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Artificial Intelligence and the Future of Stroke Rehabilitation in Nigeria: Opportunities for Personalized Physical Therapy, Clinical Decision Support, Digital Patient Monitoring, Health Data Utilization, and Improved Continuity of Rehabilitation Care

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Abstract

Background. Stroke is a leading cause of long-term disability, and rehabilitation led by physical therapy is central to recovery. In Nigeria, rehabilitation is limited by few specialized services, uneven geographical distribution of health workers and facilities, and weak follow-up and data systems. These problems affect how progress is assessed, monitored and continued after hospital discharge, and they raise the question of whether artificial intelligence (AI) could help.
Objective. To review how AI might support physical therapy and stroke rehabilitation in Nigeria, and to examine the opportunities, limitations, ethical considerations and implementation challenges.
Review approach. This is a narrative literature review of existing academic and institutional evidence. It is not a systematic review and involved no original data collection or AI development. International, other African and Nigerian evidence is distinguished throughout.
Main findings. International reviews describe AI applications in movement and gait assessment, outcome prediction, exercise monitoring and remote rehabilitation, with promising but uneven evidence. A mapping review found that external validation and explainability were rarely reported (Morone et al., 2025). No Nigerian evaluation of AI-assisted stroke rehabilitation was identified among the literature reviewed. Nigerian evidence relates mainly to rehabilitation access, feasibility of low-technology telerehabilitation and the state of stroke services and data. Barriers include unreliable power and connectivity, cost, workforce training, data quality, privacy and the under-representation of African populations in AI development.
Conclusion. AI has potential to support more personalized assessment, monitoring, decision support, use of rehabilitation data and continuity of care. It should augment, not replace, physical therapists. Realistic progress in Nigeria depends on local evidence, infrastructure, training, data quality, privacy protection, affordability, equity and human clinical oversight.

Keywords: artificial intelligence; stroke rehabilitation; physical therapy; clinical decision support; digital monitoring; telerehabilitation; rehabilitation data; digital health; Nigeria

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1. Introduction

Stroke is a leading cause of long-term disability worldwide (Senadheera et al., 2024). Most of the global burden is in low- and middle-income countries, where about 86% of stroke deaths and 89% of stroke-related disability-adjusted life years occur (Feigin et al., 2022). In Africa, stroke incidence has been reported to be up to two to three times higher than in western Europe and the United States (Akinyemi et al., 2021). In Nigeria, hospital-based studies have reported 30-day case fatality of 21.2% to 40% (Arabambi et al., 2022). For survivors, recovery depends heavily on rehabilitation, and physical therapy is a core part of it.

The author's earlier article on the role of physical therapy in stroke rehabilitation focused on mobility, independence, quality of life and the challenges that limit access to rehabilitation in Nigeria. Thinking about those challenges raised further questions about how therapy can be monitored and continued: how can a therapist know how a patient is progressing between visits, how can that progress be recorded in a form that others can use, and how can care continue after discharge? These are questions about assessment, monitoring and continuity of care, and they suggest a possible supporting role for data-driven and digital technologies, including artificial intelligence (AI), within therapist-led stroke rehabilitation.

AI should be approached critically. A mapping review of 240 clinical studies of AI in rehabilitation found that the evidence rests largely on small, single-type datasets, that over half of the studies had no comparator, and that few reported external validation or explainability (Morone et al., 2025). A review of AI in physical rehabilitation concluded that the field is growing but that its clinical effects had not yet been established (Sumner et al., 2023). Claims about AI are therefore easy to overstate, and claims about Nigeria even more so, because the Nigerian evidence identified is limited.

The central question of this review is: how might AI support physical therapy and stroke rehabilitation in Nigeria, and what opportunities, limitations, ethical considerations and implementation challenges should be considered? Section 2 describes the review approach. Section 3 outlines stroke rehabilitation in Nigeria. Sections 4 to 10 examine AI concepts and applications. Sections 11 to 15 address Nigeria-specific opportunities, barriers, ethics, the role of the physical therapist and recommendations, and the final sections discuss limitations and conclusions.

2. Review Methodology

2.1 Stroke and Its Impact on Physical Function

This is a narrative literature review based on existing academic and institutional evidence. It is not a systematic review, followed no registered protocol and carried out no formal quality appraisal. The author did not collect patient data, recruit participants, conduct interviews or experiments, develop or test an AI system, or run a clinical trial.

