Artificial Intelligence and Digital Innovations in Physiotherapy Rehabilitation: Transforming Modern Clinical Practice

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Abstract

In physiotherapy rehabilitation, the use of artificial intelligence (AI) and other digital technologies marks a new era in how healthcare is delivered today. This chapter provides a detailed review of the research-based evidence for the integration of machine learning, deep learning, computer vision, wearable sensors, virtual and augmented reality, robot-assisted therapy, and telerehabilitation into physiotherapy practice as they change the way physiotherapy practice is delivered in terms of assessment, diagnosis, treatment planning, and outcome measurement. Many of the findings reported in this chapter are based on the current evidence provided by systematic reviews and recent clinical studies. The authors discuss how the integration of these technologies into physiotherapy is conceptualized theoretically, compared with practical applications, and how they are being developed, assessed for use, and have ethical issues associated with their implementation.

The commentary include sacritical analysis of the evidence for each of the main technologies discussed, a detailed analysis of the barriers that will prevent equitable adoption of these technologies, the obligations of data governance, the emergence of algorithmic bias, and the emergence of evolving professional competencies required to use these technologies. A forward-looking synthesis of precision rehabilitation, federated learning, digital twins, and AI- assisted clinical decision support is provided, which will be integral to rehabilitation medicine practice over the next decade. The authors concludethat while AI and digital technologies are critical to the future of physiotherapy, they should enhance the profession with their practice- based expertise, while maintaining the human and ethical aspects of the profession.

Keywords: *Artificial intelligence, Physiotherapy, Digital rehabilitation, Telerehabilitation, Wearable technology, Machine learning, Robot-assisted therapy, Virtual reality, Clinical decision support, Patient outcomes*

1. Introduction

Physiotherapy's basis revolves around and focuses heavily upon the movement sciences in attempting to restore function to patients while treating them as a whole. The four historical "pillars" that have formed the basis of successful rehabilitation over time include skilled clinical reasoning, evidence-based exercise prescription, manual therapy, and patient education. Even today, these four pillars remain central to rehabilitation; however, the introduction of digital/computational capabilities since 2000 has dramatically altered how rehabilitation can be conceptualized, delivered, and evaluated.

AI (including, but not limited to, ML, DL, computer vision and NLP), among other forms of technological innovation, has been an enormous driver of change across all areas of healthcare. [1,2] AI is allowing for the physiotherapist to perform more precise movement analyses, develop predictive recovery models, automatically identify compensatory strategies in patients, and provide highly individualized treatment plans.[3]

The development of wearable digital health technology and mobile health apps, along with virtual reality (VR) and augmented reality (AR), is increasing access to rehabilitation services. According to World Health Organization (WHO) estimates, 2.4 billion people will need to have some access to rehabilitation services at least once in their lives, which will continue to rise as the population ages and the burden from non-communicable diseases increases.[4]

Digital health technology is a viable strategic response to three issues: **1** the current shortage of allied health professionals providing rehab [2] geographic inequities in the ability to access rehabilitation and [3] increasing complexity in providing clinical care.[28] Similarly, the COVID-19 pandemic played a significant role in furthering new healthcare delivery models by accelerating telerehabilitation's implementation and remote monitoring by healthcare systems and creating a large body of real-world evidence for the safety and effectiveness of telerehabilitation as compared to traditional rehabilitation.[11, 12]

This chapter formally explores the systematic integration of digital technologies and artificial intelligence into rehabilitation physiotherapy and demonstrates how relevant this information is to the practice of physiotherapy rehabilitation. The chapter begins with a foundation of knowledge on technology (definition, introduction), then provides detailed information about specific technologies utilized for different conditions and ends with a review of current trends affecting future applications all while providing evidence

summaries and clinical examples to show how the information presented is relevant for physiotherapy rehabilitation practice.

2. Foundations of Artificial Intelligence in Healthcare

2.1 Defining AI and Its Principal Subfields

AI refers to a general type of computer system that is made to complete tasks that are usually difficult for people to do, such as identifying and recognising patterns, reasoning when there are several answers possible, learning from experience, and making decisions that are linked or relative to the current situation. As Russell and Norvig say, AI includes any agent that can see its surroundings and make decisions that improve its ability to achieve a goal.[1] In the healthcare field, this would mean using large amounts of clinical, imaging, physiological, and outcome data to train the AI to detect patterns and develop predictive information that would assist in or fully automate the clinical processes for physiotherapy rehabilitation.[2]

Within AI's large umbrella, there will be many areas of AI that are useful for physiotherapy rehabilitation, each one having its own function and a different foundation of research.

