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APPLICATIONS AND LIMITATIONS OF ARTIFICIAL INTELLIGENCE METHODS IN PERSONALIZED REHABILITATION THERAPY

ZASTOSOWANIA I OGRANICZENIA METOD SZTUCZNEJ INTELIGENCJI W SPERSONALIZOWANEJ TERAPII REHABILITACYJNEJ

Abstract

This chapter aims to provide a literature review on the applications of artificial intelligence (AI) in personalized rehabilitation, covering the full therapeutic process from diagnostics and planning to monitoring and therapy support. A systematic review of the literature was conducted, focusing on six key domains: patient diagnostics and clinical assessment, personalization of rehabilitation plans, monitoring and support of therapies, virtual and robotic rehabilitation, predictive models for estimating recovery trajectories, and AI support for physicians and therapists. The analysis indicates that AI can improve diagnostic precision, predictive accuracy, and dynamic adaptation of rehabilitation programs to individual patient needs. At the same time,

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the chapter highlights significant limitations, including high implementation costs, lack of standardized protocols, data privacy challenges, and the potential exclusion of underrepresented patient groups. Identifying these limitations provides a foundation for further research and the development of strategies to enable more effective, safe, and equitable integration of AI into clinical personalized rehabilitation.

Keywords: artificial intelligence, healthcare informatics, personalized rehabilitation, AI-assisted therapy

Streszczenie

Celem rozdziału jest przegląd literatury dotyczącej zastosowań sztucznej inteligencji (AI) w spersonalizowanej rehabilitacji, obejmującej wszystkie etapy procesu terapeutycznego – od diagnozy, przez planowanie i monitorowanie, aż po wspieranie terapii. Przeprowadzono systematyczny przegląd literatury naukowej koncentrującej się na sześciu kluczowych obszarach: diagnostyce i ocenie stanu pacjenta, personalizacji planów rehabilitacyjnych, monitorowaniu i wspieraniu terapii, rehabilitacji wirtualnej i robotycznej, modelach predykcyjnych prognozujących tempo powrotu do zdrowia oraz wsparciu dla lekarzy i terapeutów. Analiza literatury wskazuje, że AI może zwiększać precyzję diagnozy, poprawiać trafność prognoz oraz umożliwiać dynamiczne dostosowanie terapii do indywidualnych potrzeb pacjentów. Jednocześnie artykuł podkreśla istotne ograniczenia, takie jak wysokie koszty wdrożeń, brak standaryzacji protokołów, problemy z ochroną danych oraz ryzyko wykluczenia niektórych grup pacjentów. Wskazanie tych ograniczeń umożliwia wytyczenie kierunków dalszych badań i poszukiwania rozwiązań, które pozwolą na skuteczniejszą i bezpieczniejszą integrację AI w procesie spersonalizowanej rehabilitacji klinicznej.

Słowa kluczowe: sztuczna inteligencja, informatyka medyczna, spersonalizowana rehabilitacja, terapia wspierana AI

Introduction

The integration of artificial intelligence (AI) into healthcare has initiated a paradigm shift toward more individualized, data-driven models of diagnosis, treatment, and rehabilitation. Personalized rehabilitation therapy, which aims to tailor interventions to the unique physiological, psychological, and social circumstances of each patient, stands at the intersection of technological innovation and clinical practice. In this context, AI emerges not merely as a supplementary tool but as a transformative enabler, supporting clinicians

in diagnostics, optimizing rehabilitation strategies, monitoring therapeutic processes, and enabling advanced modalities such as virtual and robotic rehabilitation.

Recent advancements have demonstrated the potential of AI-driven models to enhance diagnostic precision, improve outcome prediction, and dynamically adapt rehabilitation pathways. However, despite these promising developments, the adoption of AI in personalized rehabilitation remains constrained by a variety of limitations, understood here broadly as encompassing both methodological shortcomings of current research and practical barriers to clinical implementation. These include technological, economic, and ethical constraints, such as the high cost of implementation, the absence of standardized therapeutic protocols, data privacy concerns, and the risk of underrepresentation of certain patient groups in AI training datasets, which may perpetuate inequalities in healthcare access and quality.

