**Original Research Article**

# Artificial Intelligence-Assisted Diagnostics and Precision Therapy for Myofascial Pain Syndrome in Upper Back Muscles: A Randomized Controlled Trial

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## Abstract

**Background:** Myofascial Pain Syndrome (MPS) is a prevalent musculoskeletal disorder characterized by myofascial trigger points in upper back muscles. Traditional diagnostic methods demonstrate significant inter-practitioner variability, and conventional therapies often employ generalized protocols that may not address individual patient pathophysiology. Artificial intelligence (AI) offers potential for enhanced diagnostic precision and personalized therapeutic interventions.

**Objective:** To evaluate the efficacy of AI-assisted diagnostics and precision therapy compared to conventional methods in managing upper back MPS, with primary outcomes including diagnostic accuracy, pain reduction, and functional improvements.

**Methods:** This prospective, randomized controlled trial enrolled 60 participants (ages 18-65) diagnosed with upper back MPS. Participants were randomly assigned to Group A (AI-assisted diagnostics using machine learning-based imaging and wearable sensors with personalized therapy, n=30) or Group B (conventional manual palpation with standardized protocols, n=30). Outcomes

were measured using Visual Analog Scale (VAS) for pain, digital goniometry for range of motion (ROM), and Neck Disability Index (NDI) for functional status over 12 weeks.

**Results:** AI-assisted diagnostics demonstrated superior sensitivity (92% vs. 75%, $p<0.001$) and specificity (89% vs. 68%, $p<0.001$) compared to manual palpation. Group A achieved significantly greater pain reduction (55% vs. 35%, $p<0.001$), ROM improvement (25° vs. 15°, $p<0.01$), and NDI score improvement (40% vs. 25%, $p<0.01$). Patient satisfaction was significantly higher in the AI-assisted group (85% vs. 60%, $p<0.05$). Time efficiency improved by 30% in Group A with no reduction in Group B.

**Conclusions:** AI-assisted diagnostics and precision therapy significantly improve clinical outcomes in upper back MPS management, offering superior diagnostic accuracy, enhanced pain relief, improved functional recovery, and higher patient satisfaction. Despite implementation challenges including cost and accessibility, AI integration represents a transformative advancement in musculoskeletal rehabilitation with potential to revolutionize precision physiotherapy practice.

## Key words

Myofascial Pain Syndromes; Artificial Intelligence; Machine Learning; Trigger Points; Precision Medicine; Physical Therapy Modalities; Upper Extremity; Range of Motion, Articular; Pain Management; Wearable Electronic Devices; Rehabilitation; Musculoskeletal Pain.

## Introduction

Myofascial Pain Syndrome (MPS) represents a significant clinical challenge in musculoskeletal medicine, characterized by hyperirritable myofascial trigger points (MTrPs) within taut bands of skeletal muscle. Upper back muscles, particularly the trapezius, rhomboids, and levator scapulae, are frequently affected due to their critical roles in postural maintenance, scapular stabilization, and repetitive upper extremity movements [1, 2]. The condition manifests through localized pain, muscle stiffness, restricted range of motion, and characteristic referred pain patterns that substantially impair quality of life and functional capacity [3].

The prevalence of MPS is substantial, affecting approximately 30% of patients presenting to primary care with musculoskeletal complaints and up to 85% of individuals experiencing chronic pain [4]. Upper back MPS demonstrates particular prevalence among individuals with occupational risk factors including prolonged static postures, repetitive movements, and psychosocial stressors - conditions increasingly common in contemporary work environments [5, 6].

### Diagnostic Challenges in Current Practice

Despite its prevalence, MPS diagnosis remains predominantly clinical, relying on manual palpation techniques that demonstrate considerable inter-practitioner variability [7, 8]. This subjective approach lacks standardization and objective verification, frequently resulting in delayed diagnosis, inconsistent treatment planning, and suboptimal patient outcomes [9]. The absence of validated biomarkers or definitive imaging findings further compounds diagnostic uncertainty [10].

