Research Article

Digital Phenotyping in Physical Health: Integrating Advanced Imaging, Movement Analysis and Functional Rehabilitation

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Abstract

Digital phenotyping is evolving from the collection of isolated digital measurements toward continuous, multimodal characterization of an individual's health state. In physical health and rehabilitation, this transition creates an opportunity to connect structural information from magnetic resonance imaging (MRI), computed tomography (CT), ultrasound and other imaging modalities with movement-derived measures from video, inertial measurement units (IMUs), gait systems, electromyography and consumer wearables. This review synthesizes the emerging evidence for integrating these data streams into clinically meaningful functional phenotypes. Advanced imaging can quantify tissue structure and imaging-derived features, while movement analysis captures performance, coordination, mobility and adaptation in real-world environments. Machine learning and deep learning provide mechanisms for feature extraction, temporal modelling and multimodal fusion, although clinical translation remains constrained by data heterogeneity, limited external validation, interoperability, privacy, bias and uncertain clinical utility. Recent reviews indicate rapid growth of digital phenotyping, wearable rehabilitation and AI-enabled movement analysis, but the evidence remains heterogeneous and frequently concentrated in feasibility or proof-of-concept studies. An integrated framework is therefore proposed in which imaging, movement and contextual data are converted into longitudinal functional phenotypes that support assessment, rehabilitation planning and outcome monitoring. The future direction is not replacement of clinical assessment but augmentation of clinician-led decision-making with objective, longitudinal and interpretable measurements.

Keywords: digital phenotyping; medical imaging; MRI; CT; movement analysis; wearable sensors; artificial intelligence; rehabilitation; digital biomarkers; precision rehabilitation

1. Introduction

Physical health is multidimensional. A patient's status cannot be completely represented by a diagnosis, a single image, or a clinic-based functional score. Imaging describes anatomy and tissue characteristics, whereas movement analysis describes how the body performs in space and time. Digital phenotyping extends this concept by collecting active and passive data through smartphones, sensors and other digital technologies to characterize health in real-world settings. Recent reviews describe digital phenotyping as a rapidly expanding field, with growing use of machine learning to transform raw sensor signals into clinically relevant features and outcomes.

The rehabilitation context is particularly suitable for this approach because recovery is inherently longitudinal. Conventional assessments are often performed at discrete visits and may miss day-to-day changes in mobility, exercise adherence, fatigue or compensatory movement. Wearable sensors can enable measurement outside the laboratory, while computer vision and markerless motion analysis can quantify movement without traditional marker-based systems. At the same time, modern imaging and radiomics can provide quantitative information that is less apparent from visual inspection alone, although repeatability and reproducibility remain important barriers.

The central proposition of this review is that advanced imaging and movement analysis should not be viewed as separate digital-health domains. Their combination may provide a more complete phenotype: what tissue looks like, how the person moves, how function changes over time, and how the individual responds to rehabilitation (1).

2. Scope and Review Approach

This narrative review synthesizes peer-reviewed literature and recent systematic/scoping reviews identified through targeted searches of PubMed-, Scopus- and publisher-indexed literature, with emphasis on publications from 2020–2026. Priority was given to systematic reviews, scoping reviews, position papers and recent high-quality narrative reviews addressing digital phenotyping, medical imaging/radiomics, wearable sensing, movement analysis, AI-enabled rehabilitation and digital twins. The purpose is conceptual integration rather than quantitative meta-analysis; therefore, reported study counts from individual reviews are presented as evidence-volume indicators and are not pooled estimates (2).