The aim of this chapter is to provide a comprehensive literature-based review of AI applications in personalized rehabilitation, spanning the continuum from patient diagnostics to recovery monitoring and therapeutic support. Specifically, it examines six key domains: (1) AI in patient diagnostics and clinical assessment, (2) AI-driven personalization of rehabilitation strategies, (3) AI in monitoring and enhancing therapeutic processes, (4) AI-enabled virtual and robotic rehabilitation, (5) predictive AI models for forecasting recovery trajectories, and (6) AI support for physicians and therapists. Through this structured analysis, the chapter seeks to identify existing gaps in the field, evaluate the applicability of current approaches, and outline directions for future development.

The contribution of this work is interdisciplinary. From a computer science perspective, it synthesizes methods for personalization within AI systems. For the medical and health sciences, it highlights evidence of both current and potential improvements in rehabilitation outcomes driven by AI integration. From an economic standpoint, it considers issues of cost-effectiveness, scalability, and the allocation of healthcare resources. Furthermore, it addresses ethical and cultural dimensions, such as the exclusion of underrepresented groups in AI training datasets, the digital divide affecting older or socioeconomically disadvantaged patients, and the cultural acceptance of AI-driven interventions. By weaving together these perspectives, this review offers a holistic understanding of both

the opportunities and limitations of AI in advancing personalized rehabilitation therapy.

AI in patient diagnostics and clinical assessment

Personalized diagnosis and treatment have gained significant importance in recent years, thanks to the rapid development of AI. New technologies have allowed us to analyze vast amounts of data and synthesize knowledge from those sources. AI has infiltrated a variety of domains, from the automotive industry to advertisements to healthcare. For years, healthcare workers have been overworked (Duong, Vogel, 2023), which directly impacts the efficiency of this sector as a whole. Implementing AI into the healthcare workflow can ease the workload and improve the inner workings of the medical sector (Wierzbicki et al., 2024).

AI provides an opportunity to perform deeper and broader analysis of medical data than traditional clinical approaches, as it can simultaneously process information from multiple sources, such as imaging, biological signals, genomics, and electronic health records. Oftentimes, medical workers have to rely on limited results since it is time-consuming to deeply analyze all the information in the patients' documentation and extract patterns and correlations that accurately describe patients' state (Miotto et al., 2018; Esteva et al., 2019).

AI has outperformed human experts in detecting pathologies from medical images such as X-rays, MRI, and CT, with notable success in breast cancer and chest X-ray analysis (Khalifa, Albadawy, 2024; Huhulea et al., 2025). Radiomics enables extraction of high-dimensional features to uncover subtle patterns, supporting diagnosis, disease monitoring, and treatment evaluation. Beyond imaging, deep learning improves analysis of biological signals (e.g., arrhythmia in ECG (Hannun et al., 2019), epileptic seizures in EEG (Craik et al., 2019)) and sensor-based systems allow automatic classification of motor dysfunction, offering clinicians objective and reproducible measures for therapy planning (Attoh-Mensah et al., 2025). Increasingly, AI also predicts disease relapse, hospital readmission, and postoperative complications (Goldstein et al., 2017).

AI-driven personalization of rehabilitation strategies

The rehabilitation process is inherently complex, and multidisciplinary. Consequently, optimizing it remains a considerable challenge. One promising approach is to place the patient at the center of treatment and rehabilitation, as this strategy holds potential for improved outcomes through individually tailored interventions. Such personalization may range from setting therapeutic goals collaboratively with the patient, adapting practices to specific needs, and ultimately creating fully individualized therapy plans that account for personal limitations and preferences (Boltaboyeva et al., 2025).

Using specialist expertise, patient records, and diagnostic data processed by AI, personalized therapy plans can be delivered. In a study by Yun & Choi (2019), a randomized trial comparing conventional therapy with AI-augmented mobile rehabilitation for knee osteoarthritis showed significant improvements in quality of life and physical activity, though the lack of full blinding warrants cautious interpretation.

A critical component of any therapy plan concerns the setting of appropriate goals and the calibration of exercise difficulty. AI techniques can provide valuable assistance in this regard. For instance, Thiengwittayaporn et al. (2021) describe the development of a predictive model for movement difficulty. In this study, subjects were required to complete several practice rounds with feedback before the model could accurately predict the expected difficulty level.

