African Journal of Education Science and Technology (AJEST) Vol. 8 No. 4 (May, 2026)
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Machine Learning for Early Risk Stratification and Longitudinal Outcomes in Children with Cerebral Palsy in Low-Resource Settings: A Systematic Review

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Abstract

Cerebral palsy is a major cause of physical disability in childhood and has a long-term impact on motor, functional, communication and developmental problems. Early detection, regular follow-up, timely intervention, rehabilitation planning and family support are all crucial but may not be available in low-resource communities. This systematic review aimed to summarizes evidence on machine learning methods for early risk stratification and longitudinal prediction of outcomes in children with cerebral palsy and to identify if these methods could be relevant to health systems with limited resources. Studies published between 2015 and 2026 were selected in PubMed, Scopus, Web of Science, IEEE Xplore, ScienceDirect and Google Scholar, and older foundational documents were included if necessary for the review, based on PRISMA. Eligible studies included those using machine learning, artificial intelligence, or predictive modelling to diagnose, predict and analyses gait, classify patients in terms of function, monitor rehabilitation, predict treatment response, or follow up patients over time. After screening, 18 studies were included. From the evidence reviewed, the use of deep learning, neural networks, random forest, XGBoost, video-based movement analysis, and sensor-based approaches were identified. Early cerebral palsy prediction, gait-event detection, gait-phase recognition, gross motor function prediction and functional outcome estimation showed promising performance results. The evidence base was, however, predominantly in high-resource contexts with some external validation and little firsthand evidence from lower-resource health systems. There was also low confidence in generalizability due to small datasets, specialized equipment, differing outcome measures, and limited implementation in real-world applications. The use of video-based approaches, simple clinical data, and lower-cost sensors could have more potential in low-resource settings but needs to be locally validated in these settings prior to their routine use. Machine learning should thus be seen as a clinical decision support tool for early referral, rehabilitation monitoring and long-term care planning, not to supplant clinical judgement.

***Keywords:** cerebral palsy; machine learning; risk stratification; longitudinal outcomes; low-resource settings.*

Introduction

Cerebral palsy is a type of condition that affects the movement and posture for life due to disturbances in the growing brain. One of the most frequent causes of physical disability in childhood can be linked to epilepsy, pain, feeding problems, communication delays, intellectual disability, musculoskeletal issues, and decreased independence. Early identification and ongoing monitoring are therefore important in order to act quickly, to rehabilitate, to provide support for the family, and to plan for longer-term care. Using a combination of clinical history, neuroimaging, and neurological assessment and standardized motor assessment, Novak et al. (2017) demonstrated that cerebral palsy could be diagnosed prior to corrected age 6 months. In some low-resource areas, however, access to these services is constrained by the lack of specialists, imaging services, standardized assessment tools, and follow-up services.

Early identification of CP is a challenge, particularly in low- and middle-income countries where there is limited evidence, albeit a significant burden of CP (King et al., 2022; McIntyre et al., 2022). Machine learning could aid in early ID and monitoring by analyzing the data from infant movement videos, clinical assessments, gait recordings, wearable sensors, neuroimaging, and functional scores. These methods have been used for prediction, diagnosis, gait analysis, gross motor assessment, monitoring during rehabilitation, prognosis, and outcomes of treatment (Balgude et al., 2024; Nahar et al., 2024).

Video-based approaches and sensor-based approaches might be especially applicable to low-resource settings due to the fact that they may not require as much advanced imaging or laboratory-based assessment equipment. The studies that have been conducted with the spontaneous infant movement videos have yielded promising results for early prediction (Groos et al., 2022; Ihlen et al., 2020). Many studies, however, are small, conducted under special circumstances, and not adequately validated with external data. Therefore, this review aims to consolidate the existing applications of machine learning in cerebral palsy (CP) and also analyze their application in low-resource regions.

Review Objectives

The two objectives of the review were;

1. To identify and synthesize machine learning techniques for early risk stratification and long-term outcome prediction in children with cerebral palsy, including the type of data, model, predicted outcomes, and reported performance.
2. To evaluate the relevance and potential use of these machine learning approaches in low-resource settings, including validation, accessibility, scalability, implementation issues, and research gaps.

