 schematically presents the results of each step of the review process.

The data extracted from reviewed articles are summarized and presented as follows: distribution of the number of articles according to the SJR quality quartile metrics over the years in Figure 2, characteristics of systems and machine learning methods in Table 3, information concerning the clinical application context in Table 4, implications and drawbacks of the selected studies in Table 5.

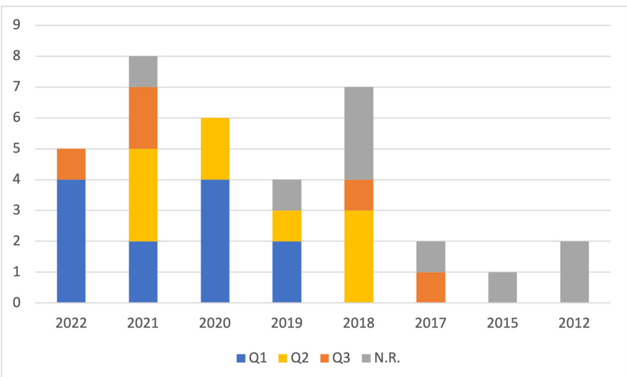


**FIGURE 2.** Distribution of the number of articles published every year and quality quartile ranking according to SJR database. Abbreviations: N.R. = not reported.

Wearable capture motion systems resulted in applications most used in selected studies. Almost all the reviewed articles addressed classification, and regression algorithms, except in work [25], which applied an unsupervised learning technique for a clustering task. Figure 3 graphically summarizes all the results retrieved.

Most AI-based machine learning algorithms have been trained to recognize activities and evaluate specific movements remotely, predicting motion data from more complex systems using unobtrusive and low-cost technology. Minor studies focused on the prediction of the patient's clinical status.

Most of the included works resulted in feasibility and validation studies conducted in supervised laboratory settings involving healthy subjects. Figure 4 compares articles for applications scope and SJR quality quartile metrics to evidence some existing literature shortcomings.

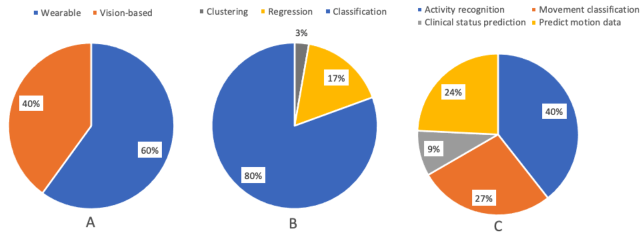


**FIGURE 3.** Results synthesis: A) capture motion technologies, B) machine learning tasks, C) machine learning applications.

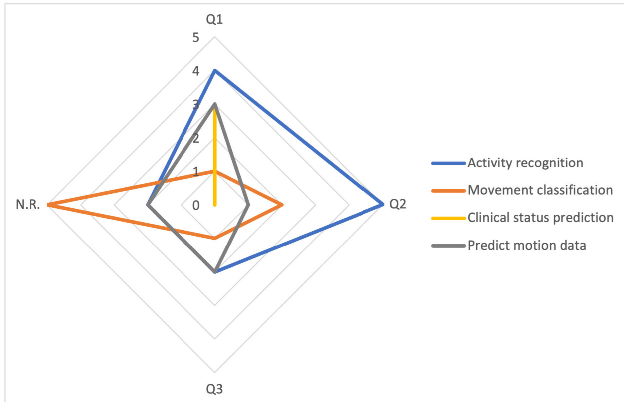


**FIGURE 4.** Radar chart comparing the reviewed articles for SJR quartile quality metrics and their application scopes. Abbreviations: N.R. = not reported.

### B. AI-BASED SYSTEMS AND TECHNOLOGIES

The remote delivery of rehabilitation services should enable therapists to optimize the timing, intensity, and duration of therapy which is often not possible due to the constraints of face-to-face treatment protocols of the traditional healthcare model. Therefore, ICTs used in decentralized rehabilitation services allow facing traditional logistic problems making treatments access equitable to geographically remote individuals.

Applications to date used to support decentralized services can be categorized as: i) synchronous systems using real-time electronic communication *via* simple webinar platforms through which healthcare professionals provide audio and video support for the patient, and ii) asynchronous systems using store-and-forward communication involving data and collection through distributed devices [60], [61]. Healthcare professionals typically use synchronous systems to interact with patients on a live communication stream, guiding and encouraging patients by monitoring their progress. Asynchronous approaches, in general, involve the acquisition, transmission, and elaboration of data to generate an appropriate action in patient care with associated decision support [13]. Such approaches have attracted recent researchers' interest, as evidenced by the results of reviewed articles. Some attempts have been made to provide real-time audio and video suggestions with asynchronous technologies.

**TABLE 3.** Summary of the paper lists and information related methods, techniques, and results retrieved. Abbreviations: ML: machine learning, LSTM: long short-term memory, DT: decision tree, MAE: mean absolute error, IMU: inertial measurement unit, KNN: K-nearest neighbor, SVM: support vector machine, RF: random forest, MLP: multilayer perceptron, CNN: convolution neural network, SOM: self-organized map, CART: classification regression tree, GCN: graph convolutional network, NB: naive bayesian, HMM: hidden Markov model, ELM: extreme learning machine.