Sources were identified through targeted searches in 2026 of the open web and of indexed scholarly repositories, including PubMed Central, publisher platforms, institutional repositories, and WHO and Nigerian government websites. Search terms combined “stroke”, “rehabilitation”, “physical therapy”, “Nigeria” and “Africa” with terms such as “artificial intelligence”, “machine learning”, “wearable sensors”, “telerehabilitation”, “clinical decision support”, “algorithmic bias” and “data protection”.

Priority was given to systematic reviews, meta-analyses, peer-reviewed studies, WHO publications and Nigerian sources, and to publications from 2020 onwards. Older sources were kept where they were the only Nigerian evidence on a topic. Only sources whose bibliographic details could be confirmed were used. Evidence is labeled as Nigerian, other African or international, because most AI evidence in rehabilitation comes from outside Africa. In total, 31 sources are cited.

3. Stroke Rehabilitation and the Role of Physical Therapy in Nigeria

Stroke rehabilitation is a multidisciplinary process that helps survivors regain function, relearn skills and adapt to lasting limitations. It can begin in the acute phase and continue for months or years, and it includes physical, occupational, cognitive and language therapies (Senadheera et al., 2024). Physical therapy addresses mobility and gait, balance and coordination, strength, and the physical basis of activities of daily living, which together support independence and participation. Functional measures such as the modified Rankin Scale and the modified Barthel Index have been used to describe functional outcomes in a Nigerian stroke study (Odetunde et al., 2020).

Continuity matters because gains can be lost. Improvements made during inpatient rehabilitation may be followed by decline within six months of discharge, which is why continued outpatient or home-based therapy is needed (Odetunde et al., 2020). A review of AI in stroke rehabilitation noted that outcomes of outpatient rehabilitation may be weaker than inpatient outcomes, possibly because therapists supervise less in free-living conditions (Senadheera et al., 2024). This is the gap that monitoring technologies are meant to address.

Several features of the Nigerian context affect this continuity. A nationwide survey found that only 5 of 58 tertiary hospitals had a dedicated stroke unit; all five had physiotherapists, the usual discharge destination was the neurology clinic, and only three kept a local stroke registry (Arabambi et al., 2022). Access to specialized rehabilitation is also shaped by how facilities and health workers are distributed. A qualitative study in Ebonyi State found that tertiary facilities were skewed towards urban areas and that physicians and nurses were unevenly distributed to rural areas (Nwankwo et al., 2022). Together with the small number of dedicated stroke units, this suggests that availability of specialized rehabilitation services remains a challenge, although the sources reviewed did not allow a current national estimate of the physiotherapy workforce.

Access can also depend on where therapy is delivered. A randomized trial in Ibadan involving 52 people recently discharged after stroke compared physiotherapy at a primary health center with physiotherapy at the patient’s home. Both groups improved, and the authors concluded that either setting could widen access in a low-income community (Olaleye et al., 2014). Cost is a further concern: one commentary reported that

more than 74% of Nigerians pay for care out of pocket (Ravi et al., 2024). Sources specific to transport costs in stroke rehabilitation were limited, and no national source on the routine collection of rehabilitation outcome data was identified among the literature reviewed. Taken together, these limits mean that assessment, follow-up and data on rehabilitation are inconsistent, which is the problem AI-supported tools might address, if they can work in this setting.

4. Artificial Intelligence in Rehabilitation: Concepts and Emerging Applications

AI refers to computer systems that perform tasks normally associated with human intelligence, such as recognizing patterns or making predictions. Machine learning is a branch of AI in which algorithms learn patterns from data and can be supervised (trained on labeled examples) or unsupervised (finding structure without labels). Deep learning uses layered neural networks and can learn features directly from complex data such as sensor signals or video (Senadheera et al., 2024). Computer vision applies these methods to images and video, for example to track body joints without markers. Predictive analytics uses data to estimate future outcomes, and a clinical decision-support system (CDSS) presents such information to clinicians to inform, not make, decisions.

In stroke rehabilitation, a scoping review of 704 studies identified four themes: impairment, assisted intervention, prediction and imaging, and neuroscience. Within the impairment theme, motor function, gait and mobility received the most attention, and the number of publications rose markedly after 2016 (Senadheera et al., 2024). A mapping review of 240 AI studies in rehabilitation found that most concerned neurological conditions, including stroke, and that research activity was concentrated in China (24.6%) and the United States (16.7%) (Morone et al., 2025). These figures show that the evidence base is international and mostly generated outside Africa.