Methodology

Review Design

This study aimed to be a systematic review of published evidence dealing with machine learning applications for early risk stratification and prediction of longitudinal outcomes in children with cerebral palsy. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) (Page et al., 2021) were used to guide the review, ensuring transparent reporting of the study identification, screening, eligibility assessment, and inclusion. A systematic review design was chosen because the study was designed to locate and integrate the evidence in a predetermined manner through search, eligibility, screening, data extraction and synthesis. The methodological differences in study design, data sources, machine learning methods, clinical outcomes and performance measures in the included studies made meta-analysis inappropriate, so a narrative synthesis approach was used instead.

Search Strategy

The literature search was done using PubMed, Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar for the period of 2015–2026. Where applicable, earlier sources for the foundations were preserved. The search terms included machine learning methods and clinical outcomes such as “machine learning”, “artificial intelligence”, “deep learning”, “neural network”, “random forest”, “predictive modelling”, “early diagnosis”, “risk prediction”, “gait analysis”, “gross motor function”, “rehabilitation”, and “longitudinal outcome”, in addition to cerebral palsy.

In addition to the above, the following concepts were used as keywords for the search: cerebral palsy AND (machine learning OR artificial intelligence OR deep learning OR neural network OR predictive modelling OR diagnosis OR prediction OR prognosis OR gait OR motor function OR rehabilitation OR outcome).
The terms “low-resource settings” and “low- and middle-income countries” were not required filter terms, since they were used only as supplementary search terms, to ensure that relevant studies from higher-resource countries were not summarily excluded.

Eligibility Criteria

Studies were included if they included infants or children with cerebral palsy or children at high risk for cerebral palsy who were the focus of the study and if they investigated machine learning, artificial intelligence or predictive modelling.

Table 1. Inclusion and Exclusion Criteria

Criterion	Inclusion Criteria	Exclusion Criteria
Population	Infants or children with cerebral palsy, or those at high risk of developing cerebral palsy	Adult-only populations or populations unrelated to cerebral palsy
Approach	Machine learning, artificial intelligence, deep learning, neural networks, predictive modelling, computer vision, or related approaches	Studies without machine learning, artificial intelligence, or predictive modelling
Clinical focus	Early diagnosis, risk stratification, prognosis, functional classification, gait analysis, gross motor function, rehabilitation monitoring, treatment response, or longitudinal outcomes	Studies without clinically relevant cerebral palsy outcomes

Study type	Peer-reviewed primary studies and relevant systematic, scoping, or comprehensive reviews	Opinion papers, editorials, incomplete conference abstracts, and non-peer-reviewed sources
Publication period	Mainly 2015 to 2026, with older foundational sources retained where necessary	Older studies without foundational or methodological relevance
Language	English	Publications in other languages
Methodological information	Sufficient information on population, data, model, outcome, or performance	Insufficient methodological information for interpretation
Clinical relevance	Clear contribution to cerebral palsy prediction, diagnosis, monitoring, rehabilitation, or outcomes	Purely technical studies without clear clinical relevance

Title and abstract screening and full-text screening were performed to ensure consistency, using the eligibility criteria.

Study Selection

The records found in the database searches were collated and duplicate records eliminated. The rest of the records were initially screened with regard to title and abstract. Studies which were clearly not related to cerebral palsy, machine learning or outcomes of interest were excluded. The full text of potentially relevant publications was reviewed and assessed using the predetermined eligibility criteria. Full-text exclusion was due to no machine learning application for the article, no clinically relevant cerebral palsy outcomes, adult-only populations, insufficient methodological information or ineligible publication type. There were 86 records found during the search. The records were screened for title and abstract, and 64 records remained after 22 duplicate records were removed. Twenty-eight articles went through full-text assessment. Of these, 10 articles were in full text and did not meet inclusion criteria, and 18 studies were included in the final review.