| Reference (Year) | System | ML Method | Aim | Results |
|---|---|---|---|---|
| [26](2022) | Kinect-based exergame platform | LSTM, DT XGBoost, Linear Regression | Estimation of weight-shifting during exergaming using kinematic data | LSTM resulted the best estimation model |
| [27](2022) | Virtual reality exergame platform | DT gradient boosted | Predict joint angles and torques with motion tracking data | Accurate predictions: joint angles (MAE < 0.78°), joint torques (MAE < 2.34 Nm) |
| [28](2022) | Smart textile garment composed by optical fiber sensors and IMU | KNN | Activity classification for smart monitoring | Accuracy of 0.94 |
| [29](2022) | Virtual coach application based on IMU sensors | SVM, DT, RF, KNN, MLP | Evaluate the performance of six classifiers in three contexts: i) recognition and evaluation in a single classifier, ii) recognition of correct exercises, iii) a two-stage approach that first recognizes the exercise and then evaluates it | SVM resulted in the most accurate algorithm: accuracy of 0.88 and 0.91 in recognition and evaluation task for a single classifier; accuracy of 0.96 in recognition and between 0.93-1.00 in evaluation adopting the two-stage approach |
| [30](2022) | Motion capture system based on computer vision | CNN-LSTM | Estimating lower limb joint angular velocities | The estimated results show the highest correlation 0.93 in squat and 0.92 in walking on treadmill action |
| [31](2021) | Accelerometer-based wearable sensors | SVM, RF, MLP | Detect and track rehabilitation exercises | MLP model accuracy > 0.80 |
| [32](2021) | IMU-based smartwatch | CNN | Measure the rate and patterns of participation in rehabilitation sessions, assess the dose-response between physiotherapy activity and recovery, and explore patient factors predictive of participation | For the binary classification task, the CNN model achieved an accuracy of 0.95, a sensitivity of 0.94; a specificity of 0.97; and AUC of 0.99. For the multi-class problem, the CNN classifier achieved an accuracy of 0.90 and an F1-score of 0.82 |
| [25](2021) | Exergame platform based on Microsoft Kinect motion sensor camera | SOM, CART | Develop a new method to personalize exergame setting (range of motion, average acceleration, moving time, points, repetitions) | Four clusters were selected by SOM with high prediction accuracy in female group (RMSE=5.75, R2=0.93, MAE=1.30) and male group (RMSE=3.75, R2=0.99, MAE=3.03); CART prediction obtained high accuracy (R2=0.89) |

**TABLE 3.** *(Continued.)* **Summary of the paper lists and information related methods, techniques, and results retrieved. Abbreviations: ML: machine learning, LSTM: long short-term memory, DT: decision tree, MAE: mean absolute error, IMU: inertial measurement unit, KNN: K-nearest neighbor, SVM: support vector machine, RF: random forest, MLP: multilayer perceptron, CNN: convolution neural network, SOM: self-organized map, CART: classification regression tree, GCN: graph convolutional network, NB: naive bayesian, HMM: hidden Markov model, ELM: extreme learning machine.**

| | | | | |
|---|---|---|---|---|
| [33](2021) | Motion Coach app based on computer vision pose estimation technique | CNN | Evaluate the ability of the system to detect and correct exercises form | No significant differences between: i) Motion Coach app and physiotherapists=0.82 inter-rater agreements; ii) physiotherapist 1 and physiotherapist 2=0.83 inter-rater agreements |
| [34](2021) | Data glove composed by flex sensors, force-resistive sensors and IMU | DT XGBoost, Logistic Regression | Automated assessment in-home rehabilitation session | The Logistic Regression classifier outperformed the XGB classifier with an average accuracy of 0.85 among all tasks |
| [35](2021) | Motion capture system based on computer vision | GCN | Assessing exercise performance | GCN methods achieved better performance than CNN and LSTM (MAE=0.02) |
| [36](2021) | Motion capture system based on computer vision | DT, RF, NB, KNN, SVM | Automatic evaluation of home-based rehabilitation exercise | SVM achieved the best accuracy 0.98 |
| [37](2021) | Wearable-based motion capture system | SVM | Classifying single-axis spinal motion using data streams from stretch sensors for exercise recognition | SVM achieved an accuracy of 0.85 |
| [38](2020) | Exergame platform composed by electromyography and inertial sensors | SVM, RF | Develop real-time gesture recognition for feedback and control during exergame session | SVM classifier showed good performance (F1-score of 0.82-0.90) |
| [39](2020) | Microsoft Kinect camera coupled with Wii-Balance Board | CNN, RF | Develop a balance evaluation system using inexpensive and portable sensors to measure the subject's balance level | CNN reduced the estimation error by about 10% compared with other state-of-the-art models for balance evaluation; the RF achieved high sensitivity and specificity to classify the four levels of balance problems (>0.80) and the two categories fall risk /no fall risk (>0.90) |
| [40](2020) | IMU-based smartwatch and mobile app | CNN | Recognize the type and frequency of rehabilitation exercises performed | The CNN with personal data involving accelerometer combined with gyroscope data was the most accurate (0.99) |

**TABLE 3.** *(Continued.)* **Summary of the paper lists and information related methods, techniques, and results retrieved. Abbreviations: ML: machine learning, LSTM: long short-term memory, DT: decision tree, MAE: mean absolute error, IMU: inertial measurement unit, KNN: K-nearest neighbor, SVM: support vector machine, RF: random forest, MLP: multilayer perceptron, CNN: convolution neural network, SOM: self-organized map, CART: classification regression tree, GCN: graph convolutional network, NB: naive bayesian, HMM: hidden Markov model, ELM: extreme learning machine.**