When considering personalized therapy, it is also essential to address the role of large language models (LLMs). In a study by Mykhalko et al. (2025), the authors prompted ChatGPT-4o to generate rehabilitation plans for 50 clinical cases. After expert evaluation, the majority of the AI-generated plans were rated as clinically appropriate, safe, and suitable for use. Nevertheless, the authors noted that these plans still required refinement and should always undergo professional review before implementation.

Personalization can further extend to supporting patients through tailored interactions that reinforce desired behaviors (MohammadNamdar et al., 2025). Such strategies not only improve patient engagement but also reduce dropout rates. By facilitating adherence to rehabilitation programs, AI-driven approaches can enhance the overall effectiveness of therapy.

Decision-support systems and AI-powered rehabilitation tools assist in designing treatment plans, predicting outcomes, and tailoring therapeutic components to patient-specific characteristics (Alshami et al., 2025). As a result, outcomes are improved, patient satisfaction increases, and clinicians receive additional support in their work. All those factors contribute to the rehabilitation optimization, though further research and validation remain necessary.

AI in personalized therapy holds promise for improving patient adherence, providing more effective interventions, and alleviating the workload of healthcare professionals (Attoh-Mensah et al., 2025). Beyond plan generation, AI systems can support continuous monitoring and adaptive adjustment of therapy intensity. Nonetheless, widespread adoption requires shifts in clinical practice, sustained funding, and close collaboration among specialists. Furthermore, issues surrounding responsibility for therapeutic failures remain to be addressed.

AI in monitoring and enhancing therapeutic processes

Advances in therapeutic interventions allow assessment of how well therapy is tailored to patients and whether outcomes are achieved. AI-driven monitoring – implemented through platforms, wearables, sensors, or chatbot interfaces (Aziz et al., 2024) – automates data collection, enables real-time analysis, and issues alerts when progress stalls, extending telerehabilitation and making home-based care more effective.

An illustrative example of sensor integration in rehabilitation is the use of physiographs designed for gait assessment and monitoring in Parkinson's disease (Jiao, 2025). Based on the acquired data, the proposed system supports clinicians through decision support mechanisms. However, its evaluation was limited to only 10 participants. Similarly, Sumner et al. (2023) described an IoT-based smart sensing system for gait monitoring. Despite promising results obtained from 14 volunteers, the study highlighted the necessity of addressing sensor limitations in future work. Issues related to small sample sizes were also emphasized in a study by Ileşan et al. (2022), where an AI-driven system was developed for upper-limb rehabilitation. Although the findings were encouraging, the limited cohort prevents clinical deployment without further

large-scale validation. Notably, the authors also addressed another critical concern in such systems – ensuring the security of transmitted data.

Data privacy and security are among the most pressing challenges for AI-enhanced rehabilitation systems (Laganà et al., 2025). Wearables, monitoring platforms, and feedback systems process and transmit highly sensitive information that must be adequately protected. Without clear regulations and robust safeguards, user trust in these technologies will remain limited.

AI-powered sensing technologies offer the capability to detect subtle abnormalities and provide rapid responses to support patients. Nevertheless, as illustrated in a study by Monge et al. (2023), AI-driven feedback must be understandable, reliable, accurate, quantitative, and context-specific in order to be clinically useful. Without such qualities, the benefits of personalization may be lost, and patient adherence to therapy compromised.

Beyond the complexity of feedback mechanisms, it is also important to recognize the inherent limitations of current sensor technologies. Not all therapeutic elements can be accurately measured – for instance, the correctness of exercise execution remains difficult to capture and evaluate reliably (Abery et al., 2025). Inaccurately gathered data may, in turn, lead to poorly trained models and potential errors in therapeutic recommendations.

Biofeedback and telemedicine systems rely heavily on multidisciplinary collaboration. Effective solutions require close cooperation between AI researchers and medical professionals to ensure a comprehensive understanding of therapeutic principles, signal interpretation, and patient needs. While wearables and sensors can substantially enhance rehabilitation systems, they may also introduce practical challenges, such as discomfort from prolonged use or the need for frequent updates (Mawson et al., 2016). Furthermore, isolated sensor data may not fully reflect the patient's overall condition. Hence, preserving the broader clinical and personal context is essential for AI-enhanced rehabilitation to be effective.

