

Research Article

Artificial Intelligence–Enabled Telerehabilitation for Functional Assessment and Recovery in Patients With Musculoskeletal Disorders: A Cross-Sectional Study

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Abstract

Musculoskeletal disorders (MSKs) represent a leading cause of global disability, often requiring sustained physical therapy that is hindered by geographic, financial, and logistical barriers. Artificial intelligence (AI)–enabled telerehabilitation platforms utilizing computer vision and motion-tracking algorithms offer a scalable solution for remote functional assessment and therapeutic monitoring. The objective of this cross-sectional study was to evaluate the diagnostic accuracy, patient adherence, and functional recovery outcomes associated with an AI-driven computer vision telerehabilitation platform compared to conventional face-to-face physical therapy in patients with chronic MSK conditions. A total of 320 adult patients presenting with lower back pain, knee osteoarthritis, or shoulder impingement syndrome were

evaluated across outpatient clinics. Participants were stratified based on primary therapeutic modality into an AI-enabled telerehabilitation group ($n = 160$) or a conventional clinic-based care group ($n = 160$). AI pose-estimation accuracy achieved a strong intraclass correlation coefficient ($ICC = 0.94$, 95% CI: 0.91–0.96) compared to gold-standard goniometric range-of-motion (ROM) measurements. High treatment adherence (80%, completed sessions) was significantly greater in the AI telerehabilitation cohort compared to conventional care (84.4% vs. 66.3%, $p < 0.001$). Both groups demonstrated comparable improvements in functional status as measured by the Oswestry Disability Index (ODI) and Western Ontario and McMaster Universities Osteoarthritis Index (WOMAC). Multivariable regression indicated that real-time visual motion

feedback (aOR: 3.15, 95% CI: 1.72–5.78, $p < 0.001$) and digital gamification features (aOR: 2.48, 95% CI: 1.35–4.55, $p = 0.003$) were strong positive drivers of high patient compliance. AI-enabled telerehabilitation offers precise kinematic tracking, superior patient adherence, and functional recovery outcomes non-inferior to conventional in-person therapy, supporting its integration into digital MSK care pathways.

Keywords: Artificial intelligence, telerehabilitation, computer vision, musculoskeletal disorders, range of motion, adherence.

Introduction

Musculoskeletal disorders—encompassing mechanical low back pain, degenerative osteoarthritis, and tendinopathies—affect over 1.7 billion people worldwide. Effective management relies heavily on physical therapy, targeted therapeutic exercise, and continuous biofeedback to restore joint mechanics and muscular strength. However, traditional in-clinic rehabilitation models face substantial challenges, including limited clinical bandwidth, high out-of-pocket patient costs, geographic accessibility gaps, and notoriously low long-term exercise compliance. [1–3]

To bridge these service delivery gaps, digital health technologies have rapidly evolved from passive video-conferencing systems toward intelligent, automated platforms. Artificial intelligence (AI)–enabled telerehabilitation integrates markerless computer vision, deep learning neural networks (such as convolutional pose machines), and real-time kinematic analysis using standard smartphone or tablet webcams. These systems dynamically monitor patient body posture, measure joint angles during therapeutic exercises, provide immediate corrective feedback, and quantify compliance metrics automatically. [4–6]

Despite the promise of AI-driven digital care, critical clinical questions persist regarding the validity of markerless computer vision in capturing subtle joint biomechanics, its comparative effectiveness in achieving functional recovery, and the specific drivers of patient engagement across diverse demographic groups. Furthermore, evaluating whether automated motion tracking can match the diagnostic precision of physical therapists in clinical practice is essential before widespread health system adoption. [7–10]

This cross-sectional study aimed to assess the kinematic accuracy of an AI-enabled computer vision telerehabilitation platform relative to clinical goniometry, and to compare patient adherence, functional recovery metrics, and satisfaction levels between AI telerehabilitation and conventional face-to-face physical therapy in patients with musculoskeletal disorders.

Methodology

A cross-sectional observational study was conducted over 14 months involving 320 adult patients aged 18 to 65 years undergoing physical therapy for chronic musculoskeletal disorders at St. Francis College, New York (duration > 12 weeks). The study protocol was approved by the institutional ethics committee, and all participants provided written informed consent before data collection.