3. From Digital Data to a Physical Health Phenotype

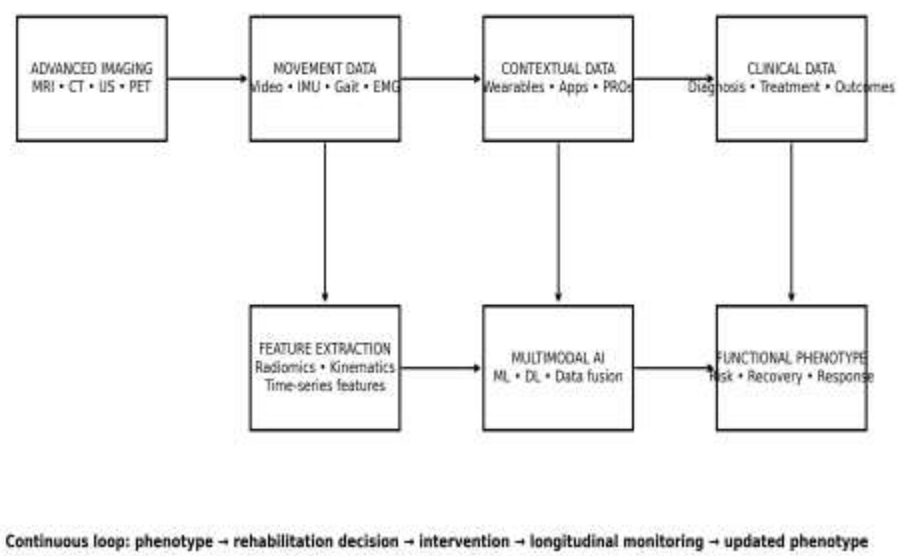


Figure 3.1. Proposed multimodal framework for digital phenotyping in physical health.

A clinically useful digital phenotype is best understood as a structured representation of measurable characteristics that change with disease, treatment and environment. In physical health, these characteristics can be grouped into structural, functional and contextual domains. Structural features may include tissue composition, lesion burden, muscle morphology or joint geometry. Functional features include gait speed, cadence, range of motion, balance, symmetry, exercise quality and activity volume. Contextual features include sleep, daily activity, adherence, environmental exposure and patient-reported outcomes (3).

Domain	Typical data source	Examples of features	Clinical relevance
Structural	MRI, CT, ultrasound	Texture, volume, tissue composition, lesion characteristics	Disease characterization; prognosis; treatment planning
Movement	Video, IMU, gait laboratory, EMG	Velocity, cadence, ROM, symmetry, joint trajectories	Functional assessment; motor recovery; exercise quality
Contextual	Smartphone, smartwatch, activity monitor	Steps, sedentary time, sleep, activity variability	Real-world function; adherence; longitudinal monitoring

Clinical	EHR, PROs, functional scales	Pain, disability, diagnosis, medication, TUG/6MWT	Clinical anchoring and outcome validation

4. Advanced Imaging as a Structural Phenotype

MRI and CT provide complementary information that can be converted into quantitative features. Conventional measurements include lesion dimensions, muscle cross-sectional area, fat fraction and tissue volume, while radiomics extends anal

ysis to high-dimensional texture and intensity descriptors. Machine-learning models can use imaging-derived features for classification and prognosis, but reproducibility across scanners, protocols and institutions remains a major translational issue. Consequently, imaging-derived digital phenotypes should be accompanied by protocol standardization, quality assurance and external validation (4).

An important conceptual shift is from imaging as a static diagnostic endpoint to imaging as one component of a longitudinal phenotype. For example, structural changes in a joint or muscle can be evaluated alongside gait, strength and activity measures to examine whether imaging changes correspond to functional consequences or rehabilitation response. Similarly, MRI-derived biomarkers have been investigated for predicting disease progression in neurological disorders, illustrating the potential value of combining imaging features with clinical trajectories (4).

5. Movement Analysis and Wearable Sensing

Human movement can be captured using marker-based optical systems, markerless computer vision, IMUs, pressure sensors, smartphones and consumer wearables. Traditional laboratory systems offer high biomechanical accuracy but are costly and constrained to controlled environments. Recent position papers emphasize that laboratory motion capture, wearable sensing and deep-learning video analysis may be complementary rather than mutually exclusive technologies (5).