| | | | | |
|---|---|---|---|---|
| [41](2020) | IMU-based wearable sensor | CNN, SVM, RF, KNN, MLP | Automatic remote exercise recognition and repetition counting | CNN achieved higher accuracy for exercise recognition (0.97) and for repetition counting task (0.90) |
| [42](2020) | Exergame platform based on pose estimation method | CNN | Comparing a transfer learning-based pose estimation model to the Kinect system and a gold-standard 3DMoCap system | No statistical difference between CNN-based pose estimation, Kinect and the gold standard system |
| [43](2020) | IMU-based wearable sensor | CNN | Segmentation of exercise repetitions | Flexion and abduction exercises achieved high accuracy (0.90-0.95), scapular movement poor accuracy (<0.85) |
| [44](2019) | Socially assistive robot | CNN, LSTM | Exercise recognition | CNN-LSTM achieved accuracy of 0.99 |
| [45](2019) | IMU-based wearable sensor | DT, SVM, KNN, RF | Recognition of shoulder rehabilitation activities | Optimal predictive accuracies for SVM (0.97) and RF (0.80) |
| [46](2019) | Conversational agent-assisted health coaching system | SVM | Provide personalize suggestions to support and engage health intervention | After 1-month individuals showed generally positive reaction to a virtual agent providing them useful health interventions and feedbacks |
| [47](2019) | Kinect-based digital coach | SVM, RF | Personalized and automatic remote monitoring and evaluation | Accuracy of SVM in patient error identification above 0.90; accuracy of RFs model for task recommendations ranged between 0.81-0.91 in all classes |
| [48](2018) | Kinect-based platform | HMM | Automatically detects the correctness of the executed movement to provide real-time feedback to the patient | High accuracy in the evaluation of the movements (0.92 of correct classification) |
| [49](2018) | Exergame platform composed by Kinect, leap motion and wearable wrist-band | Logistic Regression | Discriminating between good or bad activity performance during various serious games | High classification accuracy for all exercise evaluated |
| [50](2018) | IMUs-based wearable sensor | Logistic regression, KNN, RF | Detecting goal-directed movements and assessing the quality of motor performance | Correct movements were classified with a predictive accuracy of 0.87, the incorrectly performed exercise movements with an accuracy of 0.84 |

**TABLE 3.** *(Continued.)* **Summary of the paper lists and information related methods, techniques, and results retrieved. Abbreviations: ML: machine learning, LSTM: long short-term memory, DT: decision tree, MAE: mean absolute error, IMU: inertial measurement unit, KNN: K-nearest neighbor, SVM: support vector machine, RF: random forest, MLP: multilayer perceptron, CNN: convolution neural network, SOM: self-organized map, CART: classification regression tree, GCN: graph convolutional network, NB: naive bayesian, HMM: hidden Markov model, ELM: extreme learning machine.**

| | | | | |
|---|---|---|---|---|
| [51](2018) | Kinect | Linear Regression | Solve self-occlusion errors in motion analysis mapping the noisy Kinect-based measurements to a more accurate benchmark system measurement | The denoising method resulted in significantly better than a benchmark system |
| [52](2018) | IMU-based smartwatch | KNN, RF, SVM, CNN | Exercise recognition | CNN achieved the best accuracy ranged between 0.88-0.99 |
| [53](2018) | Wearable-based motion capture system | Linear regression, RF, MLP | Estimate the knee joint angle based on the strain sensor data | RF model achieved best results (intra-subject evaluation: walking task MAE=1.94, R2=0.97; flexion exercises MAE=3.02, R2=0.97; inter-subject evaluation: walking task MAE=4.14, R2=0.90; flexion exercises MAE=6.97, R2=0.90) |
| [54](2018) | IMU-based motion capture system | Logistic regression, SVM, DT AdaBoost, RF | Classify correct and incorrect exercise repetitions | SVM and RF achieved the best performance accuracy (0.89-0.97) |
| [55] (2017) | Leap motion system | SVM, KNN | Develop a hand gesture recognition algorithm to monitor remote rehabilitation exercise | SVM and KNN achieved an accuracy of 0.97 |
| [56] (2017) | Multisensor wearable system | Softmax regression, SVM, RF, MLP | Activity recognition | RF achieved highest accuracy 0.99 |
| [57] (2015) | Smartphone-based Tele-Rehabilitation System | Linear regression | Estimating the shoulder joint ROM by using only data from one accelerometer sensor. | Linear regression achieved an accuracy of R2=0.99 |
| [58] (2012) | Accelerometer-based motion capture system | ELM | Develop Brunnstrom stage automatic evaluation | ELM achieved an accuracy of 0.92 |
| [59] (2012) | IMU-based wearable motion capture systems | DT AdaBoost | Recognize patients' error during prescribed exercise | DT detect classes in multi-label data with 0.75 sensitivity, 0.90 specificity and 0.80 accuracy |

Retrieved systems have been used to guide and assist motion while collecting objective data on movement quality and encouraging remote rehabilitation sessions *via* digital therapeutic approaches, providing access to quality therapy from a distance without needing constant supervision by a therapist on site. Different digital strategies have been individualized: exergame solutions that engage the patient to perform some functional movements providing relevant

**TABLE 4. Summary of information concerning the clinical application context. Abbreviations: ADL: activity of daily living, ROM: range of motion.**

| Reference | Rehabilitation Field | Therapy | Subjects |
|---|---|---|---|
| [26] | Balance | A custom exergame for balance training that elicits medio-lateral weight shifts from the user | Healthy older subjects (N=12) |
| [27] | Shoulder injuries | Shoulder exercise: rotation, side arm raise, forward arm raise, external rotation, abducted rotation, press, circles | Healthy subjects (N=5) |
| [28] | Activity promotion | Daily activities: standing, sitting, squatting, up-and-down arms, walking and running | Healthy subjects (N=4) |
| [29] | Activity promotion in elderly | A set of eight exercises focused on the lower or upper limbs: knee flex-extension, squats, and hip abduction, natural gait, and heel-tip toe gait, squeezing, elbow flex-extension and extension of arms overhead | Healthy subjects (N=30) |
| [30] | Physical activity | Squat, walking on treadmill | Healthy subject(N=33) |
| [31] | Stroke | Gait training, Balance training, Upper extremity therapeutic exercise, Overall function task training | Stroke (N=2) |
| [32] | Shoulder syndromes | Exercise rotator cuff protocol | Rotator cuff pathology (N=42) |
| [25] | Upper limb motor impairments due to neurological conditions | Exergames for patients with upper and lower limb motor impairments | Motor impairments (N=294) |
| [33] | Osteoarthritis | Exercises performed: hip extension bent leg, knee flexion (leg curl), strengthening hip extensors, strengthening hip abductors, strain front of the thigh, elongation of the hip flexors | Osteoarthritis (N=24) |
| [34] | Hand rehabilitation in stroke | Fugle Mayer exercise protocols: grasping, pinching, waving | Healthy subjects (N=4); subjects with upper-limb weakness (N=3) |
| [35] | Physical activity | General ROM and muscular endurance exercises | Healthy subjects (N=10) (UI-PRMD dataset) |
| [36] | Pulmonary rehabilitation | Baduanjin exercises (N=8) | Chronic obstructive pulmonary disease (N=18); Healthy Subjects (N=5) |
| [37] | Low back pain rehabilitation | Back flexion/extension and rotations | Healthy subject(N=3) |
| [38] | Hand rehabilitation in cerebral palsy | Exercise performed to control the game: wrist extension-open fingers, wrist extension-closed fingers, finger-thumb pinch, or supination | Young cerebral palsy (N=19) |
| [39] | Balance | Balance static exercise: keep trunk upright or lean to left/right/front/back with different angles, make a step forward and steadily stepped off the board, stand on one leg | Healthy subjects (N=21); Parkinson's disease (N=20) |