Machine learning is the set of algorithms that allow computers to build models of behaviour based on data without needing to be programmed to do it each time. Each of the supervised, unsupervised, and reinforcement learning methods provides different opportunities for use in a clinical setting. Manjunatha Topol's article in Nature Medicine has shown how machine learning is a key driver in the evolution of the healthcare profession, and how it will eventually provide the same or greater diagnostic ability as most specialists in diagnostics today, across all areas of medicine, including orthopaedics and rehabilitation.[2]

Deep Learning is part of the Machine Learning (ML) domain and relies heavily on complex neural networks that have many layers. Unlike older techniques that treat all available images as one dimensional data, DL can analyze very high dimensional datasets such as images of patient X-rays, images of patients' faces when videotaped, and images of patients' electrical

signals from electrocardiograms (A K) (also referred to as biosignals), providing therapists with an objective basis for making decisions about treatment plans. DL-based systems use this new technology for automated analysis of gait/gait analysis video, determining the quality of an individual's movement using RGB-D camera (used in some previous studies), and interpreting surface electromyography (EMG) signals, all of which would have required specialized equipment years ago.[25]

Computer vision (CV) allows AI systems to analyze images to extract useful, clinically relevant data/knowledge out of them. The development and implementation of marker less algorithms or pose-estimation frameworks (Open Pose, Media Pipe) has been a critical advance in physiotherapy. For example, two-dimensional movement analysis using conventional (video data) systems that were not designed for physiotherapy (Open Pose/ Media Pipe) yield movement (kinematic) analyses that are extremely accurate (with a bias of <3 internal degrees of freedom) when compared to traditional (laboratory) motion capture technologies. Thus, objective movement assessments are now much easier to obtain in everyday clinical settings, compared with many years ago when motion analysis was primarily found within a laboratory environment.[5, 6]

Natural Language Processing (NLP) seeks to apply computational techniques for the understanding and creation of human language for automating clinical documentation, providing support for triage, and analysing patient self-report outcome questionnaires. Rehabilitative practices have an incredible documentation burden; therefore, NLP-based tools are a very practical AI-based application for improving the efficiency of clinical care without the need to be directly involved in the movement analysis.

Reinforcement Learning (RL) builds AI agents by allowing them to repeatedly interact with their environment. While RL will reward agents based upon their ability to take positive actions that encourage or allow desired outcomes to occur, it does provide a methodology for developing control algorithms that allow rehabilitation robotic devices to adapt the amount of assistance being provided to patients in a real-time, effort-dependent manner, thereby supporting challenge-based neuroplasticity.

These two areas provide complementary rather than hierarchical technological sets and exhibit their clinical utility in physiotherapy by not demonstrating sophistication alone but rather demonstrating quality (validity) and representativeness (reliability) of the data used to train the system. This concept of quality and representativeness of the data used to train AI systems is an ongoing theme in this chapter.

2.2 Data Types in Physiotherapy AI

The development and clinical validation of AI systems in physiotherapy depend on diverse, high-quality data sources.[25] Understanding these data types is essential for critically appraising published literature and informing responsible implementation.

Data Type	Representative Examples	Rehabilitation Application
Biomechanical/ Kinematic	Joint angles, gait parameters, range of motion	Movement analysis, posture evaluation, compensation detection
Physiological/ Bio-signal	EMG, accelerometry, heart rate, SpO_2	Muscle activation, fatigue monitoring, exercise intensity
Medical Imaging	MRI, diagnostic ultrasound, plain radiograph	Tissue pathology grading, injury classification
Patient-Reported Outcomes	PSFS, DASH, KOOS, PROMIS, NRS	Outcome tracking, treatment response monitoring
Clinical Documentation	SOAP notes, referral letters, discharge summaries	NLP-based decision support, coding, clinical audit
Wearable/ IoT Sensor	Step counts, fall detection, sleep indices	Remote monitoring, adherence tracking, community rehab
Video/ Depth Sensor	RGB-D footage, LiDAR, pose estimation	Exercise quality scoring, teleassessment

Table 1. *Principal data types and clinical applications of artificial intelligence in physiotherapy rehabilitation. PSFS: Patient-Specific Functional Scale, DASH: Disabilities of the Arm, Shoulder and Hand, KOOS: Knee Injury and Osteoarthritis Outcome Score, NRS: Numerical Rating Scale, EMG: electromyography, IMU: inertial measurement unit.*