Evidence quality is uneven. In the mapping review, 50.8% of studies lacked a comparator, external validation was reported in 5.8% and explainability in 10.2%, and the authors concluded that evidence rests on small, single-type datasets (Morone et al., 2025). A systematic review of AI in physical rehabilitation reached a similar overall conclusion (Sumner et al., 2023). Table 1 summarizes the main applications discussed in this review, with their possible physical therapy uses and key limitations.

Table 1. Potential AI applications in stroke rehabilitation

AI application	Possible physical therapy use	Potential benefit	Key limitation
Wearable-sensor movement and gait analysis	Objective gait and limb-movement measures between visits	More continuous, objective data (Senadheera et al., 2024)	Mostly international studies; external validation rare (Morone et al., 2025)
Computer-vision assessment	Markerless review of movement quality from video	Remote observation using cameras (Senadheera et al., 2024)	Needs devices and connectivity; no Nigerian validation identified
Outcome and service prediction	Estimating likely function or service needs	Support for goal setting and discharge planning (Senadheera et al., 2024)	Depends on data quality; limited external validation (Morone et al., 2025)
Exercise recognition and adherence monitoring	Detecting whether prescribed exercises were done	Visibility after discharge (Senadheera et al., 2024)	Early-stage evidence; privacy and power needs
ML- or robot-assisted training	Supplementary training supervised by a therapist	Improved upper limb function in a meta-analysis, with a small pooled effect (Mahmoud et al., 2023)	Small trials; equipment cost
AI-based decision support	Flagging patients who need review or follow-up	Common view of the patient for the team	Validity threats (Akay et al., 2023); explainability limited

5. AI-Assisted Stroke Rehabilitation Assessment

Physical therapists assess movement through observation, standardized tests and measurements, which are valuable but depend on the time available and on the observer. AI-assisted assessment aims to add objective and more continuous information. In the scoping review of stroke rehabilitation, functional impairment and capacity was the largest impairment topic (16% of studies) and gait and mobility the next (12%, 83 studies) (Senadheera et al., 2024).

For gait, wearable sensors such as inertial measurement units, accelerometers and pressure sensors were combined with machine learning to detect gait abnormalities and phases and to monitor mobility (Senadheera et al., 2024). For upper limb function, sensors and depth-sensing cameras were used in some studies to approximate clinical scores such as the Fugl-Meyer Assessment, and computer vision studies (3% of included studies) used video to monitor movement without markers (Senadheera et al., 2024). The same review described studies on balance control and postural behavior. The review also reported that some systems showed high agreement with therapist evaluations. This is notable because it treats the therapist's judgment as the reference standard that the AI is measured against.

These findings do not show that AI can replace clinical assessment. Many studies are small, and the mapping review found limited external validation (Morone et al., 2025). A systematic review of AI in future rehabilitation services likewise called for validation in specific clinical populations and for evidence on reliability in remote and home-based conditions (Mennella et al., 2023). AI-based assessment should complement professional clinical assessment, with the therapist interpreting results in context. No Nigerian study of AI-assisted stroke assessment was identified among the literature reviewed.

6. AI and Personalized Physical Therapy

Rehabilitation is individual: people with similar strokes recover differently. Data-driven methods are being explored to describe patient-specific patterns, predict outcomes, monitor progress and adjust programs. A narrative review of AI in personalized rehabilitation described uses such as developing personalized treatment plans, supporting ongoing patient management and adapting sessions in real time (Attoh-Mensah et al., 2025). As a narrative mini-review, it is a summary of applications rather than proof of effect.

Prediction is a major strand. In the scoping review, outcome prediction accounted for 7% of studies and service prediction for 6%. Examples included neural networks predicting discharge Functional Independence Measure scores and machine learning models predicting Barthel Index scores, which could inform discharge planning. Some studies applied explainable methods to help clinicians see which factors drove a prediction (Senadheera et al., 2024). Such tools could support goal setting by giving the therapist an additional, data-based estimate to discuss with the patient.