**TABLE 4.** ***(Continued.)*** **Summary of information concerning the clinical application context. Abbreviations: ADL: activity of daily living, ROM: range of motion.**

| | | | |
|---|---|---|---|
| [40] | Stroke | Bilateral arm training rehabilitation: bilateral shoulder flexion with both hands interlocked, wall push exercise, active scapular exercise, towel slide exercise | Chronic stroke (N=23) |
| [41] | Cardiac rehabilitation | Local muscular endurance exercises: bicep curls, frontal raise, lateral raise, triceps extension right arm, trunk twist, squats, lunges-alternating sides, leg lateral raise, standing bicycle crunches | Healthy subjects (N=76) |
| [42] | Balance | Balance training exergame that elicits medio-lateral weight shifts from the participants | Healthy older adults (N=12) |
| [43] | Post-shoulder surgery | Shoulder and scapula rehabilitation movements | Healthy subjects (N=35) |
| [45] | Subacromial shoulder pain | Exercises for subacromial shoulder pain: shoulder abduction, shoulder flexion, wall slide, wall press and shoulder rotation | Patients with subacromial shoulder pain (N=20) |
| [44] | Activity promotion in elderly | Sitting exercises (upper body twist, hip marching, arm raises, neck stretch), flexibility exercises (neck stretch, sideways bend) strength exercises (mini squats, sideways leg lift, leg extension, bicep curls), balance exercises (simple grapevine, heel to toe walk) | Healthy subjects (N=11) |
| [46] | Activity promotion | General physical activities of daily life | Non-specific volunteers (N=375); healthy subjects (N=19) |
| [47] | Balance | Balance/agility-based tasks divided in sub-actions: squat, forward lunge, backward lunge | Parkinson's disease (N=35) |
| [48] | Patients with hip prosthesis | Hip rehabilitation exercise: one step forward, one step sideways and one step backward, with variations | Healthy subjects (N=4) |
| [49] | Post-hospitalisation rehabilitation | Upper limb movements *via* exergame platform | Participants with different neurological and orthopedic conditions (N=41) |
| [50] | Upper limb rehabilitation in stroke | Upper limb goal-directed ADL tasks to train, strength, ROM, functional capacity | Stroke (N=20); healthy subjects (N=10) |
| [51] | Breast cancer related lymphedema | Evidence-based exercise program to promote lymph flow for upper limbs | Healthy subjects (N=14) |
| [52] | Shoulder rehabilitation cuff-rotator problems | Evidence-based rotator cuff physiotherapy protocol: pendulum, abduction, forward elevation, internal rotation, external rotation, trapezius extension, upright row | Healthy subjects (N=20) |

**TABLE 4.** ***(Continued.)*** **Summary of information concerning the clinical application context. Abbreviations: ADL: activity of daily living, ROM: range of motion.**

| | | | |
|---|---|---|---|
| [53] | Knee rehabilitation | Walking, knee flexion/extension exercise | Healthy subjects (N=6) |
| [54] | Knee rehabilitation | Knee exercises: the heel slide, the seated knee extension, the inner range quadriceps, the straight leg raise | Clinical subjects (N=44); Healthy subjects (N=10) |
| [55] | Hand rehabilitation | Seven hand exercise: extension-flexion, close and spread fingers, fingertip tap, radial-ulnar deviation, fingertip touch, palm rotation and finger mass extension-flexion | Healthy subject(N=17) |
| [56] | Physical activity | Squat | Healthy subject(N=4) |
| [57] | Shoulder rehabilitation | Shoulder flexion | Healthy subject(N=1) |
| [58] | Upper limb rehabilitation in stroke | Functional upper limb movements | Stroke (N=23); Healthy subjects (N=4) |
| [59] | Knee rehabilitation | Standing hamstring curl, straight leg raise exercises | Knee osteoarthritis (N=8) |

video and audio feedback during a serious game session [25], [26], [27], [38], [42], [49]; digital coach solutions that, *via* speech [29], [33], [47], sometimes involving social humanoid robot to encourage activity participation [44], or app-based text notifications [46], offer automated conversational interaction to replace some human care tasks (reminders and motivational messages for medication, nutrition, and exercise, routine condition checks and health maintenance based on personal monitoring data).

Over the past decade, significant efforts focused on developing unobtrusive, effective, and objective motion-modeling systems have been made, taking advantage of the progress made in sensor technology which has become more compact and more efficient [62]. In almost all the included works, motion capture technologies based on wearable sensors and optical sensor-based systems have been mainly individualized as useful systems to support the remote monitoring of physical rehabilitation tasks. Such technologies allow for providing crucial information about the patient's movement during physical exercise sessions by analyzing significant kinetic (force, torque, moments, *etc.*) and kinematic (angle, orientation, velocity, *etc.*) features collected in an unobtrusively way [63].