AI-enabled virtual and robotic rehabilitation

Virtual reality (VR) is a technology that enables the creation of computer-generated 3D environments in which the user can immerse themselves and interact using specialized devices, such as VR headsets or haptic gloves. In

contrast, augmented reality (AR) overlays digital elements onto the real world, enhancing the user's perception with additional visual, auditory, or tactile information. As noted in a study by Alshami et al. (2025), both technologies, when combined with AI, open new perspectives in rehabilitation, allowing for the creation of personalized therapeutic environments and the adaptation of treatment programs to individual patient needs. AI analyzes patient data, such as movement patterns, biomechanics, and physiological responses, enabling progress prediction and real-time optimization of therapy plans.

Rehabilitation robotics using machine learning (ML) algorithms allows precise adjustment of resistance, range of motion, and training intensity according to the patient's capabilities and limitations. AI-assisted exoskeletons are particularly useful in gait and lower limb rehabilitation, providing not only mechanical support but also intelligent adaptation to the patient's evolving clinical condition (Abery et al., 2025). Publication by Zhu et al. (2023) emphasizes that robot-assisted therapies improve functional outcomes, although evidence regarding long-term efficacy for lower limbs remains limited. Simultaneously, issues such as implementation costs and the lack of standardized protocols hinder broader adoption.

VR/AR in rehabilitation, supported by AI, allow the simulation of realistic therapeutic environments, increasing patient immersion and motivation. Applications include post-stroke rehabilitation, balance disorder therapy, and neurological rehabilitation. Systematic reviews (Mizna et al., 2025) indicate that VR can improve motor therapy outcomes; however, effectiveness depends on the quality of intervention personalization and the method of patient monitoring in home settings. AI-based therapeutic games (Cardone et al., 2025) are also important, adjusting difficulty levels according to the patient's current abilities, thereby supporting neuroplasticity and increasing engagement.

Despite growing evidence on the therapeutic value of VR, AR, and AI-assisted robotics in rehabilitation, their clinical adoption remains limited by high acquisition and maintenance costs and the continuous training required for staff (Devittori et al., 2024). The lack of standardized protocols and multicenter trials with sufficiently powered cohorts further constrains generalizability, as most findings stem from small, context-specific studies. Ethical and regulatory issues concerning data privacy and cybersecurity risks raise additional concerns, potentially undermining trust among patients and clinicians (Mizna

et al., 2025). Effective integration also depends on infrastructure investment and systematic personnel upskilling, as deficits in preparedness often relegate these technologies to experimental rather than routine use (Devittori et al., 2024). Finally, psychological and sociocultural barriers, including variable patient acceptance, risk of cybersickness, and lower digital literacy among older populations, limit equitable access and sustained engagement.

Predictive AI models for forecasting recovery trajectories

One of the most critical aspects of personalized treatment and rehabilitation is that one can tailor the program for the needs of the patient, but more importantly, one can assess progress on a case-by-case basis, providing a prognosis of the patient's state. The ability to predict how a patient's condition will evolve and how a patient will respond to the therapy over time proves to be the focal point of patient-centered healthcare. Personalized rehabilitation can be further enhanced by additional input from the AI model, which would predict the trajectory of recovery. The team in China conducted a study to predict recovery time in a cohort of over 13,000 patients (Xu et al., 2022). The authors utilized five ML methods, and in 7-day and 14-day recovery time predictions, the authors achieved over 90% accuracy. Similarly, AI proved to be significantly effective in cognitive rehabilitation therapy (Khalid et al., 2024). A variety of applications have been created and tested to elevate patients' mental state in the battle with dementia, neurological or developmental disorders, or neurodegenerative diseases, among many. For example, using an AI-driven application, users tend to become engaged in cognitive tasks.

Another important aspect of safe and effective rehabilitation is appropriate adjustment of intensity. Medical practitioners assess patients' performance at discrete intervals, often weeks apart. Such an approach is inherently at risk of missing crucial datapoints and fluctuations in performance. Real-time continuous monitoring prevents loss of information and provides a full picture of patients' conditions throughout the time period, while at the same time enhancing patients' safety (Khalid et al., 2024). The idea of continuous real-time monitoring is a beneficial practice in treating diabetes (Beck et al., 2017), where continuous glucose monitoring (CGM) has transformed disease management.