Evidence on AI-assisted treatment is more limited. A meta-analysis of ten studies with 481 stroke patients concluded that AI and machine learning interventions were feasible and safe and improved upper limb function compared with conventional therapy, although the pooled effect was small (standardized mean difference 0.10) (Mahmoud et al., 2023). The sample is small and the interventions are varied, and the meta-analysis does not indicate how such tools would perform in Nigerian settings, so the result is encouraging rather than conclusive. Nothing in the reviewed evidence shows that AI can independently prescribe rehabilitation. In the scoping review, skilled therapists remained involved in both automated and conventional approaches (Senadheera et al., 2024). Clinical judgment therefore remains essential.

7. AI-Based Clinical Decision Support

A CDSS can combine patient information, such as imaging, functional scores and risk factors, and present patterns or predictions to the clinical team. For stroke rehabilitation, possible uses include interpreting patient information, identifying risk patterns, supporting rehabilitation planning, predicting outcomes and flagging patients who may need additional follow-up. Service-prediction studies, which forecast the type, intensity and duration of rehabilitation a person may need, point towards the planning use (Senadheera et al., 2024).

The five Nigerian stroke units surveyed all had physiotherapists and multidisciplinary teams (Arabambi et al., 2022). A CDSS could in principle help such teams to share a common view of the patient. However, a systematic review of AI-based decision support in acute ischemic stroke found important threats to validity, inconsistent reporting and obstacles to clinical translation (Akay et al., 2023). That review concerned acute care, not rehabilitation, but its cautions apply. One commentary on digital health in Nigeria argued that AI-assisted diagnosis should keep a registered clinician in the loop (Ravi et al., 2024).

AI should therefore be presented as a decision-support tool. It can offer a second source of information, but responsibility for decisions stays with the clinicians who know the patient. For physical therapists, the useful questions are what the tool was trained on, how it was validated, and whether its output can be explained. Explainability is often limited: many AI rehabilitation tools have been criticized for their “black box” nature (Senadheera et al., 2024).

8. AI, Wearable Technologies and Digital Patient Monitoring

Monitoring technologies include wearable sensors, accelerometers, smartphones, motion sensors, cameras and smart rehabilitation devices. AI is used to turn raw signals into meaningful information, such as recognizing which exercise a person is doing, estimating gait characteristics or tracking activity levels. The scoping review described human activity recognition for continuous monitoring of ambulatory function, wearable devices for upper limb use, and smartphone-based systems explored for independent remote rehabilitation, with possible benefits for cost and compliance. It also summarized a trial in which smartwatch data from 22 stroke survivors were analyzed with a neural network that detected four selected exercises with high accuracy (Senadheera et al., 2024). This is a small international study.

The relevance to continuity is direct. When exercises are not monitored outside the clinic, survivors may not be doing them as prescribed (Senadheera et al., 2024). Remote monitoring could show a therapist how much and how well a patient has exercised, and whether function is changing, after discharge. The same systematic review of AI in rehabilitation services identified unobtrusive motion-capture technologies as strategic for remote monitoring, but again stressed the need for validation in specific clinical populations and in home-based conditions (Mennella et al., 2023).

No Nigerian study of AI-supported wearable monitoring for stroke was identified among the literature reviewed. The available evidence on the setting suggests caution. Mobile subscriptions have been reported at 91 per 100 people, but most rural communities were described as having no mobile internet or only 2G speeds (Ravi et al., 2024), and unreliable power and poor connectivity were identified as barriers to electronic health record implementation (Babatope et al., 2024). Tools that need constant charging or data access may be difficult to sustain. Simpler approaches, such as storing data on the device and uploading when a connection is available, would need testing in Nigerian settings before any claim is made.

9. AI and Telerehabilitation

Telerehabilitation delivers rehabilitation at a distance, and AI could add automated movement recognition, feedback, adherence tracking, progress summaries and alerts about concerning changes, while the therapist communicates with the patient. It is important to separate what is established from what is emerging.

Established (international evidence). A Cochrane review of 22 trials with 1,937 participants found no significant differences between telerehabilitation and in-person therapy on the outcomes compared, suggesting that telerehabilitation is not inferior, although more research was needed (Laver et al., 2020). That review concerned telerehabilitation in general, not AI. The AI layer remains newer: the scoping review placed personalized rehabilitation and telerehabilitation in the most recent period of research (2019 to 2024) and noted that the COVID-19 pandemic highlighted the need for telehealth (Senadheera et al., 2024).