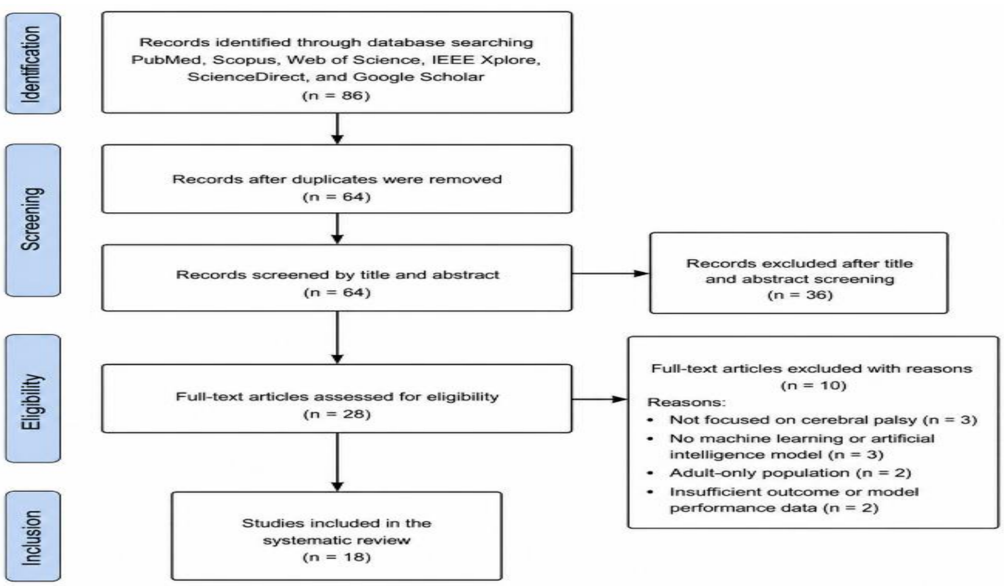

Figure 1. PRISMA flow diagram showing the identification, screening, eligibility assessment, and inclusion of studies in the systematic review

Data Extraction

Data were gathered using a structured framework which was in line with the aim of the review. The information extracted comprised author, year of publication, study setting, study design, sample size (if available), population characteristics, type of machine learning model, input data, clinical application, predicted outcome, validation method, and reported model-performance measures. Accuracy, sensitivity, specificity, positive predictive value, negative predictive value, F1 score, mean absolute error, concordance correlation coefficient, area under the curve and other outcome-specific measures were all used as performance measures. Information on low-resource applicability was also gathered, such as the type of technology used, the need for specialist equipment or personnel, whether the data source could be scaled down, the need for follow-up, whether validation was required across different populations, and whether the data source might be suitable for low-resource services.

Methodological Appraisal

Due to the variety of study designs, data sources, endpoints, and machine learning techniques used, no formal risk of bias tool was used for all studies. Rather, methodological rigor was identified according to predetermined criteria in the extraction and synthesis. The appraisal assessed the clarity of the study objectives, the study population was considered adequate, the sample size was appropriate, the machine learning approach was appropriate, the definition of the outcome was considered clear, the training and testing of the model was considered appropriate, the validation strategy was appropriate, the performance was not missing, the machine learning approach was clinically relevant and there were recognized study limitations. External validation was particularly emphasized, as performance in a developmental data set does not necessarily reflect performance in other data sets. There was no limitation in excluding studies based simply on methodological issues. However, constraints in terms of the strength and generalizability of the reported findings were taken into account instead.

Results and Discussion

Characteristics of the Included Evidence

Eighteen sources were included in the review. Eleven were primary empirical studies that used machine learning or artificial intelligence applications, and seven were systematic reviews, scoping reviews, evidence reviews, prevalence studies, or methodological guidance papers for providing contextual evidence. The main studies that were targeted were early prediction of cerebral palsy, infant movement classification, gait assessment, gross motor function, monitoring of rehabilitation, neurodevelopmental prediction, and independent walking. Of the 11 main studies, four primarily predicted or diagnosed the condition in the early days, four focused on functional assessment, gross motor function, or rehabilitation monitoring, two focused on gait analysis, and one focused primarily on longitudinal prognosis with prediction of independent walking.