Wearable systems are based on compact, lightweight sensors directly mounted on the interesting body part to analyze, sometimes resulting in embedded smart textile systems such as garments and gloves [28], [34], [37] or wrist-worn devices such as smart bands and smartwatches [32], [40], [49], [52], [53], [57], or as the hardware part of immersive virtual reality systems (haptic interfaces and headset) [27]. The Inertial Measurement Unit (IMU) was the most common motion capture technology thanks to its low cost and wearability. IMUs combine linear acceleration from the accelerometer and the angular turning rates from gyroscopes resulting in accurate motion data. Moreover, IMUs coupled with different sensors such as optical fiber sensors [28] and flex and force resistive sensors [34] are useful to acquire more information about the amount of deflection or bending and the force applied during a rehabilitation task. Acceleration signals were also used and coupled to electrocardiogram (ECG) data in order to better recognize the patient's physical activity form [56].

Recently, the advancements in optical sensor-based motion capture technologies attracted researchers to perform unobtrusive motion analysis. The vision-based sensor technology uses the contactless approach for motion capture; at the same time, it provides reliable movement tracking without influencing its naturalness, extraction of kinetic and kinematic parameters, and accuracy in non-controlled environments [64]. The Microsoft Kinect camera was the vision-based system majorly used in motion tracking. Meanwhile, the Leap Motion system was more specifically applied in the field of hand rehabilitation [55].

Besides all these types of motion capture technologies, the recent developments in the computer vision field extended the use of low-cost RGB and depth sensors to perform motion analysis by means of human pose estimation algorithms based on deep learning frameworks [30], [33], [42]. Human pose estimation is a field of computer vision that aims to predict the poses of human bodies by extracting joints from images and videos for motion analysis [65]. Contrarily to wearable sensors, AI-based human motion modeling enables commercial systems equipped with a camera and low-cost hardware, such as tablets and smartphones, to perform inexpensive and unobtrusive home-based monitoring in patients' daily life [33], [35], [36].

### C. MACHINE LEARNING METHODS

Machine learning is an artificial intelligence application that allows systems to automatically learn and improve from experience without being explicitly programmed to do so

**TABLE 5.** Summary of studies characteristics, implications, and drawbacks. Abbreviations: Lab: laboratory, n.r.: not reported, ADL: activity of daily living.

| Reference | Type of study (setting) | Implications | Drawbacks |
|---|---|---|---|
| [26] | Preliminary experimental study (lab) | Facilitate in-home balance training by incorporating accurate feedback on weight-shifting performance | A limited sample of participants; limited collected data focused exclusively on sideways leaning movements |
| [27] | Technical study (lab) | The method used only controllers and headset data of an intuitive gaming system, making it ideal for at-home rehabilitation and evaluation sessions | Limited sample of participants; limited results generalizability due to data collected on subjects with same clinical characteristics |
| [28] | Feasibility study (lab) | Optimized option for remote healthcare applications to identify activities and extract different parameters using low-cost and compact components integrated into a usual clothing | Testing the whole system in real healthcare scenario |
| [29] | Feasibility study (lab) | The work contributes to the development of virtual coaches that help to achieve healthy aging by supporting regular daily exercise, improving adherence to the physical routine, and monitoring it | More features should be used to improve the characterization of complex exercise |
| [30] | Feasibility study (lab) | Monitor joint angular velocities using video information without wearable sensors | Angular velocity error between 15 to 20 rad/s |
| [31] | Pilot study (lab) | Monitoring patients' performance during in-home rehabilitation exercises | Limited sample; manual annotated dataset |
| [32] | Clinical longitudinal cohort study (lab, home) | Track shoulder physiotherapy participation using inertial data collected in an unobtrusive and easy-to-use way | The accuracy of the system depends on the correct use of the technology by patients |
| [25] | Case study (lab) | Predict individualized profile settings for patients with a certain condition | n.r. |
| [33] | Clinical validation study (lab) | Digital therapeutic solution accessible to a broad patient population that provides feedback during exercise performance | The sample was heterogeneous in terms of gender distribution and localization of impairments; limited numbers of raters for inter-rater agreements |
| [34] | Preliminary experimental study (lab) | An in-home inexpensive automated assessment system for rehabilitation of upper-extremity patients with high recovery | The differing hand sizes can affect the input data |
| [35] | Preliminary experimental study (lab) | Method validated on existing benchmark dataset | n.r. |
| [36] | Preliminary experimental study (lab) | System evaluation score correlated to clinician based scores | Limited data |
| [37] | Feasibility study (lab) | Method based on a small number of stretch sensors to estimate the spinal motion | Limited sample size |

**TABLE 5.** ***(Continued.)*** **Summary of studies characteristics, implications, and drawbacks. Abbreviations: Lab: laboratory, n.r.: not reported, ADL: activity of daily living.**

