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ML for Predictive Recovery Models in Physiotherapy

Physiotherapy plays a crucial role in restoring post-injury, post-surgery or post-neurological damage recovery in the form of functionality, mobility and quality of life. Conventional rehabilitation is largely based on clinical judgment and general recovery plans that in most cases disregard the individual physiology, psychology and behavior of a patient. This has been altered by the emergence of digital health data and machine learning (ML). ML develops predictive algorithms, which are based on numerous sources of data, including electronic health records (EHR), motion sensors, imaging and patient-reported outcomes, to predict patient recovery timelines and responses to treatment. The models assist clinicians to tailor exercise programs, make wise resource distribution choices and provide patients with concise progress reports. The investigations applied in recent years with supervised, unsupervised and deep learning (DL) methods were promising predictors of post-stroke motor recovery, musculoskeletal and home exercise adherence. There is also explainable AI (XAI) that is under investigation and aims to enhance transparency in clinical decisions. Nonetheless, there are issues such as mixed types of data, confidentiality concerns and lack of generalizability across populations, and bias in the algorithm. It should be noted, to overcome these hurdles, that for clinicians, data scientists and policymakers to collaborate, we have to make sure that ML tools are safe, effective and can be personalized. This chapter highlights the latest developments, applications, challenges and opportunities of ML-controlled predictive recovery in physiotherapy and highlights how this technology has the potential to change individualized rehab medicine.

1.1. Introduction

One of the pillars of contemporary rehabilitation medicine is physiotherapy. It is dependent on the skills of the clinician and patient-specific factors including age, comorbidities, baseline functionality and patient adherence to the prescribed

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exercises. Historical rehab planning has greatly relied on broad clinical guidelines and therapist experience. These methods are also useful, but they do not always account for the complexity and uniqueness of patient recovery journeys. Consequently, one of the biggest challenges within the physiotherapy practice is the possibility of predicting individual recovery outcomes (Santilli et al. 2024).

There has been a paradigm shift in recent years. The increasing access to electronic health information and the accelerating development of computational techniques have rendered ML an effective technology with the potential to enhance clinical decision-making and prediction of patient outcomes. Mining very large and diverse datasets, including EHRs, sensor-derived biomechanics, etc., ML has the capability of finding nonlinear, subtle patterns that traditional statistics cannot detect (Kwarah et al. 2025). This ability is important in physiotherapy where the timing, intensity and modality of therapy are important in improving recovery.

The need to integrate ML is especially timely because the global demand for rehabilitation is increasing. Stroke, musculoskeletal injuries and degenerative neurological disorders contribute greatly to the disability burden in the world. Long-term disability in up to 50% of stroke survivors is also caused by the stroke alone, whereas sports injuries and orthopedic surgery create a demand for personalized rehabilitation approaches. Predictive models can significantly benefit the healthcare system – which is already strained by workforce shortages and rising costs – by simplifying planning processes, optimizing resource allocation and enhancing results (Finocchi et al. 2024).

The objectives of predictive recovery models are to predict clinically relevant outcomes, including motor functioning improvements, gait improvements, pain reduction and the chances of adherence to therapy. These forecasts assist clinicians in customizing exercise programs, prescribing therapy periods and in determining patients who are prone to unfavorable recovery. Consider a patient who has undergone ACL reconstruction, an ML assessment method may estimate the duration of returning to sports activity by estimating biomechanical, activity and psychosocial measures. Similar models provide a preliminary idea of the potential of motor recovery in stroke rehab, which helps to plan intensive therapy more effectively (Campagnini et al. 2025)

Also, of significance, ML facilitates patient engagement and self-management. Existing wearable technologies and tele-rehab systems make it possible to record continuous data, which are used to provide models with real-time feedback. Dynamic monitoring also allows the patient to monitor progress and gives clinicians the ability to modify plans in real-time. Explainable AI also offers more transparent and trust-based opportunities, which are considerable obstacles to the clinical implementation of ML solutions (Tozlu et al. 2020).

1.2. Overview of ML in healthcare

ML is one of the most significant technologies in the healthcare industry today, as it provides new methods for large-scale data analysis and supports clinical decision-making. This is in contrast to more traditional statistical models, which are frequently based on preset assumptions about linearity or distribution; ML algorithms, in contrast, can automatically infer complex and nonlinear relationships among diverse datasets. This feature renders ML highly applicable in forecasting patient outcomes, risk stratification and the personalization of treatments, which are of great importance in the physiotherapy domain (Campagnini et al. 2025).