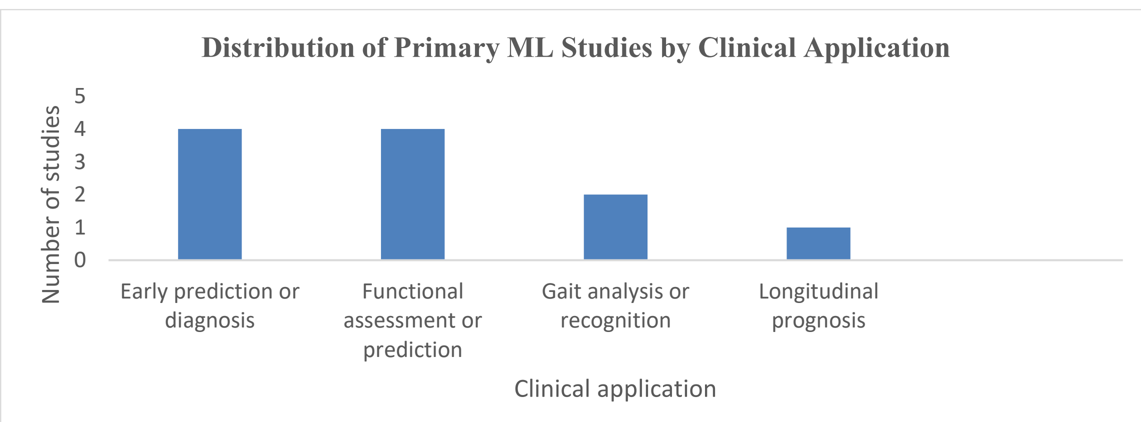

Figure 2. Distribution of primary machine learning studies by clinical application

The distribution of research interest reveals that more has been done on the issue of early prediction than of long-term prognosis and more on functional assessment than on early prediction. This is essential, as long-term prognosis is important for rehabilitation planning, family counseling, and follow-up care.

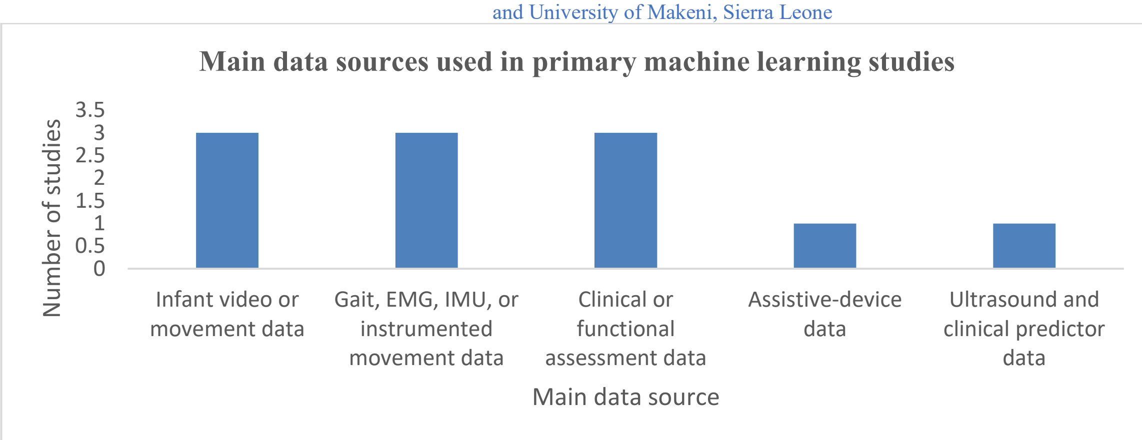

Figure 3. Main data sources used in primary machine learning studies

The reviewed studies included a variety of data sources. Data from infant videos and spontaneous movement was primarily employed for early prediction. Electromyography, inertial measurement units, and instrumented gait data were used for movement and gait analysis. The functional and prognostic prediction was performed using clinical assessments, gross motor function records, assistive-device information, and imaging data.

Machine Learning Approaches and Clinical Applications

Deep learning, neural networks, random forests, XGBoost, pose estimation, movement assessment, and recurrent neural networks were the primary studies.

Studies of infant movement and sensor-based data were notable for the use of deep learning. When using deep learning on spontaneous infant movement videos, Groos et al. (2022) obtained an accuracy of 90.6%, a sensitivity of 71.4%, and a specificity of 94.1%. Using computer-based analysis of spontaneous infant movements, Ihlen et al. (2020) reported 92.7% sensitivity and 81.6% specificity.

The assessment of gait was also performed using machine learning. A neural-network approach for gait-event prediction using electromyography was used by Morbidoni et al. (2021); they achieved an F1-score of 0.95. H. Pang et al. (2025) used inertial sensor data and showed that they could achieve 97.83% gait-phase recognition accuracy using an SDA-LSTM model.