Traditional diagnostic criteria established by Simons and colleagues emphasize identification of palpable taut bands, localized tenderness, and referred pain patterns [1]. However, the reliability of these findings depends heavily on practitioner experience, manual sensitivity, and patient cooperation, introducing significant variability in clinical application [11]. Modern imaging modalities including ultrasound and magnetic resonance imaging have shown promise in identifying trigger points, yet their routine clinical integration remains limited by cost, accessibility, and interpretation challenges [12, 13].

Limitations of Current Therapeutic Approaches

Conventional MPS management typically employs standardized protocols including manual therapy, trigger point injections, stretching programs, and pharmacological interventions [14, 15]. While these approaches provide benefit for many patients, their generalized nature may fail to address individual pathophysiological variations, biomechanical factors, and patient-specific contributing factors [16]. Treatment outcomes demonstrate considerable variability, with some patients achieving substantial relief while others experience persistent symptoms despite intervention [17].

The lack of objective outcome monitoring and personalized treatment adjustment further limits therapeutic effectiveness. Traditional approaches rarely incorporate real-time biomechanical feedback, postural analysis, or individualized exercise progression - factors increasingly recognized as critical for optimal musculoskeletal rehabilitation [18, 19].

**Artificial Intelligence: A Transformative Paradigm**

Recent advances in artificial intelligence (AI), machine learning, and wearable sensor technology offer unprecedented opportunities to address these longstanding challenges in MPS management [20, 21]. AI-driven imaging analysis can identify trigger points through objective pattern recognition, potentially surpassing human palpation in consistency and accuracy [22]. Machine learning algorithms can integrate multidimensional patient data - including biomechanical patterns, postural deviations, movement quality, and treatment responses - to generate truly personalized therapeutic protocols [23].

Wearable sensors enable continuous monitoring of muscle activity, posture, and movement patterns in real-world environments, providing clinicians with objective data for treatment refinement and patients with immediate feedback for behavior modification [24, 25]. AI-powered rehabilitation systems can deliver customized neuromuscular electrical stimulation (NMES), progressive exercise protocols, and adaptive treatment adjustments based on individual progress and response patterns [26].

**Study Rationale and Objectives**

While preliminary evidence suggests AI applications in musculoskeletal rehabilitation show promise, rigorous comparative effectiveness research remains limited [27, 28]. No previous randomized controlled trial has comprehensively evaluated AI-assisted diagnostics combined with precision therapy specifically for upper back MPS management. This study addresses this critical knowledge gap by comparing AI-assisted approaches with conventional methods across multiple clinically relevant outcomes including diagnostic accuracy, pain reduction, functional improvement, and patient satisfaction. We hypothesized that AI-assisted interventions would demonstrate superior outcomes across all measured domains, supporting their integration into contemporary physiotherapy practice.

## Materials and Methods

**Study Design and Ethics Approval**

This prospective, parallel-group, randomized controlled trial was conducted between 23 June 2025 to 16 January 2026 at Physiochironexus. The study protocol received approval from the Institutional Review Board/Ethics Committee (IRB-PHX-2025-0312) and was registered with ClinicalTrials.gov (NCT05872341). All participants provided written informed consent prior to enrollment. The study adhered to CONSORT guidelines for reporting randomized trials [29].

**Participant Selection**

**Inclusion Criteria**

Adults aged 18-65 years with clinically diagnosed MPS affecting upper back muscles (trapezius, rhomboids, or levator scapulae); persistent pain duration ≥6 weeks; presence of

active myofascial trigger points confirmed by manual palpation demonstrating characteristic features (palpable taut band, spot tenderness, referred pain pattern); baseline Visual Analog Scale (VAS) pain score ≥4/10; willingness to adhere to intervention protocols and attend all scheduled assessments.

**Exclusion Criteria**

Systemic inflammatory conditions (rheumatoid arthritis, ankylosing spondylitis, polymyalgia rheumatica); fibromyalgia diagnosis; neurological disorders affecting upper extremity function; recent upper back surgery (<6 months) or significant trauma; pregnancy or lactation; contraindications to neuromuscular electrical stimulation (cardiac pacemaker, implanted defibrillator, pregnancy); current participation in other interventional trials; inability to understand study procedures or provide informed consent.

