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Artificial Intelligence Driven Musculoskeletal Rehabilitation: Current Evidence, Clinical Translation, and a Human-in-the-Loop Framework for Functional Recovery

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Abstract: **Musculoskeletal disorders generate substantial global disability and require rehabilitation models that are effective, scalable, personalized, and capable of supporting recovery beyond episodic clinic visits. Artificial intelligence (AI) is increasingly incorporated into rehabilitation through machine learning, computer vision, wearable sensing, adaptive telerehabilitation, robotics, exergaming, and clinical decision support. This critical review evaluates the clinical promise and limitations of AI-enabled musculoskeletal rehabilitation and proposes a human-supervised translational framework, the Artificial Intelligence–Driven Rehabilitation Framework for Musculoskeletal Recovery (AI-DRF-MSK). Recent randomized and synthesized evidence suggests that selected AI-assisted strategies can improve pain, physical function, or range of motion. However, the evidence remains heterogeneous across diagnoses, technologies, comparators, outcome measures, and follow-up periods. In low back pain, statistically significant pooled improvements have not consistently exceeded prespecified thresholds for clinical importance, illustrating the need to distinguish statistical effects from patient-important recovery. The AI-DRF-MSK framework integrates six functions—intelligent assessment, AI-supported clinical profiling, personalized rehabilitation, real-time feedback, adaptive monitoring, and human clinical oversight—within a closed-loop model. Safety, explainability, equity, privacy, external validation, and post-deployment monitoring are treated as structural requirements. The most defensible near-term role for AI is therefore not autonomous replacement of physiotherapists, but augmentation of physiotherapist-led rehabilitation. Future research should prioritize multicenter prospective validation, clinically meaningful outcomes, long-term follow-up, transparent reporting, cost-effectiveness, workflow effects, subgroup performance, and surveillance for model drift and unintended harm.**

Keywords: **artificial intelligence; musculoskeletal rehabilitation; physical therapy; functional recovery; digital rehabilitation; telerehabilitation; machine learning; clinical decision support.**

Highlights

- AI-enabled rehabilitation is supported by an expanding but heterogeneous clinical evidence base.
- Statistical improvement should not be interpreted as clinically meaningful functional recovery without reference to MCIDs, responder analyses, and patient goals.
- Digital rehabilitation should not be labeled AI unless it contains a demonstrable algorithmic function such as prediction, computer-vision inference, learning, or adaptive decision-making.
- The proposed AI-DRF-MSK framework places physiotherapist oversight, safety, equity, explainability, and external validation inside the rehabilitation pathway.
- The most credible near-term model is human-in-the-loop rehabilitation in which AI augments measurement, feedback, personalization, and monitoring.

1. INTRODUCTION

Musculoskeletal (MSK) disorders are among the most consequential causes of pain, disability, activity limitation, and rehabilitation need worldwide. The World Health Organization estimates that approximately 1.71 billion people live with MSK conditions, with low back pain remaining a leading contributor to disability [1]. At the same time, rehabilitation services face persistent constraints, including unequal access to skilled clinicians, geographic barriers, limited observation of home exercise, variable adherence, inconsistent follow-up, and difficulty tailoring progression between face-to-face encounters [1,2].

These limitations make rehabilitation a particularly relevant setting for artificial intelligence (AI). Unlike many one-time diagnostic decisions, rehabilitation produces longitudinal data: joint motion, movement quality, exercise repetitions, pain response, strength, balance, activity, adherence, patient-reported outcomes, and participation can all change repeatedly during recovery. AI systems may help interpret these data to support individualized progression, movement feedback, prediction of response, risk stratification, and earlier identification of non-response.

The central question, however, is not whether AI can be inserted into rehabilitation. The clinically important question is whether AI improves outcomes that matter to patients, whether those improvements are durable and generalizable, and whether the technology can be integrated without weakening safety, equity, professional accountability, or therapeutic relationships. This distinction is increasingly important because enthusiasm for AI in rehabilitation is accelerating, while responsible implementation remains an active concern in the rehabilitation literature [16].

This article critically synthesizes current evidence relevant to AI-enabled MSK rehabilitation and develops a clinically grounded framework for translation. The principal argument is deliberately calibrated: selected AI-assisted approaches show promise, but current evidence does not justify a universal claim that AI is superior to conventional physiotherapy. The most defensible near-term model is human-in-the-loop rehabilitation, in which AI extends measurement, feedback, and personalization while the physiotherapist retains contextual judgment and clinical responsibility.