IMUs are particularly useful for continuous gait and mobility assessment because they can be used outside the laboratory. A 2024 systematic review of wearable inertial sensors highlighted their potential for gait analysis while also identifying sensor placement, signal selection and algorithm design as determinants of validity. In rehabilitation, commercially available wearables have been studied across orthopaedics, stroke, oncology and surgical populations; a 2024 systematic review found consistent feasibility and evidence that wearable-driven feedback can increase physical activity, while also emphasizing the need for larger and better-designed trials (5).

6. AI, Multimodal Fusion and Functional Rehabilitation

AI provides the computational layer needed to transform heterogeneous data into clinically interpretable information. Convolutional neural networks are widely used for imaging and video, recurrent or temporal models can represent sequential movement data, and multimodal architectures can combine structural and functional information. A 2026 systematic review of deep learning for movement analysis in physical rehabilitation reported frequent use of hybrid CNN and recurrent architectures, with lower-limb rehabilitation and gait recovery prominent among applications (6).

However, high algorithmic accuracy in a development dataset does not automatically translate into clinical usefulness. A systematic review of AI-supported physical rehabilitation found that only a small proportion of identified projects had randomized controlled evaluation and that clinical effects were inconsistent. More recent work similarly emphasizes the gap between technical performance and real-world clinical performance, including issues of external validation, safety, usability, adherence and equity (6).

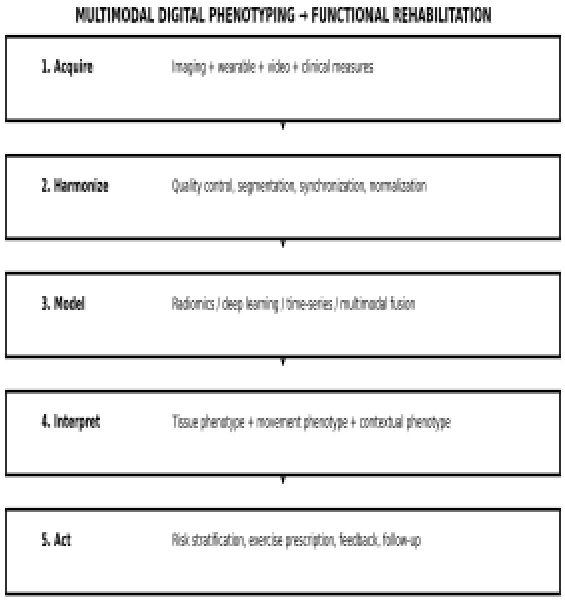


Figure 6.1. Suggested clinical integration pathway from data acquisition to rehabilitation action.

7. Functional Rehabilitation: From Measurement to Action

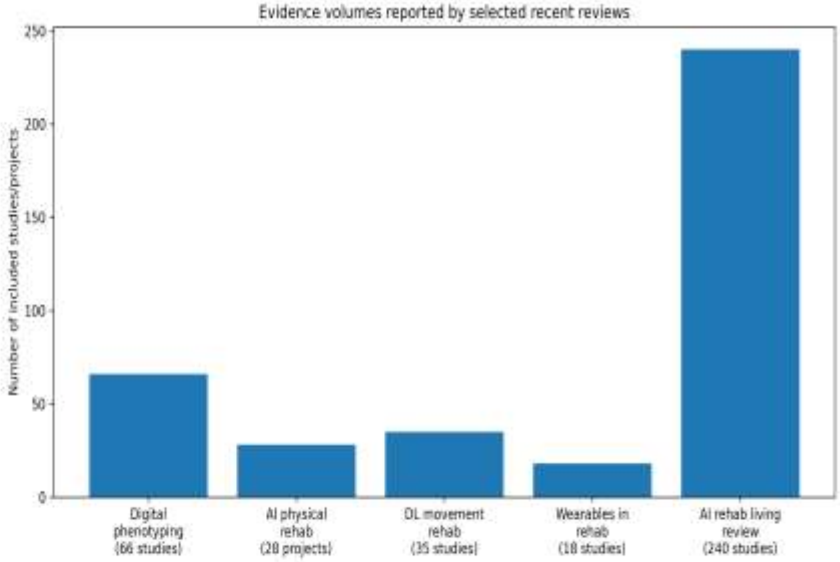
The clinical value of digital phenotyping ultimately depends on whether measurements change care. A practical model is to use digital data for five purposes: baseline characterization, risk stratification, individualized exercise selection, real-time or near-real-time feedback, and longitudinal outcome monitoring. Sensor-derived information can complement established measures such as the Timed Up and Go, 6-Minute Walk Test and balance scales rather than replacing them (7).