In rehabilitation, wearable sensors – much like glucose monitors in diabetes – provide instant access to patient data. Combined with robotic exoskeletons, they can adjust exercise resistance and, through continuous monitoring, detect abnormal vitals, movement, or pathologies (Attoh-Mensah et al., 2025). AI further integrates multimodal data to reveal hidden patterns and recovery bottlenecks, helping identify factors that delay progress.

In the case of post-COVID-19 rehabilitation, Xu et al. (2022) concluded that older age, comorbidities (such as diabetes and hypertension), and higher viral loads were associated with longer recovery durations. Campagnini et al. (2022) conducted a study on 278 post-stroke patients with the goal of developing ML models that predict the functional prognosis. While the models' outcomes are not clear-cut, the authors have managed to identify the most important factors in rehabilitation efficacy: trunk control, bedsores, and communication levels. Beyond clinical factors, Khalid et al. (2024) indicate that personal and behavioral factors also play a role in the recovery process. Missed therapy sessions, insufficient home exercise, or inadequate sleep can significantly delay recovery. Patients who stuck with the schedule and were engaged in rehabilitation obtained better results than those who weren't adhering to the rehabilitation program.

Psychological variables impact the rehabilitation process in a significant way (Mascanzoni et al., 2024). Self-esteem and emotional regulation were identified as leading factors that increase the quality of rehabilitation. Conversely, depression and anxiety were highlighted as leading negative factors hindering rehabilitation. These findings underline the importance of psychological support during the rehabilitation process and point towards a holistic approach in personalized rehabilitation, especially the incorporation of psychological care with the goal of improving overall well-being.

Rehabilitation can be a lengthy process, taking weeks, months, or even years, with the goal of improving comfort of life, maximizing functional abilities, or mitigating the effects of illnesses, injuries, or disabilities. Creating a well-adjusted long-term plan for each individual case is a key factor for long-term success. Clinicians need tools to perform a forecast of patients' performance and adjust the rehabilitation program accordingly.

Digital twin is a concept involving the creation of a data-rich replica of a patient, used for simulating and testing various rehabilitation strategies to

predict the patient's likely response and identify the most promising approach (Bruynseels et al., 2018). This tool enables long-term simulation of rehabilitation programs, the evaluation of multiple treatment variants, and ensures patient safety by operating entirely on multimodal patient data.

Another approach that utilizes AI to increase the effectiveness of long-term rehabilitation is survival analysis, which serves as a tool for explaining and understanding the relationship between patients' covariates and efficacy of the rehabilitation (Katzman et al., 2018). The authors introduce DeepSurv – “a Cox proportional hazards deep neural network and state-of-the-art survival method for modeling interactions between a patient's covariates and treatment effectiveness in order to provide personalized treatment recommendations”. The obtained results prove the model's ability to capture complex relationships and its long-term modeling capabilities. Among a number of experiments authors managed to obtain results comparable with state-of-the-art solutions or outperform them, which directly translates to better care for patients and prolonging their lives.

AI support for physicians and therapists

Shifting the perspective towards physical therapy specialists, it becomes evident that many are both aware of and expectant of the increasing role of AI in their professional practice (Aldhahi et al., 2025). They anticipate that AI will ease their workload, assist in task optimization, and a considerable proportion (47.9%) express enthusiasm for integrating AI into physical therapy. Nevertheless, despite this generally optimistic outlook, researchers highlight a notable gap in education: physical therapy professionals often lack adequate training in AI, including its potential applications and limitations. This knowledge gap is reflected in their limited trust towards AI-based solutions.

Building trust in AI is a complex and multifaceted challenge. As outlined in a study by Alonso et al. (2025), trust is influenced by several factors, such as:

- the function of AI (e.g. therapy plan recommendations, therapy monitoring);
- the accuracy, reliability, and robustness of outputs;
- the type of pathology under consideration;
- the treatment modality and its degree of explainability;

- the attitudes and predispositions of healthcare professionals;
- the way in which AI outputs are presented;
- the clinical context in which AI is applied.