2. SCOPE AND APPROACH

This article is a critical evidence synthesis and conceptual framework paper. It is not presented as a newly conducted systematic review or meta-analysis. The synthesis prioritizes recent systematic reviews, meta-analyses, randomized trials, international reporting standards, and authoritative guidance relevant to AI in rehabilitation. The purpose is to evaluate the maturity and clinical meaning of the evidence and to connect that evidence to a responsible implementation model.

For effectiveness questions, randomized evidence and systematic syntheses are given greater weight than narrative descriptions or technical model-development studies. For translation and governance, the discussion draws on PRISMA 2020, CONSORT-AI, SPIRIT-AI, DECIDE-AI, World Health Organization guidance, and the FUTURE-AI consensus [8-11,14,15]. These standards are particularly relevant because AI studies require clarity about model inputs and outputs, intended users, human-AI interaction, poor-quality data, error handling, external validation, and workflow effects.

A future systematic version of this work should prospectively document database searches, dates, duplicate removal, screening, extraction, risk-of-bias assessment, and a PRISMA flow diagram. Those elements are not retrospectively invented here.

3. WHAT SHOULD COUNT AS AI IN REHABILITATION?

A recurring conceptual problem is the tendency to use 'AI rehabilitation' as a broad label for any technology-assisted intervention. Digital rehabilitation is broader than AI. A video consultation, exercise library, reminder system, or virtual-reality environment is not inherently intelligent. A defensible AI classification requires a demonstrable algorithmic function, such as learning from data, probabilistic prediction, computer-vision inference, adaptive decision-making, or intelligent feedback [7].

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Modality	Typical AI function	Potential rehabilitation role
Machine learning / predictive analytics	Estimation of prognosis, response, risk, adherence, or recovery trajectory	Supports stratification and clinician decision-making
Computer vision	Pose estimation, joint-angle inference, repetition recognition, movement-quality classification	Extends movement assessment and feedback beyond the clinic
Wearable-sensor intelligence	Algorithmic interpretation of inertial, activity, physiologic, or biomechanical signals	Continuous monitoring of activity and recovery
Adaptive telerehabilitation	Data-driven modification of exercise dose, difficulty, or feedback	Individualizes remote rehabilitation
Robotics	Adaptive assistance or resistance according to performance	Supports task-specific movement practice
Exergaming	Adaptive therapeutic challenge and movement recognition	May improve engagement while delivering exercise
Clinical decision support	Risk estimates or recommendations presented to clinicians	Supports, rather than replaces, clinical reasoning

4. CURRENT CLINICAL EVIDENCE

4.1 Cross-condition musculoskeletal evidence

A 2025 network meta-analysis by Luo and colleagues synthesized 33 randomized controlled trials spanning 13 AI-assisted rehabilitation strategies [3]. Therapeutic and gamified exergaming, robotic approaches, and AI-feedback motion training ranked favorably for selected pain, functional, and range-of-motion outcomes. This is important because it demonstrates that AI-associated rehabilitation is no longer represented only by technical feasibility studies.

Network rankings should nevertheless be interpreted cautiously. Surface under the cumulative ranking curve values and related ranking probabilities describe comparative performance within a network; they do not establish that one technology is universally superior across diagnoses or clinical contexts. Transitivity, consistency, intervention definitions, comparator intensity, patient populations, and outcome measurement all influence the credibility of the network. Heterogeneity therefore limits simple 'AI versus conventional care' conclusions.

4.2 Low back pain: the difference between statistical and clinical importance

Condition-specific evidence illustrates why effect size interpretation matters. Kashoo and colleagues' 2026 systematic review and meta-analysis included five randomized trials involving 1,939 participants with nonspecific low back pain; three trials contributed to pooled analyses [4]. AI-based physical therapy was associated with statistically significant reductions in pain (pooled mean difference -0.721; 95% CI -1.047 to -0.395) and disability (pooled mean difference -1.031; 95% CI -2.020 to -0.042). However, the pooled effects did not reach the review's prespecified minimal clinically important differences, and certainty was rated low because of risk of bias and imprecision [4].

This finding is clinically instructive. A statistically detectable average difference may still be too small to represent a meaningful improvement from the patient's perspective. Rehabilitation trials should therefore prespecify clinically important thresholds, report responder analyses when appropriate, and prioritize validated measures of function, participation, quality of life, and durability rather than relying on p-values alone.