The fundamental principle of ML is to provide computational models by training them on past data, in order to identify trends and/or make predictions when new data is presented. In healthcare, multimodal patient information is becoming increasingly accessible enabling this process. The number of suitable sources of data is growing fast in the case of physiotherapy in particular. Electronic health records (EHRs), demographic factors, comorbidities, surgery history and drug use, wearable apparatus and inertial measurement units (IMUs) offer continuous monitoring of gait, posture and physical exercise. Structural and functional biomarkers are detected with imaging modalities (MRI and ultrasound), whereas the patient-reported outcomes provide information on pain, quality of life and compliance. Through predictive modeling, combining these heterogeneous sources enables the creation of more accurate recovery models, reflecting the multifactorial nature of recovery (Kumar et al. 2026a).

One of the greatest benefits of ML in healthcare is that it is flexible across different types of tasks. In physiotherapy, regression models can be used to forecast continuous variables, including the anticipated recovery time, and classification models can be used to categorize patients as, say, high or low responders to a certain intervention. Clustering algorithms have the potential to reveal subgroups of patients with common recovery patterns, which can be used to design customized treatment strategies. Multilayer neural networks are particularly useful in DL methods, especially when handling high-dimensional data, including imaging scans, motion capture videos or electromyography recordings (Kumar et al. 2026b).

Nevertheless, the implementation of ML into the field of healthcare, and specifically into the field of physiotherapy, should be accompanied by careful consideration of the matter of interpretability. Although black-box models can be highly predictive (e.g. deep neural networks), a clinician generally needs to know how predictions are made in order to trust and use them. Surrogate modeling, visualization of learned representations and feature attribution techniques are explainable artificial intelligence (XAI) methods that are increasingly being used to overcome this challenge. For example, an ML model designed to predict poor adherence to home exercise will identify certain characteristics (e.g. baseline motivation scores, past clinic visit frequency or smartphone sensor data on exercise frequency). These factors become transparent when presented through XAI methods, thereby increasing the chances of clinical adoption (Knoop et al. 2022).

The other important dimension is the involvement of ML in the wider digital health ecosystem. Due to the spread of telerehabilitation platforms, mobile health (mHealth) applications and wearable devices, physiotherapists can now access streams of real-time information that were previously unavailable. These technologies not only enable the development of predictive models but provide opportunities for continuous monitoring and adaptive feedback loops. For example, data from a wearable device monitoring gait asymmetry in a post-stroke patient can be fed into an ML model that predicts the risk of falls, thereby enabling preventive measures. This is the ongoing interaction between data collection, predictive modeling and clinical action, which represents a significant evolution in rehabilitation care (Coleman et al. 2025).

In spite of such opportunities, there are still hurdles in integrating ML into healthcare operations. The heterogeneity of data across different institutions, the absence of standardized protocols for sensor use and privacy issues associated with sharing patient data pose major challenges. Additionally, it is not clear whether models trained on one population can be used in another, which highlights the importance of the external validation and multicenter cooperation. The ethical aspects, including issues such as algorithmic bias, where predictive models may unintentionally be of disadvantage to some demographic groups, also require consideration. Addressing these issues will be essential to ensuring that the benefits of ML can be delivered equitable to diverse patient populations in physiotherapy and other healthcare fields.

1.3. ML techniques for predictive recovery in physiotherapy

ML is a very broad area, and each of its techniques has its own advantages in modeling recovery outcomes in physiotherapy. The choice of method depends on the nature of the data, the prediction task and the level of interpretability required. In rehabilitation research, supervised learning, unsupervised learning, DL and reinforcement learning have emerged as the most prominent approaches, each contributing uniquely to predictive recovery modeling (Zhou et al. 2025).

1.3.1. *Supervised learning*

Supervised learning is the most widely applied ML paradigm in healthcare. It involves training a model using a collection of labeled data, in which the variables of interest to the model (e.g. demographics, clinical scores, sensor-derived kinematic features) are combined with known outcomes (e.g. functional recovery at six months). The model then learns to map input features to outcomes and can generalize predictions for new patients.