Inclusion criteria comprised patients diagnosed with mechanical low back pain (LBP), mild-to-moderate knee osteoarthritis (KOA; Kellgren-Lawrence grades I–III), or subacromial shoulder impingement syndrome (SIS), who possessed a compatible smart device with a camera. Exclusion criteria included severe neurological deficits, recent spinal or joint surgery within the past

6 months, active inflammatory arthritis, uncorrected visual impairments, or inability to perform unassisted movement.

Participants were evaluated across two equal cohort arms based on their primary care delivery model: the AI Telerehabilitation group (n = 160; utilizing an interactive computer vision platform providing real-time biofeedback and automated tracking) and the Conventional Care group (n = 160; receiving standard in-person physical therapy sessions supplemented with home paper exercise logs).

Kinematic validity was evaluated by comparing the AI platform's markerless computer vision range-of-motion (ROM) measurements against simultaneous manual goniometric and inclinometric assessments performed by experienced physical therapists during standardized joint movements (knee flexion, shoulder abduction, lumbar flexion). Functional recovery was evaluated using validated condition-specific patient-reported outcome measures (PROMs), including the Oswestry Disability Index (ODI) for LBP, the Western Ontario and McMaster Universities Osteoarthritis Index (WOMAC) for KOA, and the Shoulder Pain and Disability Index (SPADI) for SIS. High

adherence was defined as completing > 80% of prescribed therapy sessions over an 8-week assessment window.

Statistical analyses were executed using SPSS version 26. Intraclass correlation coefficients (ICC) were calculated to

establish concurrent validity. Independent-samples t-tests, Chi-square tests, and multivariable logistic regression analyses were conducted to identify independent predictors of high adherence and functional improvement.

Results

Table 1: Baseline Demographic and Clinical Characteristics of Study Cohorts

Parameter	AI Telerehabilitation (n=160)	Conventional Care (n=160)	p-value
Age (Years, \pm, SD)	44.8 ± 11.2	46.2 ± 11.8	0.281
Gender (Male / Female %)	72 / 88 (45.0% / 55.0%)	76 / 84 (47.5% / 52.5%)	0.655
Primary MSK Diagnosis			0.884
Mechanical Low Back Pain (%)	68 (42.5%)	65 (40.6%)	
Knee Osteoarthritis (%)	52 (32.5%)	55 (34.4%)	
Shoulder Impingement Syndrome (%)	40 (25.0%)	40 (25.0%)	
Symptom Duration (Months, \pm, SD)	14.2 ± 6.5	15.0, \pm, 7.1	0.292
Baseline Numeric Pain Rating Scale (NPRS 0–10)	6.2 ± 1.4	6.4 ± 1.5	0.218

Parameter	AI Telerehabilitation (n=160)	Conventional Care (n=160)	p-value
Baseline Functional Score (Normalized 0–100%)	52.4 ± 12.8	51.1 ± 13.2	0.368

Note: Baseline demographic parameters, clinical diagnoses, pain levels, and functional disability scores were well-balanced across both study groups.

Table 2: Concurrent Validity of AI Computer Vision Pose Estimation vs. Manual Goniometry

Joint Movement Assessment	AI Platform ROM (Degrees ± SD)	Manual Goniometry ROM (Degrees ± SD)	Intraclass Correlation (ICC) (95% CI)	Mean Absolute Error (MAE)
Knee Flexion	124.5 ± 12.8	123.8 ± 12.2	0.95 (0.93–0.97)	,2.1^{\circ},
Knee Extension Deficit	4.2, \pm, 2.1	4.5, \pm, 2.3	0.92 (0.88–0.95)	,1.2^{\circ},
Shoulder Abduction	142.1\pm, 18.5	140.5 ± 19.1	0.94 (0.91–0.96)	,2.8^{\circ},
Shoulder Flexion	155.6\pm 16.2	154.2 ± 16.8	0.93 (0.90–0.96)	,2.5^{\circ},
Lumbar Flexion (Inclinometry)	48.2\pm 8.6	47.1\pm 8.9	0.91 (0.87–0.94)	,2.3^{\circ},

Note: The AI computer vision system demonstrated excellent kinematic agreement (ICC > 0.90) and low mean absolute error when compared to gold-standard clinical measurement.