Additional 2026 syntheses of AI-based interventions for low back pain and comparative care models show that the field is moving from a feasibility question—'can AI be used?'—toward a comparative effectiveness question—'which AI-enabled model works, for whom, under what conditions, and compared with what?' [5,6].

4.3 Broader rehabilitation and translation evidence

Recent rehabilitation reviews describe expanding use of AI across physical, occupational, and neurorehabilitation, while repeatedly identifying gaps between technical performance and real-world clinical benefit [12,13]. Common concerns include limited prospective validation, inconsistent definitions of AI, weak or variable comparators, and incomplete evidence regarding implementation. These concerns are especially relevant to MSK rehabilitation, where technology may be deployed directly in patients' homes and may influence exercise progression without continuous clinician observation.

5. HOW AI MAY ENHANCE FUNCTIONAL RECOVERY

Personalization

AI can integrate baseline function, symptoms, movement performance, adherence, and longitudinal response to support dynamic progression. The potential advantage is not simply a digital exercise prescription, but adjustment of dose and challenge as the patient's status changes.

Real-time movement feedback

Computer vision and wearable sensors can estimate repetitions, joint position, or movement quality and may extend therapist observation into the home. Measurement validity must be demonstrated across body types, clothing, lighting, camera positions, devices, and movement speeds.

Continuous monitoring

Wearable and app-based data can reveal patterns between appointments, potentially identifying poor adherence, symptom flare, plateau, or functional deterioration earlier than periodic review.

Prediction and triage

Predictive models may identify patients who need greater supervision, slower progression, or referral. Such outputs should be treated as probabilistic decision support rather than deterministic labels.

Engagement and adherence

Gamification, adaptive goals, and feedback may improve participation for some patients. Engagement metrics should not be used as substitutes for validated functional outcomes.

Access and scalability

Remote AI-assisted rehabilitation may extend support to patients affected by geography, mobility limitations, or workforce shortages. Conversely, device access, connectivity, language, and digital literacy can create or worsen inequity.

6. CRITICAL APPRAISAL OF THE EVIDENCE BASE

- Intervention heterogeneity. The term AI rehabilitation can conceal fundamentally different mechanisms. Pooling technologies without attention to function may obscure which component is responsible for benefit.
- Comparator asymmetry. If an AI arm receives more structured exercise, feedback, contact, or novelty than usual care, the apparent treatment effect cannot automatically be attributed to AI.
- Small samples and short follow-up. Many technology studies are optimized for feasibility rather than durable functional recovery.
- Blinding limitations. Participants and therapists are usually aware of rehabilitation modality, creating potential expectation and performance effects.
- Outcome multiplicity. Pain, range of motion, function, adherence, satisfaction, and technology metrics may be assessed at multiple time points, increasing selective-reporting risk.
- External validity. A model developed in one dataset, device ecosystem, health system, or population may perform differently elsewhere. External and prospective validation are essential.
- Algorithm drift. Model performance can change as software, sensors, workflows, or patient populations change. Post-deployment surveillance is therefore necessary.
- Explainability and human factors. A technically accurate recommendation can still fail clinically if users cannot interpret it, alerts are poorly timed, interfaces increase workload, or responsibility is unclear.
- Equity and bias. Training and validation data may underrepresent age groups, body shapes, disability levels, languages, socioeconomic contexts, or low-resource settings.
- Publication and novelty bias. Positive technology studies may be preferentially disseminated, while rapidly changing products can become obsolete before long-term evidence matures.

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7. THE AI-DRF-MSK FRAMEWORK

The Artificial Intelligence–Driven Rehabilitation Framework for Musculoskeletal Recovery (AI-DRF-MSK) is proposed as a human-supervised, outcomes-based model connecting AI capabilities to rehabilitation reasoning. It is a conceptual framework intended for empirical validation; it should not be interpreted as a currently validated clinical instrument.

Domain	Function	Clinical safeguard
1. Intelligent assessment	Combines diagnosis/context, pain, disability, ROM, strength, functional tests, psychosocial factors, goals, PROMs, movement, and wearable data.	Red-flag screening remains clinician-led.
2. AI clinical profiling	Characterizes movement deficits, response patterns, adherence risk, and recovery trajectory.	Uncertainty and intended use should be visible.
3. Personalized rehabilitation	Supports clinician-approved selection of exercise type, dose, progression, education, and self-management.	No autonomous prescription outside predefined clinical boundaries.
4. Real-time feedback	Uses computer vision or sensors to assess performance and provide bounded feedback.	Feedback operates within validated measurement and safety limits.
5. Adaptive monitoring	Tracks symptoms, adherence, and functional change over time.	Deterioration or non-response triggers clinician review.
6. Human clinical oversight	Physiotherapist interprets AI output in context, incorporates preferences, manages red flags, and remains accountable.	Human responsibility is explicit and non-delegable.