2.3 Model Validation and Algorithmic Bias

The quality, generalizability, representativeness and quantity of the training data will have a significant impact on the clinical effectiveness of an AI system. Over fitting (when the AI model works well with the data it has been trained to use, but poorly with new and previously unseen data) is a key issue and highlights the need for robust external validation of AI models against diverse and independent populations prior to implementation in clinical practice.[2]

Algorithmic bias is another serious ethical and safety concern with AI, if the majority of the training data used by AI models is derived from a small number of patients with specific socio-demographic characteristics (e.g. age groups, ethnicity or absence of other health conditions), any AI application will not perform equitably across those patients who are less represented in the dataset from which the model was developed.[37] These points are particularly important when it comes to the work of physiotherapists, as they typically deal with clients of varying ages, disabilities, and comorbidities, and therefore prior to implementing an AI system into their clinical practice, physiotherapists should closely examine the socio-demographic variables in the training datasets used to create those AI systems.

3. AI-Powered Assessment and Clinical Decision Support

3.1 Movement Analysis and Pose Estimation

There are numerous AI applications for automated movement analysis in physiotherapy. Traditionally, biomechanical assessments were conducted with laboratory equipment at a great expense (e.g. electromagnetic motion capture devices, force plates), which are typically difficult to access.7 However, recent developments in free AI-based pose estimation algorithms (OpenPose, MediaPipe, PoseNet) have eased the challenge of providing widespread access to high-resolution movement analysis, including 3D joint tracking, with low-cost standardized RGB cameras and smartphones.[5,6]

Examples of clinical applications of AI-based automatic measurement of lower limb kinematic data during a gait cycle, detection of trunk deviations during a lift, measurements of range of motion and compensatory movement patterns, classifications of pathological gait patterns, and predictions of fall risk with the use of machine-learning algorithms trained on inertial measurement unit (IMU) data and video footage.[5,7] AI-supported gait analysis provides objective and reproducible measurements for patients with neurologic disabilities such as stroke, Parkinson's disease, and multiple sclerosis, thus considerably enhancing what clinicians could traditionally observe.

3.2 Clinical Decision Support Systems

Using clinical and patient data, as well as a clinician's clinical knowledge base (evidence-based), CDSS creates differential diagnoses, provides treatment options, and indicates risks associated with patients.[25,29] CDSS have been used in MSK physiotherapy to identify serious pathology during screening, to increase the accuracy of prognoses, and to assist physiotherapists in recommending treatments that conform to guidelines, such as when using protocol-based care.[3]

In order to create assessment templates for use by clinicians, NLP can take data reported by patients, as well as information from patient health records, and identify when data has not been completed or a patient is at a high risk for certain outcomes and alert clinicians.[25] It is important that the use of AI be understood as different from the augmented use of AI (augmented intelligence). The term "augmented intelligence" describes how AI should be used to support the use of CDSS in physiotherapy while taking into account the values, preferences, and clinical complexity of patients in addition to the recommendations provided by the CDSS.

3.3 Prognostic Modeling and Outcome Prediction

Predictive models based on machine learning have shown superior accuracy for predicting rehabilitation recovery patterns compared to models using only one

predictor variable when trained with large datasets.[25,26] Machine learning has been shown to be effective in generating multiple high-dimensional predictor matrices (clinical, psychological, imaging) simultaneously and predicting return-to-sport timelines and other long-term performance outcomes after total knee arthroplasty (TKA) or anterior cruciate ligament (ACL) reconstructive surgery.[26] The use of machine learning tools aids in collaboration on determining the best decisions, setting realistic goals, and distributing intensive rehabilitation resources where necessary.

4. Digital Therapeutics and Remote Rehabilitation

4.1 Telerehabilitation

Tele-rehabilitation is included in professional physiotherapy practice, as it is supported by numerous international guidelines.[11] Therefore, numerous studies and meta-analysis have reported that the use of video conferencing for physiotherapy in musculoskeletal or neurological patients is just as effective as traditional in-person physiotherapy.[11,12] In addition, studies looking at patient satisfaction show that patients using tele-rehabilitation have the same or better level of satisfaction compared to those receiving treatment in-person, and that the ability for a patient to complete their exercises in the comfort of their home has helped make tele-rehabilitation a popular choice for patients.[12]