AI-driven virtual rehabilitation and telerehabilitation are expanding the setting in which functional assessment can occur. Scoping evidence suggests that AI-enabled virtual rehabilitation can support remote monitoring, personalization and engagement, but implementation remains dependent on technology access, usability and clinical validation. The most clinically realistic model is therefore a hybrid one: clinician-defined goals, digitally measured performance, AI-assisted interpretation and clinician-supervised adaptation (8).

8. Emerging Concept: The Functional Digital Twin

Digital twins extend digital phenotyping by creating a dynamic computational representation of a person that can be updated as new observations become available. Reviews in healthcare describe potential uses in prediction, simulation and personalized decision support, while also identifying technical, biological, ethical and regulatory challenges. In rehabilitation, a functional digital twin could theoretically integrate imaging, movement, symptoms, treatment exposure and longitudinal outcomes to simulate alternative rehabilitation pathways. At present, this should be regarded as an emerging research direction rather than an established clinical standard (9).

9. Evidence Landscape



Graph 9.1. Evidence volumes reported by selected recent reviews. These counts are not pooled estimates and reflect different inclusion criteria and research questions.

Recent literature demonstrates substantial activity but also heterogeneity. A systematic review of machine-learning approaches to digital phenotyping included 66 eligible studies after screening thousands of records. A systematic review of AI in physical rehabilitation identified 28 clinical projects, whereas a 2026 systematic review of deep learning for movement analysis included 35 rehabilitation studies plus additional sport/rehabilitation studies. A 2024 systematic review of consumer wearables for rehabilitation included 18 studies involving 1,754 patients. These figures illustrate the expanding evidence base but should not be interpreted as evidence of comparative effectiveness (9).

10. Major Challenges to Clinical Translation

Table 10.1. Major Challenges to Clinical Translation (10)

Challenge	Why it matters	Practical response
Data heterogeneity	Different scanners, sensors, protocols and sampling rates reduce comparability.	Protocol harmonization; standardized preprocessing; metadata capture.
External validation	Models can perform well on internal data but fail across sites or populations.	Multi-centre datasets; site-wise and subject-wise validation.
Reproducibility	Radiomic and sensor features may vary with acquisition and preprocessing.	Test–retest studies; robustness analysis; transparent pipelines.
Clinical interpretability	Black-box outputs may be difficult to act on.	Explainable features; clinician-facing summaries; calibrated uncertainty.
Privacy and governance	Continuous monitoring creates sensitive longitudinal datasets.	Data minimization; secure storage; consent and governance frameworks.
Equity and accessibility	Technology performance and access may vary across populations.	Inclusive datasets; usability testing; low-cost alternatives.
Workflow integration	Extra data can increase clinician workload.	Automated summaries; interoperability; decision-

		support rather than data overload.

11. Conclusion

Digital phenotyping offers a framework for moving physical healthcare from episodic measurement toward continuous, multidimensional characterization. Advanced imaging can provide structural and tissue-level information, while movement analysis and wearable sensing describe function in controlled and real-world environments. AI can connect these domains through automated feature extraction, temporal modelling and multimodal fusion. The emerging opportunity is therefore not simply to collect more data, but to convert heterogeneous observations into a longitudinal functional phenotype that is clinically interpretable and actionable. Current evidence supports feasibility and rapid technological development, but widespread clinical adoption requires stronger external validation, reproducibility, prospective outcome studies, interoperability, privacy protection and demonstration of added clinical value. A future rehabilitation ecosystem may combine imaging-derived structure, movement-derived function and contextual digital signals within a clinician-supervised decision-support loop.

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