| | | | |
|---|---|---|---|
| [38] | Clinical study (home) | The classification methods facilitated practice of targeted therapeutic gestures | Ground truths were established manually *via* synchronized video evaluation |
| [39] | Laboratory validation study (lab) | Accurate and quantitative balance assessments based on validated clinical instrument mini-BEST test | Kinematic data were collected only on the frontal plane |
| [40] | Clinical prospective comparative study (home) | Facilitate participation in-home training and improve the functional outcomes | Limited sample size |
| [41] | Comparative study (lab) | High accuracy in exercise recognition tasks | The tasks of exercise recognition and repetition counting was assessed in an offline mode with a windowing method |
| [42] | Comparative study (lab) | Accurate camera-based motion capture for balance training monitoring | Limited sample size; kinematic data were acquired only on the frontal plane |
| [43] | Feasibility study (lab) | Accurate segmentation of exercise repetitions to provide information on exercise performance | Data was collected on non-specific target population |
| [45] | Preliminary clinical validation study (lab) | Promote patients' engagement and personalized treatment strategies | System was evaluated in a supervised and controlled scenario |
| [44] | Preliminary experimental study (lab) | Accurate techniques for remote exercise recognition | Data collected in supervised laboratory conditions |
| [46] | Design and validation study (lab, home) | A text-messaging-based mobile application to easily promote behavioral change interventions | Along-term follow-up is required to clinically validate the tool |
| [47] | Feasibility study (lab) | Automatic monitoring and assistance tool for balance rehabilitation | The detection accuracy could degrade when tracking more complicated movements |
| [48] | Preliminary experimental study (lab) | The system is composed of a user interface for the patients performing the therapeutic physical exercises and another interface to enable the health professionals to remotely monitor the recovery process and update the rehabilitation program | Limited sample |
| [49] | Preliminary clinical validation study (lab) | Automatic evaluation of patient activity performance | Heterogeneous sample |
| [50] | Feasibility and usability study (lab) | Develop individualized therapy plans to maximize a patient's ability to perform ADL and live independently | Sample characteristics limited to chronic stroke survivors with mild-to-moderate upper-limb motor impairments |
| [51] | Technical study (lab) | Correct errors in Kinect measurements due to self-occlusion | n.r. |
| [52] | Feasibility study (lab) | Objective measurement of therapy adherence in-home rehabilitation protocols | Data was collected on non-specific target population |
| [53] | Pilot study (lab) | Unobtrusive wearable system for monitoring daily life activities | Small sample size, laboratory evaluation setting |
| [54] | Case study (clin) | Application for real-time biofeedback regarding exercise performance | Heterogeneous clinical characteristics and conditions |

**TABLE 5.** ***(Continued.)*** **Summary of studies characteristics, implications, and drawbacks. Abbreviations: Lab: laboratory, n.r.: not reported, ADL: activity of daily living.**

| | | | |
|---|---|---|---|
| [55] | Preliminary experimental study (lab) | Unobtrusive motion system for monitoring hand rehabilitation exercises | n.r. |
| [56] | Feasibility study (lab) | The fusion of the best classification rate with high computational efficacy makes the RF a reasonable solution for embedded implementation on wearable devices | n.r. |
| [57] | Preliminary experimental study (lab) | Using device based only on accelerometer data to monitoring ROM | Data collected in supervised laboratory conditions |
| [58] | Preliminary experimental study (lab) | Automatic assessment based on a clinical validated method | Small training set, heterogeneous clinical characteristics |
| [59] | Preliminary experimental study (lab) | The system assesses the quality of motion performed and provides detailed feedback to the user | Data collected in supervised laboratory conditions |

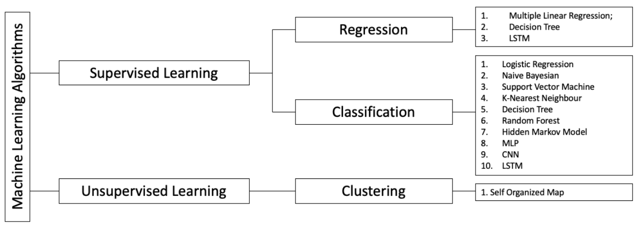


**FIGURE 5.** **Categorization of machine learning algorithms. Abbreviations: LSTM: long short-term memory, MLP: multilayer perceptron, CNN: convolution neural network.**

using previously selected features. Depending on scopes and tasks, machine learning algorithms can be divided into unsupervised and supervised learning. Unsupervised learning is well known for feature extraction, while supervised learning is suitable for predictive modeling by building relationships between features and the target of interest [66]. Retrieved machine learning algorithms are schematically presented in Figure 5.

In only one study that emerged, an unsupervised machine learning technique known as Self Organized Map (SOM) was used to individualize some clusters according to patients' demographic and clinical characteristics [25]. SOMs are artificial neural networks that generate a feature map to produce a low-dimensional and discretized representation of the input training samples for clustering, visualization, and classification scopes [67].

Almost all the articles involved supervised machine-learning techniques for classification tasks. Regression analysis modeling relationships between dependent and independent variables involved linear regression algorithms in analyzing and learning from the existing training data. Linear regression algorithms have been applied in fewer works aiming, for example, to reduce the system complexity of an exergame platform by estimating ground reaction forces from kinematic features [26], or to solve self-occlusion errors in motion analysis mapping the noisy Kinect-based measurements to a more accurate benchmark system measurements [51].

Random Forest (RF) and, more specifically, Decision Trees (DT) algorithms were the most used classifiers. DT algorithm was also used for a regression problem concerning the feasibility of using motion tracking data to predict joint angles and torques during an immersive virtual exergame [27]. DT is one of the oldest machine learning algorithms; it bases its decision logic on a tree-like architecture [68]. Its ease of interpreting and its rapid learning speed made it popular to use in the healthcare domain, especially in multiclass activity recognition problems in rehabilitation. The reason is that when examining the tree for a classification sample, the results of each node will provide relevant information to be inferred about its class. RFs are sets of randomized DTs combined using bagging techniques to reduce overfitting problems when the dataset is relatively large [69]. An RF model is particularly useful for categorizing classes of patients according to their clinical assessment characteristics [39]. Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) were the other traditional supervised machine learning algorithms most used in selected studies, followed by logistic regression classifiers, Naive Bayes (NB) algorithm, and the Hidden Markov Model (HMM) algorithm. HMM is a Markov chain process that finds application in posture recognition and characterization of skeletal tracking spatial-temporal data as a parametric stochastic model [70]. HMM was applied as a probabilistic approach to model a given action into hidden states representing an arbitrary decomposition of the whole movement into successive phases. For example, an HMM algorithm was applied to classify the performed exercise into six possible correctness classes according to its execution [48]. Also, logistic regression was used for movement evaluation [34], [49] and activity monitoring [50]. Logistic regression is considered the baseline supervised machine learning algorithm to classify an observation, and its outputs can be easily interpreted as probabilities of the occurrence of a class [71]. In the case where authors handled multiple classes [56], a generalization of logistic regression was used: the softmax regression algorithm [72]. A more simplest approach used to make class-probability inference was the NB algorithm. The NB classifier is fast and easy to implement, resulting in particularly used for the implementation of a recommendations system. However, one of its biggest disadvantage is that the algorithm is based on Bayes' theorem that assumes independence between the features which are dependent in most of the real-life cases [73].