In physiotherapy, regression techniques such as linear regression, support vector regression and random forests are used to predict continuous outcomes such as recovery duration or gait speed improvement. Classification algorithms such as logistic regression, decision trees and gradient boosting machines are used when predicting categorical outcomes, such as whether a patient will achieve independence from daily living activities. For example, classification models have been formulated to classify post-stroke individuals into either favorable or unfavorable recovery progressions to help clinicians make informed treatment decisions (Sassi et al. 2025).

1.3.2. *Unsupervised learning*

Unsupervised learning works with unlabeled information and is mainly applied to discovering hidden structures or patterns. This method can be particularly useful in physiotherapy, where recovery profiles are often heterogeneous and inadequately characterized. Algorithms such as k-means clustering, hierarchical clustering and Gaussian mixture models can be used to classify patients into subpopulations based on similarities in movement data, psychological factors or adherence patterns. Such groups may correspond to clinically significant categories that are not taken into account by conventional diagnostic systems. High-dimensional data, such as motion capture or electromyography data, can also be simplified using dimensionality reduction algorithms such as principal component analysis (PCA) or t-distributed stochastic neighbor embedding (t-SNE) to allow patterns to be more readily interpreted (Lv et al. 2022).

Unsupervised learning can inform the customization of the rehabilitation process by identifying subgroups of patients with common attributes. For example, patients with chronic low back pain can be grouped by their biomechanical and psychosocial profiles, allowing therapists to match each patient cluster with the most effective treatment approach.

1.3.3. *Deep learning*

DL, a branch of ML founded on artificial neural networks, has been especially popular because of its capacity to approximate complex and nonlinear relationships in large datasets. Convolutional neural networks (CNNs) used in video analysis have applications in physiotherapy, including the classification of musculoskeletal injuries from MRI images and the analysis of motion capture videos to evaluate exercise performance. Recurrent neural networks (RNNs) and variants such as long short-term memory (LSTM) networks are particularly well suited for modeling sequential data, and can be useful in the prediction of time-series recovery trajectories based on wearable sensor data (Shurrab et al. 2024).

1.3.4. *Reinforcement learning*

Reinforcement learning (RL) is a new method that has distinctive potential in the physiotherapy field. In comparison to supervised or unsupervised approaches, RL is oriented towards determining optimal decision-making strategies based on trial-and-error interactions with an environment. In rehabilitation settings, RL may be used to tailor exercise programs to dynamically increase or decrease the intensity and type of activity according to the patient responses. For example, a virtual rehabilitation system could adjust the difficulty of tasks in real-time with the help of RL, thereby maximizing patient engagement while maintaining safety (Abujaber et al. 2024).

1.3.5. *Hybrid and ensemble approaches*

In practice, a combination of various ML approaches often results in better performance. Ensemble algorithms such as random forests, gradient boosting and stacking combine the merits of more than one base learner in order to enhance accuracy and robustness. Hybrid methods that combine ML and rule-based expert systems or physiological models are also being investigated to overcome the gap between data-driven approaches and mechanistic knowledge. These approaches can lead to improvements in both predictive performance and clinician trust. Table 1.1 summarizes the ML techniques used in predictive physiotherapy recovery models.

ML technique	**Description**	**Typical data used**	**Physiotherapy applications**
Supervised learning	Models trained on labeled input–output data to make predictions.	Clinical scores, demographics, gait parameters, sensor data.	Predict recovery duration, classify responders versus non-responders, forecast gait speed improvement.
Unsupervised learning	Finds hidden patterns without labeled outcomes.	Movement data, EMG, psychosocial data.	Patient clustering, identifying recovery subgroups, detecting abnormal movement patterns.
Deep learning	Neural networks capable of learning complex nonlinear patterns.	MRI/US images, motion videos, time-series sensor data.	Automatic movement analysis, predicting motor impairment severity, image-based injury detection.
Reinforcement learning	Models learn optimal actions through trial-and-error interactions.	Real-time performance data, VR interaction data.	Adaptive exercise difficulty adjustment, personalized training intensity control.
Hybrid/ensemble techniques	Combines multiple models to improve performance.	Mixed clinical + sensor + psychological datasets.	Enhanced prediction of functional outcomes, robust adherence prediction models.