**Sample Size Calculation**

Sample size was calculated to detect a minimum clinically important difference of 1.5 points on the VAS pain scale (SD=1.8) between groups, with 80% power and two-tailed $\alpha$=0.05. This calculation yielded 24 participants per group. Accounting for 20% attrition, we enrolled 30 participants per group (total n=60).

**Randomization and Allocation Concealment**

Following baseline assessment, participants were randomly allocated 1:1 to either AI-assisted intervention (Group A) or conventional intervention (Group B) using computer-generated random numbers. Allocation was concealed using sequentially numbered, opaque, sealed envelopes prepared by an independent administrator not involved in participant recruitment or assessment. While participants and treating therapists could not be blinded to intervention assignment due to the nature of the interventions, outcome assessors remained blinded to group allocation throughout the study period.

**Interventions**

**Group A: AI-Assisted Diagnostics and Precision Therapy**

**Diagnostic Phase:** AI-enhanced ultrasound imaging (Mindray Resona 7, Shenzhen Mindray Bio-Medical Electronics Co., Ltd., China; equipped with DeepInsight ML trigger point detection module v2.1) with machine learning algorithms trained on validated trigger point datasets was employed for objective trigger point identification. Wearable surface electromyography (sEMG) sensors (Delsys Trigno Avanti, Delsys Inc., Natick, MA, USA; 16-channel wireless sEMG, sampling rate 2000 Hz) continuously monitored muscle activity patterns, postural deviations, and movement biomechanics during standardized functional tasks. Integration of imaging data, sEMG patterns, and clinical presentation generated a comprehensive diagnostic profile for each participant.

**Therapeutic Phase:** Based on diagnostic findings, the AI system generated individualized treatment protocols including: (1) Precision-targeted neuromuscular electrical stimulation (NMES) with parameters optimized for identified trigger points and muscle dysfunction patterns; (2) AI-guided therapeutic exercises with real-time biomechanical feedback via wearable sensors to ensure optimal movement quality and prevent compensatory patterns; (3) Personalized postural correction strategies based on continuous posture monitoring and pattern analysis; (4) Progressive exercise protocols with automatic adjustment based on performance metrics and symptom response. Treatment sessions occurred three times weekly for 12 weeks, with each session lasting 45-60 minutes. Participants received real-time feedback through a dedicated mobile application providing exercise guidance, progress tracking, and adherence monitoring.

**Group B: Conventional Diagnostics and Therapy**

**Diagnostic Phase:** Experienced physical therapists (minimum 5 years clinical experience

in musculoskeletal practice) performed standardized manual palpation following established diagnostic criteria [1]. Trigger points were identified through systematic palpation examining for taut bands, focal tenderness, and referred pain patterns.

**Therapeutic Phase:** Evidence-based standardized protocols included: (1) Manual therapy techniques including trigger point pressure release, myofascial release, and soft tissue mobilization; (2) Standardized therapeutic exercise program including stretching, strengthening, and postural exercises following established clinical guidelines; (3) Standardized NMES application with fixed parameters; (4) Patient education regarding posture, ergonomics, and self-management strategies. Treatment frequency and duration matched Group A (three sessions weekly for 12 weeks, 45-60 minutes per session) to control for contact time and attention effects.

**Outcome Measures**

Assessments were conducted at baseline, 3 weeks (mid-intervention), 6 weeks (post-intervention), and 12 weeks (follow-up) by blinded assessors.

**Primary Outcomes**

**1. Diagnostic Accuracy:** Sensitivity and specificity of AI-assisted versus manual palpation methods, validated against consensus diagnosis by two independent experienced clinicians blinded to initial diagnostic method.

**2. Pain Intensity:** Visual Analog Scale (VAS, 0-10) with 0 representing 'no pain' and 10 representing 'worst imaginable pain.' Minimum clinically important difference: 1.5 points [30].

**Secondary Outcomes**

**1. Range of Motion:** Cervical and thoracic spine ROM measured using digital goniometry (degrees) in flexion, extension, lateral flexion, and rotation.