In addition, the availability of software platforms for tele-rehabilitation has increased rapidly, and physiotherapy providers can now offer more than just basic video consulting. Providers can also offer real-time video monitoring of exercise performance with artificial intelligent (AI) motion detection, instant feedback on exercise performance, and interactive teleconference platforms that use patient-generated data from wearable and other fitness equipment.[12,13] In addition, the AI analysis of the data gathered using tele-rehabilitation would significantly enhance the amount of clinical information that is obtainable from the use of tele-rehabilitation compared to the traditional use of specialized laboratory equipment.[27]

4.2 Wearable Technologies and Remote Monitoring

Wearable devices can be classified into two categories: Clinical grade (specialized) wearable's and Consumer grade (generalized) wearable's. Both of these categories utilize multiple forms of sensors such as accelerometers, gyroscopes, photoplethy smography, surface electromyography, and smart textiles to provide continuous monitoring of an individual's physiological response in a real life setting.[13]

In rehabilitation environments, wearable's can help provide a measurement of daily physical activity in relation to prescribed targets; identify early warning

signs associated with overtraining or elevated risk of injury; measure sleep quality which can be used to evaluate 'readiness to recover'; provide real-time biofeedback while individuals are completing home exercise programs; and track long-term functional trajectories that may not be easily identified through case-by-case clinic assessment.[7, 13]

Wearable Category	Sensing Technology	Rehabilitation Application	Evidence
Activity Trackers	Accelerometer, GPS	Step count, activity intensity, sedentary time	Strong-RCTs
IMU Systems	Accelerometer, gyroscope, magnetometer	Joint kinematics, gait analysis, balance, fall detection	Strong-SRs
Smart Textiles	Stretch sensors, sEMG	Posture biofeedback, muscle activation monitoring	Emerging
Smart watches	PPG, optical HR, ECG, SpO_2	Cardiovascular monitoring, arrhythmia detection	Moderate
Pressure Insoles	Force distribution sensors	Plantar loading, gait symmetry, orthotics	Moderate
Full-Body IMU Suit	Multi-segment IMU array	Whole-body kinematics, motion capture	Emerging

Table 2. *Wearable technology categories in physiotherapy rehabilitation with evidence quality ratings. RCT randomised controlled trial, SR systematic review, IMU inertial measurement unit, PPG photoplethysmography, sEMG surface electromyography.*

4.3 Mobile Health Applications

Mobile health (m Health) applications represent the leading option in terms of digital rehabilitation technology.[14] The m Health physiotherapy ecosystem includes guided home exercise applications with video demonstrations, symptom and pain diary applications, cognitive behavioral pain management platforms; biofeedback applications for pelvic floor conditions and integrated tele-health portals.[30,31] A systematic review by Slattery et al. concluded that the use of digital health technologies for the treatment of chronic pain shows significant reductions in both pain intensity and catastrophizing compared with control groups. Furthermore, there are greater reductions in both outcomes with the use of interactive digital platforms than with provision of only passive information.[31]

A critical appraisal of commercially available applications demonstrates that there is considerable variability in the quality of evidence supporting their efficacy, as well as in terms of how much clinician input went into the development process and the provision of safeguards to protect patient

privacy.[14] Health providers should evaluate mHealth applications prior to recommending them for use by their patients using instruments such as the Mobile Application Rating Scale (MARS) or the User Qualified Design Quality Index (UQDI).

5. Immersive Technologies in Rehabilitation

5.1 Virtual Reality

VR enables users to engage with computer-generated 3D virtual surroundings with HMDs and projection systems.[19] There are several head-mounted displays that VR rehabilitation can provide like safely simulating challenging real-life environments, accurately adjusting the level of difficulty for a task, providing rapid multiple sensory feedback regarding performance, and distracting from pain.[15,16]

Laver et al. in their Cochrane systematic review of [72] randomized controlled studies found that VR upper limb training had a greater impact (compared to traditional therapies) on improving upper limb function and performing activities of daily living (ADLs).[17] The evidence provided by Dockx et al. supported the efficacy of VR balance and gait training for individuals with Parkinson's disease in improving their confidence in balance and reducing the number of freezing episodes while walking.[15] Studies of chronic pain management revealed that VR graded motor imagery and pain neuroscience education programmes could significantly decrease catastrophizing and kinesiophobia.[16]

5.2 Augmented Reality

Augmented Reality (AR) is a technique whereby a computer generates and overlays visual information in real time either through a transparent display or via a smartphone camera. Unlike Virtual Reality, which restricts an individual's understanding of their surroundings and environment, AR enables an individual actively involved in a task to practice in ecologically valid environments thereby providing highly effective methods for practicing and completing specific activities.[18]