The KNN is another algorithm often applied in classification problems. KNN is a non-parametric classification algorithm known for its simplicity and effectiveness, used to classify data based on closest or neighboring training examples in each region [74]. The KNN classifier is based on distance metrics and was widely used in real-time applications for activity monitoring [29], [41], [45], [50], [52] as it is free from the underlying assumptions about the distribution of the dataset. Finally, Support Vector Machines (SVM) was the third most used traditional machine learning classifier applied for classification tasks in activity recognition [29], [31], [38], [41], [45], [52], movement classification [47]but also for clinical assessment scopes [46]. SVM algorithms present good generalization ability for sequential data structures and datasets that are not too large and for linear and non-linear problems.

Artificial neural networks were also a common choice among researchers interested in implementing solutions for monitoring and assisting decentralized physical rehabilitation. Artificial neural networks are a subset of machine learning algorithms inspired by neuroscientific studies concerning the functioning of the neurons' brain, whose branch is known as deep learning [75]. The recent advancements in deep learning, such as hybrid and lightweight deep neural networks, have been exploited to develop a framework for exercise performance evaluation and smart assistance for home-based rehabilitation sessions. Convolutional neural network (CNN) was the commonest architecture applied in selected papers. CNNs are designed to learn spatial hierarchies of features automatically and adaptively through backpropagation by using multiple building blocks, such as convolution layers, pooling layers, and fully connected layers [76]. The CNNs have been trained on large-scale datasets and on graph-structured data for motion analysis issue [35], [77]. CNNs achieved outstanding accuracies in the computer vision field for human detection and pose estimation that is useful to compute position and orientation data of interesting joints [33], [39], [42], [44], but also for activity monitoring [32], [40], [41], [52] and movement evaluation [43]. Particularly CNN architectures such as ResNet [78] and AlexNet [79] achieved the highest accuracy respectively in pose estimation method for tracking human motion [42]and activity monitoring by processing some kinematic data [41]. Also, recurrent neural network (RNN) models achieved high accuracy in activity monitoring, which, thanks to the redundant connections between the network's neurons, can capture temporal dependencies in input data [26], [80]. More in detail, long short-term memory (LSTM), which is an RNN variant model [81], is particularly useful for analyzing temporal sequences between motion data frames [44]. The latest common deep learning approach among articles was the multilayer perceptron (MLP). MLP showed to achieve high accuracy above all in detecting specific movements [31]. MLP is a feed-forward fully connected network consisting of an input layer that receives data, an output layer that makes the decision or prediction about the input signal, and one or more hidden layers between these two that are considered the network's computational engine [82]. MLP, not requiring preliminary feature engineering, is considered easier to develop and apply in smart assistant applications than other deep learning methods. Also, a more simple learning algorithm, called extreme learning machine (ELM) that is composed of a single-hidden layer feed-forward neural networks [83], was able to achieve high accuracy in multi-class classification task in work [58].

### D. CLINICAL APPLICATIONS

Besides technical requirements, it is fundamental to integrate clinical knowledge into technologies to be used at home in a minimally supervised way. Hence, the role of AI in clinical practice should be to provide a combination of medical, psychological, and technical knowledge in the form of embedded algorithms analyzing and processing online the data generated by digital technologies. AI is expected to play a crucial role in clinical decision-making, the online adaptation of therapy exercises, and the monitoring of progress through the extraction of validated assessment scores [84]. All the information regarding the clinical application context is reported in Table 3. Based on the reviewed papers, three main approaches have been introduced to manage the remote monitoring and evaluation of physical rehabilitation therapies by means of machine learning applications. These approaches could be categorized as activity recognition, movement classification, and clinical functional assessment.

Machine learning algorithms address activity recognition tasks aimed to identify specific rehabilitation actions to remotely track patients' adherence to the prescribed therapy and sometimes to measure the treatment outcomes based on patients' activity in real-world life [85]. Most of the reviewed papers covered the problem of recognizing activities for specific body parts like strength training exercises for upper and lower limb [29], [41], [44], [56], exercises to improve range of motion [38], flexibility and balance exercises

[37], [44], specific rehabilitation exercise for upper limb and lower impaired limb in stroke [31], [40], [55], and shoulder impairments [32], [45], [52]. Other articles monitored activities of daily living (ADL), detecting general activities such as standing, sitting, squatting, walking, and running useful for health promotion programs in the elderly [28], [44], and other routine activities involving upper limb goal-directed tasks in stroke rehabilitation [50].

Movement classification approaches aimed to assess the quality of rehabilitation exercises performed remotely. Algorithms addressing movement classification tasks have been used to evaluate exercise performance in terms of the well and poorly-executed tasks. Some approaches relied on classifying the movement into discrete score classes based on clinician rating, such as low, moderate, and high performance of hand movements in stroke rehabilitation [34], [58]and well or badly performed upper limb movements while playing exergame [49]. Always based on clinical expertise knowledge, other approaches classify movements in correct or erroneous execution classes defined by a set of pre-established rules [36], [47], [48], [54]. For example, a set of predefined rules was used to label correct and compensatory movements in different possible classes to provide real-time feedback during remote hip rehabilitation exercises [48]. Noteworthy, another approach based on the movement classification task was applied to develop an accurate segmentation of exercise repetitions to evaluate the patient's performance in a detailed way [43], [59].

The last interesting approach in reviewed papers aimed to manage rehabilitation interventions through preventive and personalized solutions by predicting the patient's clinical functional status. A personalized exergame based on classifying the user profile according to related impairment characteristics was introduced to adapt therapeutic settings during a motor neurorehabilitation session [25]. An accurate and quantitative balance assessment based on a validated clinical instrument mini-BEST test was proposed to recognize the level of patient impairment and predict the fall risk [39]. Finally, a multi-class classifier was used to separate new users into three groups based on their initial activity level (vigorous, mild, and sedentary users) to develop a conversational agent-assisted health coaching system to support behavioral change *via* personalized recommendations [46].