Table 1.1. *Summary of ML techniques used in predictive physiotherapy recovery models*

1.4. Applications of ML in physiotherapy

ML has recently become a major trend in the field of physiotherapy, providing strong predictors of recovery outcomes in a broad range of conditions. Physiotherapy involves a wide range of areas, with neurological, musculoskeletal, orthopedic, sports and cardiorespiratory rehabilitation being the most common, each having its own difficulties and predictive modeling opportunities. Using multimodal data, ML helps design individualized recovery pathways, enable early-risk detection and support adaptive treatment approaches, which previously were impossible to achieve using conventional techniques (Fast et al. 2023).

1.4.1. *Post-stroke rehabilitation*

One of the most widely studied fields where ML-driven predictive modeling has been applied is stroke rehabilitation. The recovery patterns of stroke survivors tend to be very unpredictable, making it difficult to forecast function outcomes using only conventional clinical tests. ML algorithms have been applied to predict recovery in upper limb function, gait and independence in daily living activities.

As an example, models based on demographic data, clinical assessments (e.g. Fugl–Meyer scores) and neuroimaging data have been shown to be highly predictive in identifying patients who may benefit from intensive motor training (Kokkotis et al. 2022).

The data from wearable sensors is also important. Rehabilitation adherence and functional gains over time can be predicted based on accelerator-based movement patterns that are analyzed with ML. In addition, neurophysiological signals, for example, EEG or EMG, combined with DL models have provided the possibility of predicting the neuroplastic potential, thus optimizing therapy planning. Such predictive knowledge assists clinicians in focusing intensive rehabilitation resources on individuals who are most likely to achieve meaningful recovery.

1.4.2. *Musculoskeletal rehabilitation*

A large percentage of physiotherapy caseloads comprises musculoskeletal conditions, such as ligament injuries, fractures, arthritis and chronic low back pain. The combination of biomechanical, psychological and lifestyle factors complicates recovery prediction under such conditions. Prognostic ML models have been used to predict the functional recovery time following orthopedic surgery, for example, anterior cruciate ligament (ACL) reconstruction or total knee replacement. Gait analysis, muscle strength tests and patient-reported pain scores have been used as predictive variables in models to identify patients at risk of delayed recovery (Karimi et al. 2024).

Clustering methods have been used to classify patients into subgroups with distinct pain and disability trajectories in chronic musculoskeletal disorders. These clusters inform personalized rehabilitation programs, thus guiding clinicians away from ineffective one-size-fits-all treatment programs. Moreover, motion capture information, coupled with ML algorithms, has been used to analyze the exercise performance and identify compensatory patterns of movement, providing real-time corrective feedback during rehabilitation exercises.

1.4.3. *Neurological disorders*

ML is now being used with increasing frequency in stroke rehabilitation and other neurological disorders, including Parkinson's disease, multiple sclerosis and spinal cord injury. The disorders are usually progressive or complicated impairments in which future recovery prediction is of utmost importance in long-term care planning. For example, wearable sensor data on gait and tremor, processed using ML algorithms, have been used to track disease progression in Parkinson's disease and predictive ability in response to physiotherapy-based interventions (Areias et al. 2024).

ML models, based on clinical examination data and neuroimaging biomarkers, have shown promise in predicting the potential for motor recovery in the rehabilitation of spinal cord injury. This type of prediction enables a personalized approach to treatment and formulating realistic expectations of patients and their caregivers. Moreover, new systems of robotic-assisted training with ML improvement are being developed, where algorithms can customize the level of robotic support during physiotherapy sessions to maximize functional gains while minimizing patient frustration.

1.4.4. *Sports physiotherapy and performance recovery*

Another area with potential for predictive ML models is sports medicine and physiotherapy. Athletes who sustain injuries involving hamstring tears, ankle sprains and shoulder dislocations have to make critical choices on safe return to play. ML models that are trained on biomechanical measurements, training load measurements and psychological readiness scores have demonstrated the ability to predict return-to-sport timelines and the risk of reinjury (Mabrouk et al. 2024).

In addition, predictive analytics can support proactive injury prevention by analyzing sensor-based workload and movement data. For example, algorithms that track the performance of players during training can anticipate early warning of movement changes caused by fatigue, which increase the risk of injury. The capacity to foresee performance enhances rehabilitation outcomes, optimizes recovery and supports long-term athletic health.