Another significant application was the development of functional outcome prediction. The gross motor function was predicted using random forest methods by Von Elling-Tammen et al. (2023), and Gross Motor Function Measure-66 scores were predicted using XGBoost by Gross et al. (2025). Wang and Yang (2025) took the application of machine learning to the next level by predicting independent walking for a longitudinal prognosis.

Table 2. Machine Learning Models, Clinical Applications, and Reported Performance

Study	ML Approach	Main Data Source	Clinical Application	Reported Performance
Ahmad et al. (2024)	Deep learning	Cranial ultrasound and clinical predictors	Neurodevelopmental outcome prediction	Performance reported in original study
Duran et al. (2022)	Artificial intelligence	Gross motor assessment data	Functional assessment	Performance reported in original study
Groos et al. (2022)	Deep learning	Infant movement videos	Early CP prediction	Accuracy 90.6%; sensitivity 71.4%; specificity 94.1%
Gross et al. (2025)	XGBoost	Instrumented gait data	GMFM-66 prediction	MAE = 6.32
Ihlen et al. (2020)	Movement assessment model	Infant movement videos	Early CP prediction	Sensitivity 92.7%; specificity 81.6%

Letzkus et al. (2024)	Pose estimation and ML	Infant movement data	Movement classification	OKS = 0.91
Morbidoni et al. (2021)	Neural network	Electromyography	Gait-event detection	F1 = 0.95
Pang et al. (2025)	SDA-LSTM	IMU data	Gait-phase recognition	Accuracy = 97.83%
Schafmeyer et al. (2024)	AI-based technology	Gross motor assessments	Functional-change detection	Performance reported in original study
von Elling-Tammen et al. (2023)	Random forest	Assistive-device and functional data	Gross motor function prediction	CCC = 0.75
Wang and Yang (2025)	Prognostic ML model	Longitudinal clinical data	Independent walking prediction	Validation reported

It is not appropriate to use the reported metrics to directly compare algorithms, as these represent different aspects of performance, and the study populations, outcomes, validation methods, and data quality were also different.

Review and Contextual Evidence

Interpreted the primary evidence with the help of review studies. Novak et al. (2017) and King et al. (2022) reported on early diagnosis and LMIC evidence gaps, and Nahar et al. (2024), Balgude et al. (2024) and Kohnehshahri et al. (2024) gave a summary of machine learning applications. The context of burden was provided by McIntyre et al. (2022), and PRISMA reporting was guided by Page et al. (2021).

Methodological Rigour and Validation

The results of the validation were inconsistent between studies. External evaluation was reported by Groos et al. (2022), and a multi-site cohort was reported by Ihlen et al. (2020). There were other studies that had positive outcomes but used a specific population, pilot designs, or a specialized dataset.

Table 3. Comparison of Machine Learning Evidence by Resource Setting

Resource Setting	Main Applications	Common Data or Technology	Potential Strength	Main Limitation
Higher-resource settings	Early prediction, gait analysis, gross motor function prediction, rehabilitation monitoring, and prognosis	Infant movement videos, EMG, IMU sensors, instrumented gait systems, imaging, and structured clinical data	Greater access to technical infrastructure, specialist expertise, and model-development resources	Findings may not transfer directly to low-resource health systems because of differences in infrastructure, populations, and clinical services
Mixed-resource or multicountry settings	Mainly early cerebral palsy prediction	Standardized infant movement videos and deep-learning approaches	Allows evaluation across more than one healthcare environment	Representation of lower-resource populations remains limited
Low-resource settings	Limited direct primary machine learning evidence	Potential use of smartphone video, simple clinical assessments, and lower-cost sensors	Greater potential for affordable and scalable screening or monitoring	Very limited locally validated evidence, infrastructure constraints, limited specialist capacity, and weak external validation

Table 3 shows clearly that there is a bias in the available evidence. A lot of machine learning development and evaluation efforts have been conducted in higher-resource environments, with limited evidence from lower-resource health systems. While video-based methods and other more basic clinical data and lower-cost sensor technologies may offer more practical solutions for resource-limited services, these methods need further local validation before they can be recommended for routine clinical use.