Developing a comprehensive framework that addresses these factors would significantly increase healthcare professionals' readiness to adopt AI and thereby unlock its full potential in rehabilitation practice. This aligns with patient perspectives reported in a study by Foresman et al. (2025), where respondents underline that final treatment decisions should remain in human hands, given AI's current limitations in transparency and explainability. Patients also underscored the need for personalization in rehabilitation, noting the difficulty of applying a common model to individuals with highly specific needs. While AI can serve as a valuable support tool in rehabilitation, it should not be deployed without human oversight.

To effectively integrate medical specialists into AI workflows, it is important to educate them. Such efforts should begin at the curricular level, but also extend to collaborative testing of AI solutions with practitioners (Ayorinde et al., 2024). Involving clinicians in system development allows them to articulate desired functionalities and emulate professional expertise, while simultaneously gaining exposure to AI technologies. This co-development process helps with mutual learning and better alignment between technical design and clinical requirements. Lee et al. (2020) presented an AI system for stroke rehabilitation assessment developed in collaboration with therapists. During the design phase, clinicians initially struggled to interpret the technical terminology used to describe model features. This required AI specialists to adjust and rename the features to enhance clarity. It shows that even such small elements of the design process are being impacted, when working with end users, therefore it is worth including them from the very beginning of the process. After completing the system and testing it, therapists evaluated the decision support system as more useful, informative, and less effortful compared to traditional methods. However, the study's limitations included a small sample size and a relatively narrow focus on supporting a single decision-making task.

Beyond decision support, AI in rehabilitation holds promise for streamlining administrative processes, such as the creation and maintenance of medical records. By accelerating documentation, AI may help alleviate

time pressures and reduce dissatisfaction among professionals, leading to both improved record quality and better work-life balance (Omon et al., 2025). Reducing the administrative burden is often cited as one of the key advantages of implementing AI in healthcare. This, in turn, has significant economic implications, enhancing cost-effectiveness through more efficient resource allocation and supporting personalized rehabilitation. Nevertheless, despite long-term cost-saving potential (Cano-de-la-Cuerda et al., 2024), the initial financial investment required for AI in rehabilitation is substantial. It entails expensive hardware, ongoing system development, maintenance, and interdisciplinary collaboration. Moreover, these high entry costs may exacerbate inequalities in access, particularly across underfunded regions or minority populations, thereby risking the reinforcement of existing healthcare disparities.

Discussion

The analysis of current literature reveals that, despite substantial advances in the use of AI in personalized rehabilitation, a number of recurring and section-specific limitations constrain its practical implementation. To illustrate these overlaps and divergences, Figure 1 presents a circular diagram where identical colors mark limitations that are shared across multiple thematic domains, while unique issues are highlighted in distinct shades.

As indicated in light blue, data-related issues – such as quality, heterogeneity, and sensor accuracy – are consistently reported in diagnostics, personalization, and monitoring processes. Similarly, green nodes highlight recurring concerns regarding data privacy and ethical accountability, a theme particularly pronounced in diagnostics, personalization, monitoring, and robotic rehabilitation. Methodological limitations, including insufficient validation and interpretability of AI models, are clustered in light pink, illustrating a common research gap across personalization, monitoring, and predictive modeling.