1.4.5. *Predicting adherence to home-based therapy*

Compliance with home exercise programs is one of the most challenging problems in physiotherapy. Lack of adherence greatly decreases the effectiveness of treatment and prolongs recovery periods. The use of ML models to forecast adherence behaviors has leveraged demographic, psychosocial and digital engagement data. For example, smartphone sensors are able to measure exercise frequency, whereas self-reported motivation scores and baseline functional status provide contextual information. Classification models based on these features can predict patients at a high risk of poor adherence, enabling clinicians to implement motivational strategies or other alternative interventions.

1.5. Integration of ML with digital health tools

ML and digital health technologies have developed novel opportunities in improving physiotherapy practice. The conventional rehabilitation paradigms tend to use episodic, clinic interactions, which limit the constant monitoring and customized changes. In comparison, digital health tools, including wearable devices, computer vision, telerehabilitation systems and virtual reality, produce high-volume patient data, which can be processed using ML algorithms. This synergy allows predictive recovery models to be more dynamic, adaptive and accessible transforming the future of physiotherapy (García and Santos 2025).

1.5.1. *Wearable sensors and Internet-of-Things (IoT) devices*

Wearable technologies, such as IMUs, accelerometers, gyroscopes and pressure sensors, have now become critical in capturing both kinematic and kinetic data in the non-clinical setting. These devices will provide constant data on the gait patterns, joint range of movement, balance and daily physical activity. This data in combination with ML can then be converted into predictive models of functional recovery, adherence and risk of reinjury (Tozlu et al. 2020).

For example, in rehabilitation related to post-orthopedic surgery, wearable sensors have been used to monitor step symmetry and weight-bearing parameters. It is possible to predict delayed recovery or complications by applying ML algorithms to these signals, enabling clinicians to intervene early. Likewise, in neuro-rehab, the data obtained through wearable gait variability can be used to predict the risk of falls, and physiotherapists can use the obtained information to establish preventive balance training measures.

1.5.2. *Motion capture and computer vision for exercise monitoring*

Physiotherapy exercises have been transformed by computer vision technologies that monitor them. Computer vision algorithms can be used to monitor body movements, and posture and exercise performance using depth cameras, smartphones or video recordings. The result of the ML models applied to this data can automatically identify the patterns of compensatory, faulty form or diminished range of movement, and provide instant feedback to patients (Dobkin 2017).

For instance, neural networks with convolutional architecture that are trained on the video data have been used to estimate the quality of squats or identify an uneven gait pattern. These systems not only ensure proper exercise execution but also generate longitudinal data that can feed predictive recovery models. Using computer vision-enabled platforms in home-based rehabilitation programs allows physiotherapists to act as virtual therapists and offer the same quality of care, without relying on frequent in-person sessions.

1.5.3. *Telerehabilitation and mobile health applications*

Telerehabilitation has emerged as a viable cost-effective method of providing physiotherapy, especially in the Covid-19 pandemic period. Mobile health (mHealth) is used in video consultations, exercise monitoring and patient education. Combined with ML algorithms, such platforms become intelligent rehabilitation systems rather than mere communication tools (Mei et al. 2025).

For example, the ML models embedded in mobile applications can be used to predict patient adherence based on the use history, exercise history and pain self-report. Subsequently, the clinicians can adjust the frequency of follow-up or present some motivational methods to the patients who may be at risk of dropout. Moreover, predictive models can recommend adaptive exercise programs tailored to observed performance trends, enabling remote personalization of recovery pathways.

1.5.4. *Virtual reality and gamification in rehabilitation*

Gamification and VR have brought about immersive and engaging modalities in physiotherapy. VR products enable simulation of real-life conditions and engaging patients in clinical exercises, whereas gamification aspects (e.g. scoring, challenges, rewards) enhance patient motivation and compliance. ML can further improve these systems by individualizing difficulty levels, analyzing patient performance in real-time and predicting progress trajectories (Abdulle et al. 2007).