Table 4. Methodological Considerations and Validation of Primary Studies

Study	Validation Information	Main Methodological or Practical Consideration
Ahmad et al. (2024)	Limited detail in the extracted review data	Requires imaging equipment and clinical expertise
Duran et al. (2022)	Limited detail in the extracted review data	Further validation across settings is needed
Groos et al. (2022)	External evaluation reported	Transferability to routine low-resource services requires further study
Gross et al. (2025)	Study-specific validation	Instrumented gait analysis may limit implementation
Ihlen et al. (2020)	Multi-site cohort	Requires standardized infant video recording
Letzkus et al. (2024)	Pilot study	Limited generalizability
Morbidoni et al. (2021)	Study-specific evaluation	EMG equipment may limit accessibility
Pang et al. (2025)	Study-specific evaluation	Requires wearable sensors and technical support
Schafmeyer et al. (2024)	Study-specific evaluation	Requires repeated functional assessments
von Elling-Tammen et al. (2023)	Study-specific evaluation	Depends on detailed clinical and assistive-device information
Wang and Yang (2025)	Validation reported	Requires longitudinal follow-up data

Based upon the appraisal, potential for good numerical performance should be taken into account, as well as validation quality, technology, study design, and clinical relevance. One of the biggest challenges to wider adoption is the lack of external validation.

Interpretation of the Findings

Video recording of the movement seems promising for identifying the risk for early cerebral palsy. Ihlen et al. (2020) and Groos et al. (2022) demonstrated that the spontaneous infant movements can be computed to aid in early prediction. These methods could be more feasible than sophisticated imaging in certain low-resource areas, but they also need to be standardized in their recording, validated locally, clinically interpreted, and organized in a clear referral system. Longitudinal prediction is less advanced. While the number of longitudinal studies is rather small, studies predicting gross motor function and independent walking indicate machine learning can help in rehabilitation planning, family counselling, and follow-up care.

The transferability of models is one of the main concerns. Performance may be lower when models are used in settings not for which they were created due to population differences, equipment differences, differences in the recording conditions, differences in clinical practice, and differences in follow-up systems. If the accuracy is high in one study, it is not necessarily the case in another. The feasibility is also a key point. Complex or expensive models or models requiring specialist knowledge or complex infrastructure may only be of limited value in low-resource areas. If they can be locally validated, then potentially the video from a smartphone, the simple clinical assessment, and lower-cost sensors has greater potential.

Ethical and data-governance concerns also need to be addressed, as videos, imaging, movement information, and clinical records of infants are sensitive information. Thus, suitable consent, safe data management, privacy safeguards, and consideration of model bias are crucial. In general, machine learning ought to be used to assist rather than supplant the use of professional judgment. It could serve as a tool to facilitate early detection, referral, monitoring of rehabilitation, and the prognosis of future functional outcomes.

Policy and Practice Implications for Kenya

The results of the study are significant to cerebral palsy care in Kenya and other resource-limited environments. Most reviews of machine learning studies were outside low-resource health care systems, thus requiring local testing of existing ML models before they can be used routinely. Video movement analysis, easy clinical evaluations, and cheaper sensors should be prioritized over more expensive options.
Implementation needs to be connected to referral, rehabilitation, and follow-up services and be backed by trained health professionals and safe digital systems. Local representative datasets, multicenter validation, affordable technologies, and the integration with existing child health and rehabilitation services are key areas to be explored in future research in Kenya. Predictive accuracy is just one of the strengths of a model, and it is important to consider costs, availability, user-friendliness, and infrastructure in assessing models.

Conclusion and Recommendations

Based on this systematic review, machine learning can be applied in the field of cerebral palsy care with promising results in early risk prediction, gait analysis, gross motor function assessment, rehabilitation monitoring, and predicting functional outcomes. There are, however, several methodological differences between the studies that make it difficult to directly compare the models.

There is limited evidence from low-resource contexts, and the majority of studies took place in higher-resource settings. Future studies, therefore, should be based on larger and more diverse data sets, validation with external data sources, and longitudinal outcomes. More focus should also be directed at cost-effective solutions like smartphone video, basic clinical evaluations, and more inexpensive sensors.

In Kenya and similar environments, locally produced data and validation studies should be conducted before machine learning tools can be routinely used. Machine learning must complement clinical judgment and be embedded in the right referral, rehabilitation, privacy, and data protection frameworks.

Author Contributions

Conceptualization, methodology, investigation, formal analysis, data curation, writing original draft, writing review and editing, visualization, and project administration.
Funding: None.

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