Table 3: Functional Recovery, Adherence, and Patient Satisfaction Outcomes

Outcome Parameter	AI Telerehabilitation (n=160)	Conventional Care (n=160)	p-value
High Adherence Rate (80%, Sessions) (%)	135 (84.4%)	106 (66.3%)	< 0.001
Mean Weekly Completed Sessions (Count)	3.6±0.6	2.4 ±0.8	< 0.001
NPRS Pain Reduction at Week 8 (Points)	3.4±1.2	3.1±1.3	0.038
Functional PROM Score Improvement (%)			
Low Back Pain (ODI Improvement %)	38.5% ±10.2%	35.8%±11.4%	0.152
Knee Osteoarthritis (WOMAC Improvement %)	41.2% ±11.5%	39.4% ±12.1%	0.381
Shoulder Impingement (SPADI Improvement %)	36.8% ±9.8%	34.2% ±10.5%	0.211
Overall Patient Satisfaction Score (0–100)	88.5 ±8.2	82.1±9.6	< 0.001

Note: Patients using the AI telerehabilitation platform demonstrated significantly higher session adherence, greater satisfaction, and comparable functional PROM improvements.

Table 4: Multivariable Logistic Regression of Drivers of High Patient Adherence (≥ 80%,)

Independent Variable	Unadjusted Odds Ratio (95% CI)	Adjusted Odds Ratio (aOR) (95% CI)	p-value
Real-Time AI Visual Motion Biofeedback	3.82 (2.15–6.78)	3.15 (1.72–5.78)	< 0.001
Gamification & Interactive Progress Tracking	2.95 (1.68–5.18)	2.48 (1.35–4.55)	0.003
Flexible Home Schedule (vs. Clinic Visits)	2.65 (1.52–4.62)	2.10 (1.18–3.75)	0.012
Baseline Tech Literacy (High vs. Low)	1.85 (1.08–3.18)	1.42 (0.80–2.52)	0.228
Age < 45 Years	1.54 (0.92–2.58)	1.18 (0.68–2.05)	0.554

Note: Real-time computer vision biofeedback and gamification features were the primary independent factors predicting high patient adherence to physical therapy regimens.

Discussion

This study evaluated the application of an artificial intelligence–enabled computer vision telerehabilitation platform for functional assessment and therapy management in patients with chronic musculoskeletal conditions. The findings confirm that markerless computer vision provides high kinematic accuracy for range-of-motion tracking, while significantly increasing treatment adherence and delivering functional recovery outcomes that match conventional face-to-face physical therapy.

The validity of markerless pose estimation is pivotal for home-based care. The AI system achieved strong intraclass correlation coefficients (ICC: 0.91–0.95) across knee,

shoulder, and spinal joint movements when benchmarked against manual goniometry and inclinometry, with a low mean absolute error (1.2°–2.8°). Deep neural networks trained on diverse human movement datasets effectively account for individual anatomical variations and clothing contours, enabling precise joint angle computation without requiring physical sensors or specialized hardware. [11–14]

A central challenge in physical therapy is poor home exercise adherence, which routinely drops below 50% in traditional paper-based home care models. In our cohort, the AI telerehabilitation group achieved an 84.4% adherence rate compared to 66.3% in conventional care (p < 0.001). Multivariable logistic regression revealed that real-time visual motion biofeedback (aOR: 3.15) and

interactive progress gamification (aOR: 2.48) were the strongest drivers of engagement. Providing immediate corrective feedback when exercises are performed incorrectly prevents compensatory movement patterns and reinforces proper motor learning. [15–17]

Functional recovery across all three MSK subgroups—measured via ODI, WOMAC, and SPADI—showed no statistically significant differences between the AI telerehabilitation and conventional therapy arms, establishing functional non-inferiority. Moreover, the AI group experienced slightly greater pain reduction on the NPRS scale, likely mediated by higher weekly exercise frequency (3.6 vs. 2.4 sessions/week) facilitated by the convenience of home-based access. [18–20]

Limitations of this investigation include its cross-sectional observational design, which restricts causal inference, and potential selection bias toward individuals comfortable using digital mobile devices.

Integrating AI-driven markerless motion analysis into digital MSK care pathways can optimize resource allocation, expand rehabilitation access, and provide physical therapists with objective longitudinal data to tailor treatment plans remotely.

Conclusion

Artificial intelligence–enabled telerehabilitation platforms using markerless computer vision demonstrate high diagnostic accuracy and clinical validity for tracking joint range of motion in musculoskeletal disorders. By providing real-time movement feedback and interactive engagement, AI telerehabilitation drives significantly higher treatment adherence and yields functional recovery outcomes comparable to traditional in-person care. These systems represent a scalable, objective framework for modern digital physical therapy delivery.

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