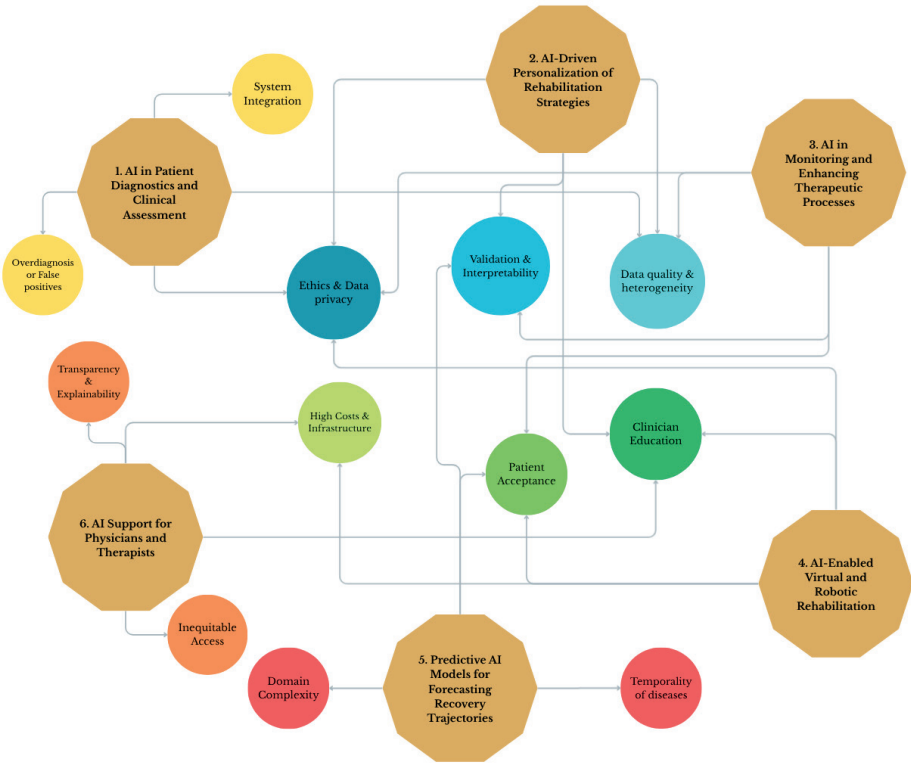


Figure 1. Shared and section-specific limitations of AI applications in personalized rehabilitation, grouped by thematic categories

Source: authors' own work.

Barriers linked to professional readiness, coded in lime, underscore the necessity of clinician training and engagement in multiple domains, whereas orange nodes emphasize the financial and infrastructural burdens that affect primarily robotic rehabilitation and clinical AI support. Finally, violet nodes represent patient-related challenges, including acceptance, adherence, and comfort, which are crucial for the successful integration of AI-driven solutions in real-world settings.

By contrast, several barriers remain domain-specific, highlighted in distinct colors such as red (overdiagnosis, false positives, and system integration in diagnostics), cyan (temporality of diseases and biomedical domain complexity in predictive models), and gold (transparency, explainability, and inequitable

access in AI support). These constraints reflect the unique methodological and contextual challenges faced by each subfield.

Overall, the diagram underscores that while some limitations are ubiquitous across domains – particularly those concerning data quality, ethics, and clinician training – others are tightly bound to specific applications. Among the critical challenges that hinder clinical deployment are:

- 1) lack of standardized, well-maintained datasets,
- 2) limited explainability and interpretability of the models and AI solutions,
- 3) limited validation from healthcare practitioners.

This dual perspective highlights the need for both system-wide strategies to address recurring barriers and domain-specific solutions to overcome unique challenges, thereby paving the way for more effective integration of AI into personalized rehabilitation therapy.

Furthermore, literature review highlighted important aspect of AI within personalized rehabilitation – lack of holistic end-to-end study that assess AI-supported diagnostic process, adaptive personalization of rehabilitation programs and long-term monitoring within a unified rehabilitation pipeline. Oftentimes, evaluation of AI solutions is conducted in the vacuum, without consideration of the process as a whole and external factors. Such approach limits assessment of real clinical utility and understanding of environmental and systematic needs for AI.

Conclusions

AI holds considerable promise for advancing personalized rehabilitation, given rise to patient-centric approaches. However, current analysis indicates that successful implementation of AI-driven solutions is dependent on overcoming limited availability of high-quality datasets, lack of explainability and interpretability of models as well as insubstantial involvement of the medical workforce in the process. All those factors are amplified by financial, methodological, ethical, and accessibility barriers which hinders widespread clinical adoption. Progress in these areas will likely require standardized evaluation protocols, explainable AI frameworks, and closer integration of clinician expertise into model design and validation workflows. In addition,

targeted training for healthcare professionals and interoperable technical infrastructure are necessary to support safe and effective deployment. Addressing these limitations is essential for translating technological potential into sustainable improvements in patient care.

Future works

The present discussion is based on a qualitative literature analysis focused on identifying the principal thematic areas, opportunities, and limitations of AI applications in personalized rehabilitation. The conclusions therefore reflect a structured synthesis of reported findings rather than a quantitative analysis of performance metrics or outcome measures. Future study could focus on a quantitatively oriented approach, including extraction and comparison of reported numerical indicators. This would allow a more evidence-based assessment of both the practical potential and the measurable limitations of AI-driven rehabilitation methods.

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