Nigerian and African evidence. The Nigerian studies identified concern feasibility and attitudes, not AI. A survey of 331 Nigerian physiotherapists found moderate acceptance but low adoption of telerehabilitation, and recommended training and an enabling technological environment (Odetunde et al., 2024). Earlier research examined perceived challenges to tele-physiotherapy in Nigeria (Odole et al., 2015). Among 200 physiotherapy students, awareness was moderate and expectations were high (Mbada et al., 2021). In a feasibility study in Ile-Ife, ten people with chronic stroke used a video home exercise program with instructions in Yoruba; half needed a caregiver to operate the equipment, and the authors stressed that such a program would not replace in-person contact (Odetunde et al., 2020). In Ghana, a pilot study examined the feasibility and user satisfaction of tele-rehabilitation after stroke (Sarfo et al., 2018).

Emerging possibilities. Automated exercise recognition, feedback and alerts are plausible additions to low-technology programs like the Yoruba video model, but no evaluation of them in Nigerian stroke rehabilitation was identified among the literature reviewed. No evidence that AI-enabled telerehabilitation is widely implemented in Nigeria was identified among the literature reviewed.

10. Health Data, AI and Stroke Rehabilitation Research

AI systems are only as reliable as the data used to develop and test them. For stroke rehabilitation, useful data include electronic rehabilitation records, stroke registries, patient demographics, clinical information, treatment details, functional outcomes over time, and standardized measures. Quality problems such as missing entries, inconsistent definitions and non-standard terminology reduce reliability. A mapping review of AI in rehabilitation pointed to small, single-type datasets as a continuing limit (Morone et al., 2025).

Nigerian data sources exist but are limited. The stroke unit survey found that only three of five units kept a local registry (Arabambi et al., 2022). A study of electronic medical record adoption described how clinicians in developing countries often depend on patients keeping their own records, with no centralized database (Akwaowo et al., 2022). One commentary noted that no national authority endorsed health informatics standards and that training AI requires large datasets recorded with standard terminology (Ravi et al., 2024). The Stroke Investigative Research and Educational Network (SIREN) shows what coordinated data collection can achieve: it was a multicenter case-control study at 15 sites in Nigeria and Ghana that enrolled 2,118 pairs with standard instruments (Owolabi & SIREN Team, 2018). It focused on risk factors, not rehabilitation, so comparable rehabilitation datasets are still needed.

Data quality is therefore a practical concern for therapist-led rehabilitation. Collecting rehabilitation data in consistent, secure and interoperable forms, such as a minimum dataset of functional scores and therapy

details, is a data-management task as well as a clinical one. Such data could support research, the

identification of rehabilitation trends, outcome prediction and the evaluation of programs. It could also support planning: service prediction studies already aim to forecast service needs (Senadheera et al., 2024), and mapping where trained staff and facilities are located could help to identify underserved populations, given the urban concentration of facilities reported in one southern Nigerian state (Nwankwo et al., 2022). These are possibilities that depend on data that do not yet exist at scale in Nigeria.

11. Opportunities for AI-Supported Stroke Rehabilitation in Nigeria

Several conditions favor cautious, staged exploration. First, mobile phone subscription levels are high, at 91 per 100 people as reported (Ravi et al., 2024), which makes smartphone-based approaches an obvious starting point. The Yoruba video exercise program shows that low-cost tools in a local language can be feasible (Odetunde et al., 2020). Second, a nurse-guided, phone-based follow-up program for blood pressure control in Ghanaian stroke survivors was found feasible in a pilot trial (Sarfo et al., 2019) and is being evaluated in ten hospitals (Amuasi et al., 2024). It is not AI and not rehabilitation specific, but it offers a model of remote follow-up to which analytics could later be added.

Third, stroke units and research networks provide a base for data work (Arabambi et al., 2022; Owolabi & SIREN Team, 2018). Fourth, there is policy attention: the Minister of State for Health reported that a National Digital Health Architecture, a health information exchange, shared health records and national registries are being developed (Federal Ministry of Information and National Orientation, 2025), and WHO has a global strategy on digital health (World Health Organization, 2021b). These are announced plans, and no independent evaluation of their implementation was identified among the literature reviewed. Fifth, acceptance among physiotherapists is moderate (Odetunde et al., 2024), and community-based or home-based therapy has been shown to be possible (Olaleye et al., 2014), so AI-assisted remote supervision could support these models. Table 2 summarizes these opportunities and the Nigerian considerations attached to each.