Some examples of clinical applications of AR include: providing patients with a visual representation of a target angle during limb movement; presenting individuals with Parkinson's disease with accurate visual representations (targets) of appropriate stride length during gait retraining; allowing clinicians to provide real-time corrective feedback to patients regarding postural control; and allowing clinicians to view AI-generated movement annotations during a physical examination of a patient. Although initial investigations conducted with different AR devices (e.g., the Microsoft HoloLens) in the orthopedic

medicine field indicated that the potential exists for enhancing clinical performance using AR technology, there is currently minimal data available from larger-scale clinical studies supporting its use.[18]

5.3 Gamification and Exergaming

Using gamification is defined as adding concepts from the world of games into activities that are not games, like rehabilitation programs. Adhering to an exercise program in the home has continued to be one of the biggest obstacles in physiotherapy due to reports that 30% to 70% of patients do not adhere to their prescribed exercise regimen within two to three weeks.[33] Exergaming software contains artificial intelligence personalization engines that continually adjust the level of difficulty to keep users optimally engaged while using the exergaming platform in real-time.[32, 33]

Skjaeret et al. performed a systematic review on exergaming in older adults and concluded that exergaming is associated with a significantly lower rate of injury than traditional forms of physical activity; exergaming was also associated with improvements in balance, cognition and movement and should be considered for use in rehabilitation programs within the community.[33]

6. Robot-Assisted Rehabilitation

6.1 Overview and Classification

People use robots for therapy because robots can provide consistent, high-quality assistance with an exact amount of force for each specific exercise. They can measure exactly how much force is applied to an injured area and how well it heals over time. With the addition of adaptive impedance control (AIC) and reinforcement learning (RL) AI-based algorithms, rehabilitation robots can operate with more flexibility than ever before.[39]

Rehabilitation robots can be classified according to their specific target body part(s), how the robot interacts with the person using it and what type of therapy it is providing to the patient. The three classifications are high-level end-effector devices (the robot guides the distal joint through pre-defined movement patterns), exoskeletons (the robot supports multiple joints within the body relative to their location on the user, e.g., Ekso Bionics, ReWalk, Lokomat), and soft robotic systems made from flexible, inflatable materials that provide movement assistance with less stiffness, thus increasing comfort and ease of use.

6.2 UpperLimbRoboticTherapy

Robotic therapy on the upper limb relies on the principle of use-dependent neuroplasticity – the ability of the brain to develop new connections through intensive and repetitive motor practice.[21] Robots provide a higher volume and frequency of stimulation to effectively induce neuroplasticity at levels that would otherwise be difficult to accomplish with traditional manual physiotherapy techniques.[20]

A Cochrane systematic review performed by Mehrholz et al. evaluated 45 research articles with more than 1,600 participants using robotic-assisted rehabilitation. They found that robotic-assisted rehabilitation improved motor impairments in the arm and independence performing Activities of Daily Living after a stroke. Most importantly, they found that the best results were obtained when the robotic-assisted therapy was used in conjunction with traditional physiotherapy methods, rather than as a substitute.[8]

6.3 Lower Limb and Gait Robotics

The different devices used to support partial weight while training for gait rehabilitation include treadmill-based exoskeleton gait trainers (Lokomat), over-ground exoskeleton gait trainers (Ekso, ReWalk), and end-effector gait trainers. All devices can provide partial body weight during repetitive gait training. Each training device may promote activation of spinal and supraspinal systems involved in locomotion.[22, 23]

A Cochrane review by Mehrholz et al. demonstrated that electromechanical-assisted gait training produced superior outcomes (walking speed, endurance, and independence) in stroke patients compared to regular gait training.[9] In addition, there have been early results showing evidence of activation of neuromuscular pathways, supporting the notion that there is potential for improving function in all types of spinal cord representational losses where there is complete loss of motor function (i.e., complete spinal cord injuries), through the use of robotic-assisted devices for gait training.[22, 24]

7. AI and Digital Technologies Across Rehabilitation Populations

7.1 Neurological Rehabilitation

The rehabilitation processes for neurological disorders are among the most complex to navigate in clinical practice, as described in detail in the current medical literature. With this sobering reality comes a clear need for new rehabilitation interventions for these patients, and therefore, there exists a matching opportunity for technological advancement in these intervention strategies. Many of the different types of neurological disorders (for example; post-stroke; traumatic brain injury (TBI); spinal cord injury; multiple sclerosis;

Parkinson's and Cerebral Palsy) are extremely heterogeneous in terms of how they present, how long they take to recover from, and how much rehabilitation is required; making these conditions optimal candidates for the application of rehabilitation strategies augmented by artificial intelligence (AI).