Closed-loop principle: assessment → AI-supported interpretation → clinician-approved intervention → measured response → adaptive progression → reassessment. The loop is intentionally bounded by safety rules and human review.

As illustrated in Figure 1, the six-domain AI-DRF-MSK pathway integrates intelligent assessment, AI-supported clinical profiling, personalized rehabilitation, real-time feedback, adaptive monitoring, and human clinical oversight within a closed-loop model for functional recovery.

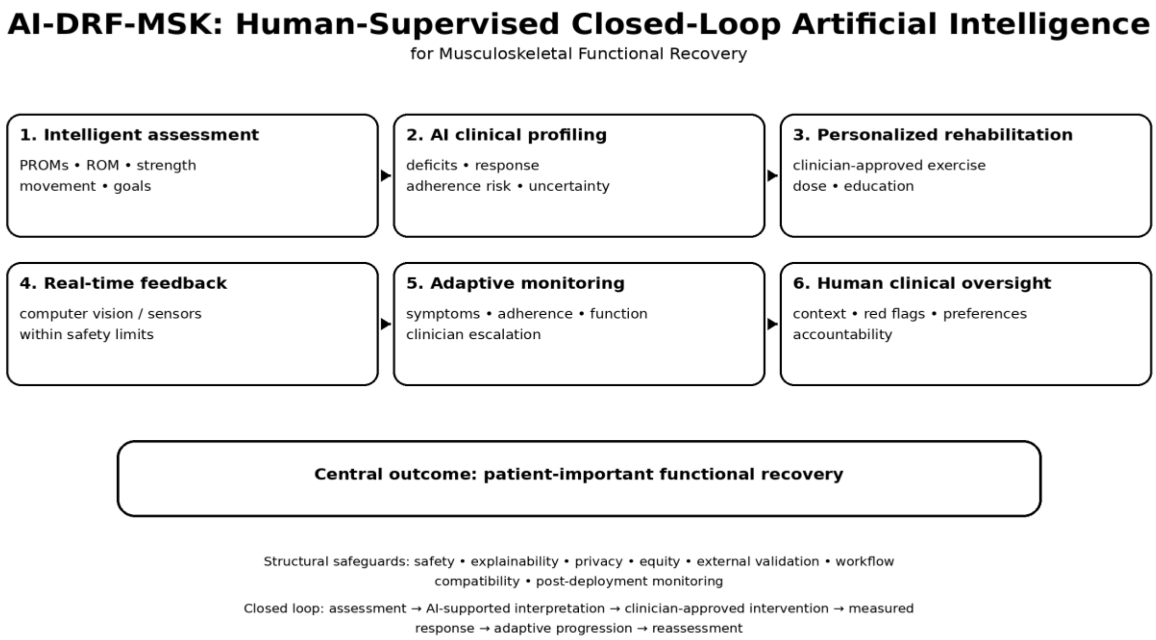

Figure 1. AI-DRF-MSK: Human-Supervised Closed-Loop Artificial Intelligence for Musculoskeletal Functional Recovery.

8. SAFETY, ETHICS, AND TRUSTWORTHY DEPLOYMENT

WHO guidance on AI for health emphasizes autonomy, well-being and safety, transparency and explainability, responsibility and accountability, inclusiveness and equity, and responsive sustainable AI [14]. FUTURE-AI further operationalizes trustworthy health-care AI around fairness, universality, traceability, usability, robustness, and explainability [15]. In rehabilitation, these principles are not abstract ethical additions: AI may directly influence exercise progression, interpretation of risk, access to services, and the timing of clinician review.

- Define the clinical purpose and intended user before selecting the technology.
- Describe training and validation populations and evaluate subgroup performance.
- Perform external validation before broad deployment.
- Make data provenance, privacy, consent, and model limitations transparent.
- Specify failure modes, escalation procedures, and responsibility for decisions.
- Version software and model changes so that performance is traceable over time.
- Monitor patient outcomes, adverse events, equity, and model drift after deployment.
- Preserve meaningful clinician challenge and override of algorithmic recommendations.