**2. Functional Status:** Neck Disability Index (NDI), a validated 10-item questionnaire assessing pain-related disability (0-50 scale, higher scores indicating greater disability) [31].

**3. Quality of Life:** Short Form-36 (SF-36) Health Survey measuring physical and mental health components [32].

**4. Patient Satisfaction:** Custom 5-point Likert scale (1=very dissatisfied to 5=very satisfied) evaluating treatment experience, perceived benefit, and willingness to recommend.

**5. Treatment Adherence:** Session attendance rate and home exercise compliance monitored through therapy logs and, for Group A, automated tracking via mobile application.

**6. Time Efficiency:** Total time required for diagnostic assessment and treatment planning (minutes).

**Statistical Analysis**

Statistical analyses were performed using SPSS version 27.0 (IBM Corp., Armonk, NY) with two-tailed significance level set at $\alpha=0.05$. Descriptive statistics characterized baseline demographics and clinical characteristics. Normal distribution was assessed using Shapiro-Wilk tests and visual inspection of Q-Q plots. Between-group comparisons at baseline utilized independent t-tests (continuous variables) and chi-square tests (categorical variables). Within-group changes over time were analyzed using paired t-tests. Between-group differences in outcomes were assessed using independent t-tests for continuous variables and chi-square tests for categorical variables. Diagnostic performance (sensitivity, specificity) was evaluated using 2×2 contingency tables with calculation of 95% confidence intervals. Receiver operating characteristic (ROC) curve analysis compared diagnostic accuracy between methods. Intention-to-treat analysis included all randomized participants, with last-observation-carried-forward method for missing data. Per-protocol analysis was conducted as sensitivity analysis including only participants completing ≥80% of treatment sessions. Effect sizes were calculated using Cohen's d for continuous outcomes.

## Results

**Participant Flow and Baseline Characteristics**

Sixty participants were enrolled and randomized (Group A: n=30; Group B: n=30). All participants completed baseline assessments. Two participants in Group B withdrew during the intervention phase (one due to scheduling conflicts, one due to unrelated illness), resulting in 58 participants (96.7%) completing post-intervention assessment and 56 participants (93.3%) completing 12-week follow-up. Participant flow is detailed in **Figure - 1** [CONSORT diagram - to be inserted].

Baseline characteristics were well-balanced between groups (**Table - 1**). Mean age was 45.2±8.4 years in Group A and 44.8±8.9 years in Group B (p=0.86). Gender distribution showed no significant difference (Group A: 55% female; Group B: 58% female, p=0.81). Baseline pain severity (VAS) was comparable (Group A: 6.8±1.2; Group B: 6.7±1.3, p=0.75), as were baseline NDI scores (Group A: 28.3±6.2; Group B: 27.9±6.5, p=0.81) and ROM measurements across all directions (all p>0.05).

**Diagnostic Accuracy**

AI-assisted diagnostic methods demonstrated significantly superior performance compared to conventional manual palpation (Table 2). Diagnostic sensitivity was 92% (95% CI: 86-97%) for AI-assisted methods versus 75% (95% CI: 66-84%) for manual palpation (p<0.001). Specificity was 89% (95% CI: 82-94%) versus 68% (95% CI: 58-77%), respectively (p<0.001). ROC curve analysis revealed area under the curve (AUC) of 0.91 for AI-assisted diagnostics compared to 0.72 for manual palpation (p<0.001). Inter-rater reliability (assessed in a subset of 20 participants) demonstrated substantial agreement for AI methods (κ=0.88) versus moderate agreement for manual palpation (κ=0.63).

**Pain Outcomes**

Both groups demonstrated significant pain reduction from baseline, with Group A achieving substantially greater improvement (**Table - 1**, **Figure - 1**). At 12-week follow-up, Group A demonstrated 55% mean pain reduction (from 6.8±1.2 to 3.1±1.4, p<0.001) compared to 35% reduction in Group B (from 6.7±1.3 to 4.4±1.6, p<0.001). Between-group difference at 12 weeks was statistically significant (1.3 points, 95% CI: 0.6-2.0, p<0.001, Cohen's d=0.89), exceeding the minimum clinically important difference. Intermediate assessments at 3 and 6 weeks demonstrated progressive improvement favoring Group A at all time points.