International tools should not be assumed to work in Nigeria. Sensor-based and camera-based systems were developed and tested elsewhere, and they may behave differently with different devices, lighting, home environments, languages, body types and patterns of stroke. Local validation and adaptation are essential before routine use.

Table 2. Opportunities and implementation considerations for Nigeria

Opportunity	Potential application	Nigerian consideration
High mobile phone subscription levels	Smartphone video guidance and phone-based follow-up	Rural 2G or no internet; language and caregiver support (Ravi et al., 2024; Odetunde et al., 2020)
Existing stroke units and registries	Structured rehabilitation data for later analysis	Only 5 of 58 tertiary hospitals had units; 3 kept registries (Arabambi et al., 2022)
Research networks	Multicenter datasets, as in SIREN	SIREN addressed risk factors, not rehabilitation (Owolabi & SIREN Team, 2018)
Policy attention to digital health	Alignment with national digital health architecture	Announced plans, not independently evaluated (Federal Ministry of Information and National Orientation, 2025)
Therapist acceptance	Pilot telerehabilitation with automated monitoring	Moderate acceptance, low adoption; training needed (Odetunde et al., 2024)
Community and home-based therapy	Remote supervision of primary-center or home programs	Similar outcomes by setting (Olaleye et al., 2014); AI layer not evaluated in the literature reviewed

12. Barriers to AI Implementation in Nigeria

Infrastructure. Epileptic power supply and poor internet connectivity have been identified as barriers to electronic health record implementation (Babatope et al., 2024), and rural communities were reported to have little or no mobile internet (Ravi et al., 2024). A commentary on AI in Sub-Saharan Africa reported that only 28% of the regional population regularly use the internet and that computational infrastructure is insufficient (Victor, 2025). These figures are regional, not Nigerian, and may change quickly.

Cost and sustainability. AI-driven rehabilitation may cost more than conventional approaches, because skilled therapists remain involved and automated systems also need specialized equipment and analytical skills (Senadheera et al., 2024). Financial limitations were the main challenge in the Nigerian EHR study (Babatope et al., 2024), and a commentary noted that digital projects funded as short-term donor pilots may stop when funding ends (Ravi et al., 2024). Nigerian cost data for AI rehabilitation tools were not identified among the literature reviewed, so maintenance and software costs remain unquantified.

People and skills. Lack of awareness and technical know-how among stakeholders has been identified as an obstacle to telerehabilitation (Odetunde et al., 2024), student awareness was moderate (Mbada et al., 2021), and half of the participants in the Yoruba study needed a caregiver to operate the equipment (Odetunde et al., 2020). Digital literacy and training therefore concern therapists, patients and caregivers. Sources on the number of AI specialists working in Nigerian health were not identified.

Data and interoperability. Registries are few (Arabambi et al., 2022), records are often held by patients (Akwaowo et al., 2022), and standards are not centrally endorsed (Ravi et al., 2024). Poorly standardized data limit what AI can learn.

Equity. Rural areas are affected by uneven distribution of facilities and health workers (Nwankwo et al., 2022) and by weaker connectivity (Ravi et al., 2024). Without deliberate planning, AI tools could benefit urban patients first. These barriers are significant but not absolute, since some low-technology tools have already been shown to be feasible (Odetunde et al., 2020).

13. Ethical, Privacy, Security and Bias Considerations

Privacy, consent and governance

Stroke records include sensitive information about health, disability and sometimes cognition and communication. The Nigeria Data Protection Act 2023 (Federal Republic of Nigeria, 2023) established the Nigeria Data Protection Commission and treats health-related data as sensitive personal data, and legal summaries note that processing is restricted unless specific conditions are met (Future of Privacy Forum, n.d.). This law applies to personal data generally. No Nigerian regulation specific to AI in rehabilitation was identified among the sources reviewed, and the author is not a legal professional, so the details should be read in the Act itself.

WHO guidance on the ethics and governance of AI for health sets out six principles: protecting autonomy, promoting well-being, safety and the public interest, ensuring transparency and explainability, fostering responsibility and accountability, ensuring inclusiveness and equity, and promoting responsive and sustainable AI (World Health Organization, 2021a). Applied to rehabilitation, these principles can be read as meaning that patients should give informed consent for use of their data, that humans should stay in control of decisions,

that it should be clear who is accountable for an AI-informed decision, and that tools should be explainable. Data ownership and governance, including who may reuse rehabilitation data for research, should be settled before data are collected.