### E. LIMITATIONS

The authors of reviewed articles evidenced and reported some drawbacks (see Table 4). They refer to issues regarding the size and characteristics of the samples and the low generalizability of results in a relevant operational environment.

In general, the data were collected from a limited sample composed mainly of healthy subjects that did not reflect the pathological behavior of the end-user population target for which the technologies have been developed. Few systems have been tested and validated on relevant clinical population targets: stroke [31], [40], [50], [58], Parkinson's disease [39], [47], cerebral palsy [38], patients with shoulder impairments [32], [45], osteoarthritis [33], [59], chronic obstructive pulmonary disease [36]. Other studies recruited subjects with various motor impairments related to orthopedic and neurological conditions [25], [33], [49], [54], thus addressing an enormous heterogeneity in collected data.

Other problems concerning the generalizability of results have been addressed as related to the reproducibility of the data collected in limited or different conditions (such as settings, users, and operators) [26], [27], [28], [32], [34], [36], [39], [42], [46], [53], [57], [59].

Considering the technology readiness level (TRL) of all the reviewed solutions, the TRL generally spans from level 3 (experimental proof of concept) to level 4 (technology validated in the laboratory) [86]. A very minority of studies validated and demonstrated the application of proposed AI-based solutions in relevant operation environments such as remote conditions and home-based settings [32], [38], [40], [46]. Finally, analyzing reviewed articles for SJR quartile quality metrics emerged that high-quality research was conducted for activity recognition and clinical status prediction applications as expected. However, future efforts are needed to increase the quality of the research interested in solving rehabilitation issues by the means of movement classification applications (see Figure 4).

## IV. DISCUSSION

This work presented a systematic review of machine learning methods and applications in the physical rehabilitation context to support the future challenge of making remote services accessible. During the last decade (from 2010 on), several system technologies coupled with machine learning methods have been applied to monitor and assess rehabilitation issues. A total of 519 publications were retrieved by a systematic search strategy performed in PubMed, IEEE Xplore, and Scopus databases. After the full-text screening, 35 articles that respected eligibility criteria were included in the data extraction process.

The study aimed to report the status of innovative developments obtained in the field of AI-based machine learning solutions supporting decentralized rehabilitation services. Study characteristics related to the type of system used, machine learning techniques and methods applied, information about the clinical application field evidencing rehabilitation scopes, the population target, and participants enrolled for validation issues were highlighted. Moreover, limitations and challenges encountered by researchers and future directions concerning the role of AI-based solutions in remote rehabilitation services were reported.

The real challenge of artificial intelligence applications resulted in the incorporation of clinical skills and knowledge in order to assist and manage patients in a minimally supervised and more efficient way.

Emerging AI-based computer vision approaches, which currently represent an intensive research topic, are promising for rehabilitation applications to provide home-based, inexpensive, and unobtrusive monitoring of patients [87].

Unobtrusive and wearable technologies coupled with algorithms that recognize performed activities will make the remote evaluation of patient's adherence to prescribed exercise affordable, which until now was based on self-reported measures by subjects [17]. Assessment-driven therapy adaptation algorithms integrated into exergame solutions should ensure that the physical therapy remains at an optimal level of challenge to maintain motivation for long-term therapy programs necessary in chronic conditions [88]. Moreover, movement classification algorithms integrated into digital coach systems and socially assistive robots could support real-time evaluations and personalized feedback. They provide emotional support to increase engagement during home-based rehabilitation therapy in clinical populations characterized by fragile psychophysical conditions [89], [90].

Gradual steps are necessary to introduce AI applications to support rehabilitation services at a distance. Firstly, AI-based monitoring systems integrated into a traditional videoconferencing application could be the way forward to a data-driven approach that helps therapists plan personalized and participatory programs during remote rehabilitation visits and sessions. Then, AI-based applications for automatic monitoring and assistance could be adopted to solve issues in long-term rehabilitation programs (to the maintenance of therapy outcomes and the overload of clinic facilities for routine practices). Furthermore, AI-based applications could also allow engaging a wide range of individuals in their home environments to easier extend preventive rehabilitation programs in pre-morbidities conditions.

Besides the potentiality of AI-based solutions to support the remote monitoring and evaluation of physical therapy programs, further developments of underlying algorithms and validation of methods will be required for broader adoption. Future studies must focus on testing AI-based applications in relevant operational environments, such as in remote conditions and home-based settings. Clinical trials comparing the effects on specific population targets of such emerging solutions versus traditional rehabilitation approaches are required to lead AI-based applications to clinical acceptance. Social and ethical considerations will also need to be considered as AI-based applications will change the paradigm of interactions occurring between healthcare professionals and patients in decentralized contexts.

## V. CONCLUSION

This work outlined the potential applicability of machine learning methods within decentralized rehabilitation services.

The systematic review approach revealed the state-of-the-art AI-based machine learning solutions implemented to assist and manage remote rehabilitation procedures during the last decade. Characteristics concerning systems and machine learning deployed in the rehabilitation context and their implications to support the delivery of therapies from a distance have been evidenced and discussed.

The above discussion suggests that AI-based solutions offer contributions in the form of quality improvement and enhancement of existing practice, as well as support new models of care based on decentralized services.

The review and recommendations provided in this paper aim to guide the design of the next generation of AI-aided rehabilitation services, their validation, and their translation to clinical practice. In the future, AI is expected to increasingly play a crucial role in driving the clinic-centered model toward a decentralized healthcare model that will overcome challenges of health service delivery due to time, distance, and logistic issues, enabling cost-effectiveness and better access to long-term therapies.

## VI. CONFLICTS OF INTERESTS

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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