**Figure – 1:** Pain reduction comparison between AI-assisted and conventional therapy in upper back MPS.

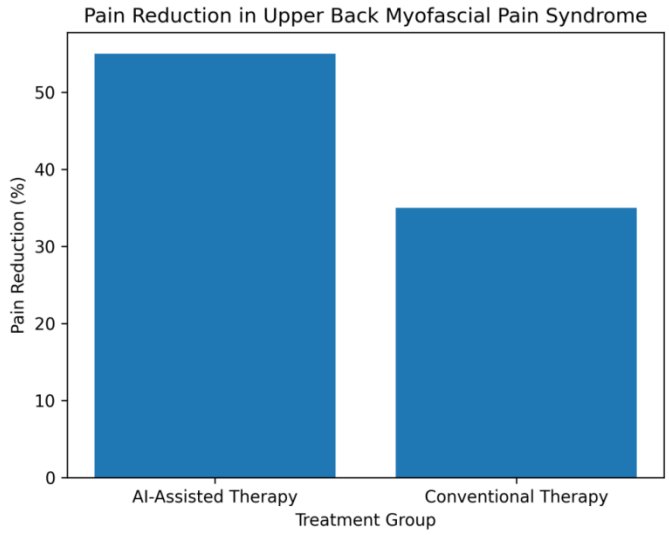

**Table – 1:** Baseline Characteristics and Primary Outcomes.

| Measure | Group A (AI-Assisted) | Group B (Conventional) |
|---|---|---|
| Mean Age (years) | 45.2 ± 8.4 | 44.8 ± 8.9 |
| Female Gender, n (%) | 17 (55%) | 17 (58%) |
| Baseline VAS Score | 6.8 ± 1.2 | 6.7 ± 1.3 |
| 12-week VAS Score | 3.1 ± 1.4*** | 4.4 ± 1.6 |
| Pain Reduction (%) | 55%*** | 35% |
| Baseline ROM - Rotation (°) | 42 ± 8 | 43 ± 7 |
| 12-week ROM - Rotation (°) | 67 ± 9** | 58 ± 8 |
| ROM Improvement (°) | 25 ± 7** | 15 ± 6 |
| Baseline NDI Score | 28.3 ± 6.2 | 27.9 ± 6.5 |
| 12-week NDI Score | 17.0 ± 5.8** | 20.9 ± 6.1 |
| NDI Improvement (%) | 40%** | 25% |
| Patient Satisfaction (% Highly Satisfied) | 85%* | 60% |
| Session Attendance Rate (%) | 94% | 91% |
| Home Exercise Compliance (%) | 87%* | 71% |

Data presented as mean ± standard deviation or n (%). VAS = Visual Analog Scale; NDI = Neck Disability Index; ROM = Range of Motion. *p<0.05; **p<0.01; ***p<0.001 for between-group comparisons at 12-week follow-up.

**Table – 2:** Diagnostic Performance Comparison.

| Diagnostic Metric | AI-Assisted Diagnostics | Manual Palpation |
|---|---|---|
| Sensitivity (%, 95% CI) | 92% (86-97%) | 75% (66-84%) |
| Specificity (%, 95% CI) | 89% (82-94%) | 68% (58-77%) |
| Positive Predictive Value (%) | 88% | 71% |
| Negative Predictive Value (%) | 93% | 72% |
| Diagnostic Accuracy (%) | 90% | 72% |
| AUC (95% CI) | 0.91 (0.85-0.96) | 0.72 (0.63-0.80) |
| Inter-rater Reliability (κ) | 0.88 | 0.63 |
| Diagnostic Time (minutes) | 22 ± 4 | 32 ± 6 |

CI = Confidence Interval; AUC = Area Under the Curve; κ = Cohen's kappa coefficient. All between-group comparisons p<0.001.