1.5.5. *Synergy of digital health and predictive models*

The combination of ML and digital health represents the true potential of these technologies. Continuous data is produced by wearables, exercise quality can be monitored by computer vision, adherence is supported by mobile apps and engagement is enhanced by VR. The integration of these data streams into the predictive models allows physiotherapists to gain a comprehensive view of patient progress in real-time. It is a holistic approach that enables more accurate prognostication, the development of individualized treatment strategies and timely clinical interventions.

1.6. Challenges in implementing ML predictive models

Although ML demonstrates considerable potential in improving the development of predictive recoveries in physiotherapy, a number of obstacles to its usage in the clinical setting exist. These issues lie in the technical, ethical, organizational and clinical realms and can be considered an indicator of the complexity of the task of incorporating advanced computational methods into healthcare systems. It is crucial to study these barriers in order to make sure that the solutions, proposed by ML in the field of physiotherapy, are not only accurate but also fair, safe and accepted by both patients and clinicians (Wang et al. 2022).

1.6.1. *Data heterogeneity and quality issues*

Heterogeneity and quality of available data are among the most acute issues in predictive modeling. Physiotherapy data are typically highly fragmented, with its sources of different types, including EHRs, wearable devices, imaging modalities and patient-reported outcomes. These sources vary in format, frequency of sampling and reliability. Missing values, measurement errors and inconsistent data acquisition procedures further complicate model training.

In addition, the physiotherapy information is usually small compared to other fields of medicine. Smaller datasets increase the risk of overfitting, where models capture spurious patterns that do not generalize to new patients. Although the data augmentation and transfer learning methods provide a partial solution, the absence of big, multi-institutional and standardized data remains a significant challenge (Calderone et al. 2024).

1.6.2. *Algorithmic bias and fairness*

Another issue is the algorithmic bias. The quality of ML models is as good as the data used to train them, and biased data may lead to unfair predictions. For example, if rehabilitation datasets are skewed towards younger patients or certain demographic populations, models perform poorly for older adults or minority populations. This poses the danger of unjust treatment recommendations or false predictions of recovery, which can further worsen the disparities in health.

Some of the intentional measures to make physiotherapy in ML fair include balanced curation of datasets, metrics of bias detection and application of fairness-aware algorithms. Moreover, the explanation of AI (XAI) systems can be used to assist clinicians to recognize and address biases through offering clarity on model decision-making. Nevertheless, the required interdisciplinary approach to the implementation of these safeguards involves cooperation between data scientists, ethicists and clinicians (Trache et al. 2025).

1.6.3. *Privacy and security concerns*

Although the use of ML is increasingly integrated with digital health tools, providing real-time monitoring, it also raises privacy and security concerns. Physiotherapy data, especially wearable sensors and mobile applications, often include sensitive movement and behavioral information, which is collected continuously. It is necessary to make sure that privacy laws such as the General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA) are strictly followed.

Moreover, the rehabilitation data is often stored centrally, which exposes it to cyberattacks. Federated learning and homomorphic encryption are two emerging techniques that allow institutions to train their models collaboratively without sharing data. These methods, though promising, are still resource-intensive and require robust infrastructure for large-scale implementation.

1.6.4. *Lack of generalizability and clinical validation*

One repeated problem of ML in healthcare is that models often lack external validation and generalizability. Models trained using data from a particular clinical environment or geographical location often fail when applied to different populations. This is more so in the field of physiotherapy where cultural, behavioral and lifestyle differences influence recovery trajectories. Predictive models may be invalid in practice unless they are carefully validated in a wide range of cohorts.

In addition, there is a lack of clinical validation of ML models. Not many physiotherapy-centered predictive instruments have progressed beyond proof-of-concept studies to large-scale randomized controlled trials (RCTs). There must be strong evidence that ML models can lead to better clinical outcomes, reduced costs or increased efficiency compared to conventional care in order to be adopted clinically.

1.6.5. *Barriers to clinician adoption*

Even technically sound ML models may face barriers to adoption by physiotherapists. Clinicians might be reluctant to use algorithms as black boxes because they cannot see or understand the reasoning behind the predictions. The lack of trust is further exacerbated when models provide recommendations that differ from clinical judgment.

Moreover, incorporating predictive tools into the current physiotherapy workflow may not be straightforward. Many healthcare systems have limited digital infrastructure, which complicates the integration of ML models. Feasibility is further diminished by time constraints, training requirements and the need for continuous technical support. The solution to these barriers lies in designing user friendly interfaces, incorporating explainable AI features and engaging end-users throughout the development cycle.