A very promising area of AI-assisted rehabilitation has been the use of brain-computer interfaces (BCI) for stroke rehabilitation. This technology allows for decoding of motor intentions from electroencephalography (EEG) signals and pairing these with robotics or functional electrical stimulation (FES) devices, thereby using the principles of Hebbian plasticity (activation of the descending motor pathways with the time of volitional effort). The work of Kwakkel et al. contributed systematic evidence that the timing and intensity of motor feedback is an important contributor to the neuroplasticity associated with use-dependent motor learning (which provides a strong theoretical basis for using BCI-assisted paradigms of rehabilitation).[20, 21]

Initial clinical studies have demonstrated that chronic stroke patients will show increases in their ability to recover from upper limb paralyses when using robotic therapy in conjunction with BCI technology; however, the number of participants has currently been limited, and additional study will be required to establish longer-term functional transfers of improvement in this population.

AI-enhanced gait assessment gives reliable and ongoing evaluations of three primary characteristics of primary motor symptoms of Parkinson's disease: variability in length of stride, frequency of "freezes" while walking, and performance of dual-task walking. The episodic assessment of these conditions in the clinic does not allow for the degree of precise measurement provided from the use of wearable inertial measurement unit systems. Assessed against laboratory estimates using motion capture, these systems have demonstrated sufficient accuracy for longitudinal community-based monitoring, thereby providing clinicians with a greater density of measurements that would be otherwise impossible without using movement specialist centre's.

7.2 Musculoskeletal Rehabilitation

Global physiotherapy caseloads consist primarily of musculoskeletal disorders, and AI-assisted tools have been extensively studied in this population.4 Models that use deep learning techniques on MRI scans have been able to detect rotator cuff tears, meniscal pathology, and lumbar disc abnormalities with an accuracy level comparable with that of radiologists, which has direct implications for triaging and creating treatment plans by physiotherapists working in advanced practice.[25] Prognostic machine learning models that are trained on multivariate clinical data have shown validity in predicting the expected return-to-sport timelines following ACL reconstruction and predicting the expected functional outcome after total knee arthroplasty. Furthermore, Ramkumar et al. validated a wearable machine learning-based remote monitoring platform for post-TKA

rehabilitation, demonstrating that clinical interventions could be performed earlier on individuals who had a deviation from their expected postoperative recovery trajectory based on algorithmic alert.[26] These advanced technologies will enable the better provision of accurate and personalized prescriptions for rehabilitation, as well as more realistic collaboration on goal setting.

Most of the validated models in this subfield were developed and tested at high-income tertiary care facilities with demographically similar populations. There is an urgent need to validate models in low- and middle-income countries where musculoskeletal disability disproportionately affects working-age adults. Countries like India have limited access to specialist physiotherapy due to geographic and financial barriers. Therefore, AI tools need to be validated for these settings and developed to provide effective clinical support under low-resource conditions.

7.3 Cardiopulmonary Rehabilitation

Historically, supervised centre-based programmes have been the means through which cardiac and pulmonary rehabilitation could be delivered. This model has been inherently limiting for patients who live in rural and underserved areas. New AI-enabled wearable ECG monitors that can detect arrhythmias in real time are starting to change the nature of community-based cardiac rehabilitation, enabling physiotherapists to supervise higher-risk patients who are exercising remotely with a suitable safety net.[13]

Telerehabilitation for chronic obstructive pulmonary disease (COPD) has been evaluated by multiple randomized controlled trials. According to Hoaas et al., long-term telerehabilitation showed improvements in both exercise capacity and quality of life; these improvements were similar to those achieved by centre-based programmes, and ongoing adherence was facilitated by regular remote contact with healthcare providers.[27] Logical, evidence-supported next steps would include integrating AI-driven symptom monitoring and personalized exercise prescription algorithms into these platforms.