Cybersecurity is a practical risk. A systematic literature review found that healthcare data are exposed to cyber threats and recommended a holistic approach combining people, technology and compliance (Vilakazi & Adebesin, 2023). That review was not Nigeria-specific. In Nigeria, a commentary observed that public trust in data privacy affects willingness to use digital services (Ravi et al., 2024).

Bias and the representation of African populations

AI models learn from the data they are trained on. If training data come mainly from high-income countries, a model may perform less well on patients whose body types, health conditions, environments, languages or care patterns differ. This is a reason for caution, not proof that a particular tool is biased. In rehabilitation, the evidence base is concentrated in China and the United States, and few studies report external validation (Morone et al., 2025). A commentary on AI and health equity in Sub-Saharan Africa reported that most health data come from developed countries, with about 1% from African countries, and warned that algorithms may then fail to reflect local realities (Victor, 2025). WHO also identifies bias in AI as a risk that may increase discrimination (World Health Organization, 2021a).

Inaccurate predictions carry real risk in rehabilitation. A wrongly pessimistic prediction could limit access to therapy, and a wrongly optimistic one could create unrealistic expectations. The responses implied by the evidence are local datasets with African representation, external validation in Nigerian patients, transparent reporting of performance across subgroups, and continuous monitoring after deployment.

14. The Role of Physical Therapists in AI-Enabled Rehabilitation

The evidence reviewed treats AI as something that works with therapists. Some studies measure AI against therapist assessment (Senadheera et al., 2024), the scoping review noted that therapists remain involved in automated approaches, and the Yoruba video program was designed to supplement, not replace, professional contact (Odetunde et al., 2020). WHO also states that humans should remain in control of medical decisions (World Health Organization, 2021a).

Based on this evidence, the roles that remain with physical therapists can be summarized as follows. This is the author's reasoning from the sources and not a finding of any single study. Therapists carry out clinical reasoning and patient assessment, deciding which information matters for a particular person. They set goals with patients and families, prescribe and progress exercise, monitor safety, and judge whether a prediction or alert fits the patient's circumstances. They provide motivation and a therapeutic relationship, which no sensor reproduces, and they communicate with patients and families in language and context that fit. They also interpret AI-generated information, which needs enough digital and AI literacy to question it.

Successful adoption needs collaboration. The scoping review that mapped AI in stroke rehabilitation was written by a team combining data analytics, occupational therapy and physiotherapy expertise (Senadheera et al., 2024), which illustrates the kind of cooperation needed. In Nigeria, physical therapists, physicians, rehabilitation researchers, data and AI specialists, engineers and other relevant professionals would need to work together on what data to collect, how to protect them and how to evaluate tools, with therapists involved in design and evaluation.

15. Practical Recommendations for Nigeria

The recommendations below are the author's proposals drawn from the evidence reviewed. They are not established Nigerian policy, except where a source is named, and each would need testing.

1. **Develop better digital rehabilitation records,** with a minimum dataset including functional scores and therapy details (Akwaowo et al., 2022; Arabambi et al., 2022).
2. **Improve stroke and rehabilitation data collection** by building on existing registries and research networks such as SIREN (Owolabi & SIREN Team, 2018).
3. **Encourage standardized outcome measures,** such as the modified Rankin Scale and modified Barthel Index used in a Nigerian study (Odetunde et al., 2020).
4. **Develop and validate locally relevant datasets** with African representation (Victor, 2025; Morone et al., 2025).
5. **Pilot AI-assisted tools in controlled settings,** starting with low-cost, low-bandwidth options (Odetunde et al., 2020).
6. **Evaluate tools in Nigerian patients before wider use,** including external validation (Morone et al., 2025).
7. **Train therapists and other professionals** in digital health and AI literacy (Odetunde et al., 2024; Mbada et al., 2021).
8. **Strengthen privacy and cybersecurity,** following the Nigeria Data Protection Act (Federal Republic of Nigeria, 2023; Vilakazi & Adebesin, 2023).
9. **Improve digital infrastructure,** including reliable power and connectivity (Babatope et al., 2024).
1. **Prioritize affordable, scalable technologies,** planned beyond donor pilots (Ravi et al., 2024).
2. **Include rural and underserved populations** from the start (Nwankwo et al., 2022).
3. **Maintain human clinical oversight** of all AI-informed decisions (World Health Organization, 2021a).
4. **Establish ethical and regulatory safeguards** for AI in rehabilitation, guided by WHO principles (World Health Organization, 2021a).
5. **Encourage interdisciplinary collaboration** between physical therapists, physicians, rehabilitation researchers, data and AI specialists, engineers and other relevant professionals (Senadheera et al., 2024).
6. **Conduct Nigerian research** on the effectiveness, safety, affordability and usability of AI-assisted rehabilitation, since no such evaluation was identified among the literature reviewed.