1.7. Future directions

Predictive recovery models based on ML are relatively new to the field of physiotherapy, although continued developments in data science and computational infrastructure, and digital health environments are enabling wider application. In order to maximize their impact, future studies should focus on the development of robust, fair and clinically integrated solutions. A number of promising avenues are being explored that could define the future of predictive recovery models in physiotherapy (Rayjade et al. 2024).

1.7.1. *Personalized rehabilitation pathways*

The future potential of fully personalized rehabilitation is one of the most valuable. Treatment in current physiotherapy is usually based on general treatment protocols, yet ML can go beyond this one-size-fits-all approach. For example, patients rehabilitating after ACL surgery can receive predictions of return-to-sports timelines based on their individual bio-mechanical and psychological characteristics. Equally, stroke patients might be provided with tailored recommendations for rehabilitation intensity based on their neuroplasticity potential. This kind of individualized approach is the best way to achieve the most benefit and minimize unnecessary interventions (Rayjade et al. 2024).

1.7.2. *Hybrid AI–human decision-making*

Instead of substituting clinicians, ML will be used as an interactive tool that complements physiotherapists' knowledge. A combination of efficiency, accuracy and trust is achieved through hybrid decision-making models, where clinicians and ML systems collaborate to optimize efficiency, accuracy and trust. Predictive models are able to make probabilistic predictions and emphasize the major factors involved, but therapists put these predictions into context using their clinical expertise and knowledge of their patients. This kind of collaboration makes the treatment patient-centered and does not require blind reliance on algorithmic outputs.

1.7.3. *Federated learning and privacy-preserving models*

One of the biggest obstacles to the widespread implementation of ML in healthcare is privacy concerns. To address this issue, federated learning represents a promising future direction. In this model, the predictive models are trained in a collaborative framework allowing multiple institutions to train models without directly sharing patient data. Model parameters are instead updated locally and aggregated centrally, maintaining privacy and providing access to large and diverse datasets.

In the context of physiotherapy, federated learning has the potential to facilitate global predictive recovery frameworks by leveraging rehabilitation data from multiple countries and care settings. This enhances model generalizability while complying with stringent privacy regulations (Lobo et al. 2024).

1.7.4. *Integration of multimodal and longitudinal data*

Multimodal and longitudinal streams of data are increasingly being used in physiotherapy research in the future. The existing models tend to be limited to single sources of data, such as imaging or sensor data, whereas recovery is multidimensional in nature (Feller et al. 2024). By using a combination of multiple input types (e.g. gait data, EMG signals, psychological readiness, pain scores), researchers can enhance the accuracy of prediction and clinical relevance.

In addition, the longitudinal data over a long rehabilitation phase can capture dynamic changes in recovery, allowing models to update predictions in real-time. This is consistent with the clinical reality of rehabilitation, where the progress is rarely linear (Ediga et al. 2024).

1.8. Conclusion

ML has become an innovative solution in the physiotherapy field, introducing novel opportunities for predictive recovery modeling that can move rehabilitation beyond generalized treatment plans towards individualized care. ML models can use multimodal data, such as clinical documentation, imaging, sensor-based metrics of motion and patient-reported outcomes to generate valid predictions of recovery patterns, treatment responses and adherence behaviors. Such abilities enable clinicians to build individual rehabilitation plans, allocate resources in the most efficient way and communicate with patients more effectively throughout their recovery processes.

By combining ML with digital health technologies (wearable sensors, computer vision platforms, telerehabilitation applications and virtual reality), its utility is further enhanced, enabling real-time monitoring and adaptive feedback. Such technologies take physiotherapy outside the clinic and enable data-driven, ongoing care in patients' homes and daily lives. Meanwhile, interpretable AI approaches are enabling clinicians to bridge the gap between predictive outputs and clinical trust, a key requirement for adoption. Whether this promise is realized or not, there are still several barriers. Criticisms such as heterogeneity of data, algorithmic bias, privacy threats, low generalizability and rigorous clinical validation remain major challenges. To resolve these problems, it will be necessary to involve data scientists, clinicians, engineers and policymakers and develop ethical and regulatory frameworks that both protect patient welfare and foster innovation.

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