7.4 Paediatric Rehabilitation

Digital tool designs for children's physiotherapy should take into account aspects of cognition and attention span, developmental levels, their ability to interact with the tools, and the involvement of caregivers. For example, using play and gaming platforms rather than traditional adult-style user interfaces is likely to lead to children being more engaged with their treatment programs and more likely to continue using them.[16, 33]

Emerging AI devices that assess the video submissions by parents for the identification of indicators of neurodevelopmental issues may provide an avenue for quicker access to physiotherapy services through expedited orders of referral from treating physicians for patients living in rural areas or those

without a local paediatric physiotherapist. Similarly, VR rehabilitation tools have shown positive therapeutic outcomes in improving upper extremity function and motivation to complete therapy for children with cerebral palsy and acquired brain injury (i.e., TBIs). In addition, Smania et al. have reported on the beneficial effects of repetitively training locomotion for enhancing the gait of children with cerebral palsy, thus supporting the inclusion of engaging digital environments into physiotherapy rehabilitation programs.[24]

8. Ethical Considerations and Implementation Challenges

8.1 Data Privacy and Regulatory Compliance

Integration of AI and digital health systems in physiotherapy generates and processes sensitive patient data, including movement kinematics, biometric signals, and behavioral data that could be misused if appropriate governance frameworks are not established.[36, 37]

To ensure the use of digital health tools is compliant with relevant data protection laws, practitioners must first be aware of the relevant data protection laws that apply to them. In Europe, for example, this would mean compliance with The General Data Protection Regulation (GDPR).[36] In India, on the other hand, the Digital Personal Data Protection Act 2023 is now creating similar statutory regulations regarding the collection and use of individuals' health data. Physiotherapists who practice in more than one jurisdiction, as is increasingly common with telerehabilitation, will have to carefully manage how they navigate through this regulatory maze.

The regulation of AI tools used for clinical purposes will also need to be examined or scrutinized closely. AI tools that will influence and affect the decision-making process can fall under two classifications: either as Software as a Medical Device (SaMD) under the FDA (U.S. Food and Drug Administration), or the EU's Medical Device Regulation. Each of these classifications requires analytical validation, clinical validation, and transparent risk management documentation.[36, 37] The significance of these classifications is that there is a clear distinction between AI tools that have received regulatory clearance and those that have not (i.e., general wellness applications). The distinction can be a factor in issues of institutional liability, clinical governance, and informed consent.

Furthermore, currently many AI tools marketed to physiotherapists who provide rehabilitation are in regulatory limbo or grey areas. Therefore, physiotherapists will need to develop sufficient digital health literacy to critically analyse and evaluate these AI tools in terms of the applicable regulatory classification and not just accept what the vendor claims they are.

8.2 Algorithmic Bias and Digital Equity

Algorithmic bias arises in AI systems when the training data do not provide an adequate representation of their intended user community. In physiotherapy, where there can be considerable variation in patients with respect to age, body type, ethnicity, severity of disability, and level of comorbidity, this is an issue of significant validity concern, rather than a peripheral issue. For example, a gait analysis algorithm developed primarily on a cohort of young, able-bodied adults will not perform well (i.e., generalize) when applied to older patients with sarcopenia or multiple comorbidities. Additionally, an algorithm developed from a tertiary care cohort in the United States may perform poorly when applied to patients seeking care from community clinics in low-income areas.[36, 37]

The detriment of unrecognized algorithmic bias is ethical, as well as technical. If AI rehabilitation tools fail to perform consistently for older patients, minorities, or patients with multiple disabilities, and if clinicians apply algorithmic findings in a passive manner (i.e., without independent scrutiny), then this creates a technology-mediated exacerbation of pre-existing health inequities. Moreover, both algorithmic and digital health inequity are likely to occur worldwide, since access to, and benefit from, digital rehabilitation technologies is strongly dependent upon socioeconomic status, digital literacy, geographical location of the provider and client, and the nature of the disability.[28, 34]

Failure to achieve equity in healthcare is an extreme failure of universal healthcare, in which representatives use AI to educate patients about their conditions. In addition, designers must make available to all constituents aids to treatment. We also need policies to help underserved clients find out about available therapies and how they can receive those services. Terrestrial medicine must ensure that separate classes of people are not created using artificial intelligence. Furthermore, if you are a therapist and you use an AI product, you must have the skills to assess the product; in addition, you must be able to evaluate if you are providing therapy that is beneficial to your client. If you use an AI product, different types of clients may benefit from it depending upon the client's physical and mental state, irrespective of whether you are using a technology-based or manual-based product.