16. Discussion

Three conclusions can be drawn. First, AI can realistically contribute to specific, limited tasks: producing objective movement data, estimating likely outcomes, tracking exercise between visits, and summarizing information for the team. Research activity is most extensive for sensor-based movement analysis and prediction (Senadheera et al., 2024), and a meta-analysis of small trials of AI- and ML-assisted upper limb training is promising but shows a small pooled effect (Mahmoud et al., 2023). Second, the evidence remains limited where it matters most for Nigeria: external validation is rare (Morone et al., 2025), clinical effects have not been established (Sumner et al., 2023), and decision-support research has shown threats to validity (Akay

et al., 2023). Third, no Nigerian evaluation of AI-assisted stroke rehabilitation was identified among the literature reviewed, so claims about implementation in Nigeria would be speculative.

The Nigerian evidence points to preconditions rather than applications. Services are few and unevenly distributed, and data systems are weak (Arabambi et al., 2022; Akwaowo et al., 2022; Nwankwo et al., 2022). Where Nigerian digital rehabilitation has been tested, it was low-technology, and half of the participants needed caregiver help (Odetunde et al., 2020). It is therefore realistic to see AI as a later layer built on records, registries, trained staff and dependable infrastructure, not as a shortcut around them. There is also a risk that tools designed elsewhere widen inequity if they are adopted without local validation.

AI cannot replace clinical judgment because it provides estimates, not responsibility, and because much of rehabilitation lies in goals, motivation and relationships. The more promising picture is a therapist who has better information and the skills to question it. This requires training and infrastructure, and it requires research to fill the gaps: local datasets, external validation in Nigerian patients, cost and usability studies, and evaluation of effects on continuity of care. These gaps also show why AI and digital technologies should be developed together with therapists. Questions such as how rehabilitation data should be structured, shared, protected and analyzed arise directly from the clinical problems of assessment, monitoring and continuity, and they are best answered with therapists involved in design and evaluation.

17. Limitations

This review has several limitations. It is a narrative review with purposive source selection and no formal quality appraisal, so relevant studies may have been missed and publication bias is possible, since positive findings are more likely to be published. Searches relied on web-accessible sources and English-language publications. No Nigerian evaluation of AI in rehabilitation was identified among the literature reviewed, so Nigerian conclusions rest on related evidence about access, feasibility and data, and some sources are commentaries (Ravi et al., 2024; Victor, 2025).

AI applications are heterogeneous, from gait sensors to robots, and results from one type cannot be generalized to another. AI technology is changing rapidly, so some findings may date quickly, and long-term evidence on emerging tools is limited. International health systems differ from Nigeria's, and evidence of real-world implementation in Nigerian rehabilitation settings is lacking. Legal points are summarized for context and are not legal advice. Finally, the author's background is in stroke rehabilitation, not in computing, so technical aspects are described at a general level.

18. Conclusion

AI has potential to support stroke rehabilitation in Nigeria through more personalized assessment, improved monitoring, clinical decision support, better use of rehabilitation data, remote follow-up, improved continuity of care and more informed rehabilitation planning. These potentials are drawn mainly from international evidence, which is itself uneven. No evidence was identified among the literature reviewed that AI is already solving these problems in Nigeria.

AI should augment, not replace, physical therapists and other healthcare professionals. Successful implementation in Nigeria will require local evidence, appropriate infrastructure, workforce training, good-quality data, privacy protection, ethical safeguards, affordability, equity and human clinical oversight. The recommended path is stepwise: improve records and data, pilot simple tools with evaluation, and extend only when the evidence supports it. The questions raised here about data, design, security and evaluation arise

directly from the practical problems of rehabilitating people after stroke, and they are best addressed through collaboration led by those who deliver rehabilitation.

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