9. FROM ALGORITHM TO REHABILITATION SERVICE

Clinical translation requires more than a high classification accuracy or area under the curve. An AI tool must fit a real decision in the rehabilitation pathway and improve an outcome that matters. DECIDE-AI emphasizes live clinical evaluation, safety, human factors, and human-AI interaction, while CONSORT-AI and SPIRIT-AI strengthen reporting of AI intervention trials [9-11].

1. Define the rehabilitation problem and clinical decision before selecting the AI method.
2. Establish technical validity and measurement reliability.
3. Validate performance externally in data or populations distinct from model development.
4. Conduct prospective feasibility and human-factors evaluation in the intended workflow.
5. Run adequately powered comparative studies using patient-important outcomes and meaningful follow-up.
6. Evaluate cost, access, workload, adherence, and unintended consequences.
7. Implement with clinician training, transparent patient communication, and explicit escalation pathways.
8. Monitor post-deployment performance, drift, subgroup equity, and adverse events.

10. ORIGINAL CONTRIBUTION AND TESTABLE PROPOSITIONS

The contribution of AI-DRF-MSK is not the invention of AI rehabilitation. Its contribution is the integration of clinical rehabilitation reasoning, evidence hierarchy, and trustworthy-AI requirements into a single translational model.

- Conceptual contribution: assessment, profiling, personalization, feedback, monitoring, and clinician oversight are organized as a closed rehabilitation loop.
- Methodological contribution: genuine algorithmic functions are separated from generic digital rehabilitation, and clinical meaning is prioritized over statistical significance alone.
- Clinical contribution: physiotherapists are positioned as accountable interpreters and supervisors of AI-assisted rehabilitation rather than passive recipients of algorithmic recommendations.
- Implementation contribution: external validation, equity, explainability, safety, workflow compatibility, and post-deployment monitoring are embedded in the pathway.
- Research contribution: the framework shifts future studies toward identifying who benefits, under what conditions, at what cost, and with what risks.

The framework generates testable propositions. For example, AI-supported feedback should improve functional outcomes only when measurement validity is adequate and feedback is linked to clinically appropriate progression; predictive risk estimates should improve care only when they trigger timely, interpretable actions; and remote scalability should be considered successful only when access gains do not create clinically important subgroup inequities.

11. RESEARCH AGENDA

- Large multicenter randomized trials with prespecified clinically important thresholds and responder analyses.
- Long-term follow-up to establish persistence of functional gains and self-management.
- Head-to-head designs that isolate the AI component from the digital-delivery component.
- Transparent reporting of model inputs, outputs, uncertainty, version changes, and failure modes.
- External validation across countries, languages, ages, socioeconomic groups, and levels of digital literacy.
- Cost-effectiveness and therapist-workload analyses.
- Implementation trials embedded in routine outpatient and community rehabilitation.
- Core outcome sets spanning pain, function, participation, quality of life, adherence, and safety.
- Research on therapeutic alliance, patient trust, and clinician-patient interaction.
- Prospective surveillance for model drift and subgroup harm, including privacy-preserving learning approaches where appropriate.

12. LIMITATIONS

The AI rehabilitation literature is evolving rapidly, and terminology is inconsistent. This article prioritizes recent high-level evidence and authoritative methodological guidance rather than claiming an exhaustive de novo systematic search. Some syntheses combine heterogeneous technologies and diagnoses, and the boundary between AI-enabled and merely digital rehabilitation remains contested. Network meta-analysis rankings and statistically significant pooled effects should not be generalized beyond the populations, interventions, comparators, and follow-up periods studied. The proposed AI-DRF-MSK framework is conceptual and requires formal stakeholder development, content validation, feasibility testing, and prospective clinical evaluation.

13. CONCLUSION

AI-enabled rehabilitation is moving from technical possibility toward clinical evaluation in musculoskeletal care. Selected AI-assisted strategies can improve pain, function, or range of motion, and the technology may add value through personalization, feedback, monitoring, prediction, and adaptive progression. Yet the maturity of evidence varies substantially by condition and technology, and statistically significant effects do not automatically represent meaningful recovery.

The central challenge is translation. A useful rehabilitation AI system must do more than perform accurately in a development dataset: it must improve patient-important outcomes, generalize to intended populations, remain safe across diverse users, fit rehabilitation workflows, protect autonomy and privacy, and provide sufficient transparency for accountable use. AI-DRF-MSK therefore proposes a hybrid future in which AI continuously measures and supports rehabilitation while the physiotherapist retains contextual judgment, shared decision-making, red-flag management, and clinical responsibility. The most credible future is not therapist replacement, but evidence-based human-AI collaboration designed around functional recovery.