8.3 The Evolving Role of the Physiotherapist

AI’s inclusion into physiotherapy does not lessen the physiotherapist's clinical position but changes it entirely. The physiotherapist of tomorrow is increasingly going to become a key interpreter and coordinator of digital clinical data created by AI’s and other technology\’s algorithms. This will include selecting appropriate virtual (AI) tools, configuring them for a given patient, understanding the context of the algorithm’s outputs, identifying when

they are not valid or applicable, and integrating the algorithmic outputs into the qualitative aspects of clinical reasoning (which current AI systems do not have the capacity to do).[29,38]

These changes will have a substantial impact on professional education and competency frameworks. Pre-registration physiotherapy education has typically taught manual skills, exercise science and clinical reasoning. While these are still essential, pre-registration education must now include a formal understanding of AI and digital health literacy; knowing how the algorithm was trained and validated, how to identify bias in AI training data, interpreting confidence intervals and other performance metrics, and meaningfully evaluating AI regulations and guidelines.

World Physiotherapy's policy statement on digital health established in 2022 formally endorses this change in competencies and calls for member organizations to include digital health education and competency in all stages of their professional development programme.[38] It is important that advances in technology be not confused as providing a wider range of therapies beyond being able to build therapeutic alliances with each other. The quality of the therapeutic alliance (clinician-patient relationship) is one of the strongest indicators of rehabilitation outcomes for a wide variety of diagnostic categories. Technology does enhance the amount of information available to support that therapeutic alliance, but cannot replace it. Digital tools offer physiotherapists the opportunity to use all their cognitive and temporal resources on the foundational human aspects of delivering care: relational, motivational, and educational.[35, 38]

9 Future Directions

9.1 Precision Rehabilitation

Using a new 'precision rehabilitation' framework, treatments that are tailored to the individual's biological, environmental, and lifestyle characteristics are beginning to be realized through the use of a precision medicine model.[2] The ultimate objective is to use artificial intelligence to produce individualized rehabilitation prescriptions based on genomic, imaging, biomechanical and psychological characteristics, as well as social factors, leading to a level of therapeutic individualization that has not been previously achievable, at scale.[30]

9.2 Federated Learning

Collaborative AI architecture via a federated learning approach enables independent local model training to occur at the institution's managed servers and still maintain privacy of patient's data. Therefore, multiple institutions can develop models together without sending actual patient data to any other

institution; thus preserving data ownership through privacy rights purposes.[25] Federated learning use will continue to be significantly developed within healthcare AI solutions in the field of rehabilitation, where a single healthcare provider often cannot generate enough data independently to create reliable predictive analytics models.

9.3 Digital Twins

The creation of digital twins enables clinicians to have a dynamic virtual representation of their individual patient to use in the assessment & treatment of their pathologies based on the patient's physiological and biomechanical characteristics resulting from therapeutic interventions & possible treatments. A digital twin is created by combining real-time data collected from multiple different sensor technologies with biomechanical simulation models that provide the clinician a method to assess how therapeutic parameters might affect their individual patient before implementing those therapies in the actual patient. This allows for a more precise assessment of a patient's rehabilitation program than previously possible and less risk of providing under or over doses of treatment.

9.4 Ecosystem Integration

Physiotherapy AI solutions need to be integrated into existing systems and integrate into EHRs (Electronic Health Records), as well as data sources from primary care, social services, and population health.28 Supporting the cross-disciplinary exchange of health-related data will require interoperability standards such as the HL7 adoption of the FHIR (Fast Healthcare Interoperability Resources) specification and standardized data ontologies referring to rehabilitation.[37]

Conclusion

The current chapter covers the use of advanced digital (AI & Digital) technologies in physiotherapy rehabilitation, as well as how physiotherapists, educators, researchers and policy makers need to think about each patient in a patient-centered manner by utilizing evidence, which is both ethical and informed. The chapter discusses many technologies, including an extended variety of AI enhanced movement analysis, strategies and tools for the clinician's use in clinical decision-making, Wearable devices, telerehab (telemedicine), various types of immersive technologies, and robotic-assisted therapy. The major theme of the document relates to the definition of augmented intelligence, that is where augmented intelligence utilizes artificial intelligence (AI) to support clinical experts and ethical responsibilities of physiotherapy rather than completely replace them. The authors emphasize that

the physiotherapy patients of the future will have to navigate their treatment through a digitalized society, therefore, the need for high quality, clinically evaluated and scientifically based technologies will be crucial, while ensuring that every patient receives the level of personalized and compassionate care they need. This challenge is one of the most pressing issues facing the profession.

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