Declarations:

Ethics approval and consent to participate

Not applicable. This article is a critical evidence synthesis and conceptual framework based on previously published literature and did not involve the recruitment of human participants or collection of new human-subject data.

Consent for publication

Not applicable.

Availability of data and materials

No new datasets were generated or analyzed for this article. The evidence discussed in this manuscript is derived from the published literature cited in the reference list.

Competing interests

The author declares that there are no competing interests.

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Authors' contributions

WMA conceived the article, reviewed and critically synthesized the literature, developed the AI-DRF-MSK conceptual framework, drafted the manuscript, critically revised it for important intellectual content, and approved the final manuscript.

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REFERENCES

[1] World Health Organization. Musculoskeletal health. WHO Fact Sheet. Accessed August 2026.

[2] World Health Organization. Rehabilitation: Questions and answers. September 30, 2024. Accessed August 2026.

[3] Luo Z, Wang Y, Zhang T, Wang J. Effectiveness of AI-assisted rehabilitation for musculoskeletal disorders: a network meta-analysis of pain, range of motion, and functional outcomes. Front Bioeng Biotechnol. 2025;13:1660524. doi:10.3389/fbioe.2025.1660524.

[4] Kashoo F, Agarwal S, et al. Artificial Intelligence-Based Physical Therapy Interventions for Non-Specific Low Back Pain: A Systematic Review and Meta-Analysis of Randomised Controlled Trials. J Clin Med. 2026;15(13):4920. doi:10.3390/jcm15134920.

[5] Ramanujam K, Carneiro S, Helal MM, Ramanujam V. The effectiveness of artificial intelligence-based interventions on treatment outcomes for low back pain: A systematic review and meta-analysis of randomized controlled trials. J Back Musculoskelet Rehabil. 2026. doi:10.1177/10538127261464781.

[6] Gu P, Yan Y, Tang H, et al. Comparative Effectiveness of AI-Assisted Telerehabilitation, Telerehabilitation, In-Person Care, and Usual Care for Chronic Nonspecific Low Back Pain: Bayesian Network Meta-Analysis. J Med Internet Res. 2026;28:e85410. doi:10.2196/85410.

[7] Dandinoğlu T, Kaya E. Are AI-assisted interventions truly artificial intelligence? A PRISMA-guided systematic evaluation in shoulder rehabilitation. Anatolian Current Medical Journal. 2026;8(3).

[8] Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021;372:n71. doi:10.1136/bmj.n71.

[9] Liu X, Rivera SC, Moher D, Calvert MJ, Denniston AK; SPIRIT-AI and CONSORT-AI Working Group. Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI Extension. BMJ. 2020;370:m3164. doi:10.1136/bmj.m3164.

[10] Rivera SC, Liu X, Chan A-W, Denniston AK, Calvert MJ; SPIRIT-AI and CONSORT-AI Working Group. Guidelines for clinical trial protocols for interventions involving artificial intelligence: the SPIRIT-AI Extension. BMJ. 2020;370:m3210. doi:10.1136/bmj.m3210.

[11] Vasey B, Nagendran M, Campbell B, et al. Reporting guideline for the early-stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI. Nat Med. 2022;28:924-933. doi:10.1038/s41591-022-01772-9.

[12] El Arab RA, Al Moosa OA, Almagharbeh WT, et al. Artificial Intelligence in Physical, Occupational and Neuro-Rehabilitation: Clinical Effectiveness, Prognostic Performance, and Pre-Implementation Feasibility - A Systematic Review. J Med Syst. 2026;50(1):78. doi:10.1007/s10916-026-02400-6.

[13] Hao J, Sun S, Dou T, et al. Intelligent Rehabilitation: Advances in Artificial Intelligence for Musculoskeletal Rehabilitation: A Narrative Review. Orthop Res Rev. 2026;18. doi:10.2147/ORR.S607912.

[14] World Health Organization. Ethics and governance of artificial intelligence for health. Geneva: World Health Organization; 2021.

[15] Lekadir K, Frangi AF, Porras AR, et al. FUTURE-AI: international consensus guideline for trustworthy and deployable artificial intelligence in healthcare. BMJ. 2025;388:e081554. doi:10.1136/bmj-2024-081554.

[16] Rauzi MR, et al. Guiding Technology Adoption in Rehabilitation: A Framework From the Rehabilitation Technology Implementation for Promising Solutions (Rehab TIPS) Workgroup. Arch Phys Med Rehabil. 2026;107(1):123-133. doi:10.1016/j.apmr.2025.08.008.