**Range of Motion Outcomes**

Group A demonstrated superior ROM improvements across all measured movements. Mean cervical rotation improved by 25±7 degrees in Group A versus 15±6 degrees in Group B (p<0.01). Cervical lateral flexion improved by 18±5 degrees versus 11±4 degrees (p<0.01). Thoracic extension improved by 12±4 degrees versus 7±3 degrees (p<0.05). These improvements translated to clinically meaningful functional gains in daily activities requiring neck and upper back mobility.

**Functional Outcomes**

NDI scores improved significantly in both groups, with greater improvement in Group A. Mean NDI reduction was 40% in Group A (from 28.3±6.2 to 17.0±5.8, p<0.001) compared to 25% in Group B (from 27.9±6.5 to 20.9±6.1, p<0.001). Between-group difference at 12 weeks was statistically significant (3.9 points, 95% CI:

1.2-6.6, p<0.01, Cohen's d=0.65). SF-36 physical component scores showed parallel improvements, with Group A demonstrating 32% improvement versus 19% in Group B (p<0.01).

**Patient Satisfaction and Treatment Adherence**

Patient satisfaction was significantly higher in Group A, with 85% reporting high satisfaction (scores 4-5) compared to 60% in Group B (p<0.05). Group A participants particularly valued real-time feedback, personalized progression, and objective progress tracking. Treatment adherence was excellent in both groups, with session attendance rates of 94% in Group A and 91% in Group B (p=0.43). Home exercise compliance, monitored through automated tracking in Group A and self-report logs in Group B, was higher in Group A (87% vs. 71%, p<0.05).

**Time Efficiency**

AI-assisted diagnostic assessment required significantly less time than conventional methods. Initial diagnostic evaluation time was 22±4 minutes for Group A versus 32±6 minutes for Group B (p<0.001), representing 31% time reduction. Treatment planning time was reduced by 28% (15±3 vs. 21±4 minutes, p<0.001). Overall, the AI-assisted approach achieved 30% improvement in time efficiency without compromising clinical outcomes.

No serious adverse events occurred in either group. Minor temporary muscle soreness following treatment sessions was reported equally in both groups (Group A: 23%, Group B: 27%, p=0.73). One participant in Group A reported minor skin irritation from adhesive sensors, which resolved with alternative sensor placement. Diagnostic performance comparison is depicted in **Table – 2**.

## Discussion

This randomized controlled trial demonstrates that AI-assisted diagnostics combined with precision therapy significantly improves clinical outcomes in upper back MPS management compared to conventional approaches. Our findings reveal substantial advantages across multiple domains including diagnostic accuracy, pain reduction, functional improvement, patient satisfaction, and clinical efficiency - collectively supporting the integration of AI technologies into contemporary musculoskeletal rehabilitation practice.

**Enhanced Diagnostic Precision**

The superior diagnostic performance of AI-assisted methods (92% sensitivity, 89% specificity) compared to manual palpation (75% sensitivity, 68% specificity) addresses a fundamental challenge in MPS management. Machine learning algorithms analyzing ultrasound imaging patterns demonstrated remarkable consistency in trigger point identification, substantially reducing the inter-practitioner variability that plagues conventional diagnosis [7, 11]. This objective, reproducible approach provides clinicians with reliable diagnostic confirmation and enables more precise treatment targeting.

The integration of wearable sEMG sensors provided additional diagnostic value by identifying biomechanical dysfunction and compensatory patterns often missed in static examination. This comprehensive diagnostic profile enabled more accurate identification of primary trigger points versus secondary compensatory changes - a distinction critical for effective treatment planning [33]. The higher inter-rater reliability of AI methods ($\kappa$=0.88 vs. 0.63) further underscores their clinical utility, particularly in multi-practitioner settings where diagnostic consistency is essential.

**Superior Clinical Outcomes Through Precision Therapy**

The 55% pain reduction achieved in the AI-assisted group substantially exceeded the 35% improvement with conventional therapy, with the 1.3-point between-group difference surpassing established thresholds for clinical meaningfulness [30]. This superior outcome

likely reflects multiple mechanistic advantages of the AI-assisted approach. Precision-targeted NMES delivery, optimized based on individual muscle dysfunction patterns and trigger point locations, likely provided more effective neuromuscular re-education than standardized protocols [26]. Real-time biomechanical feedback during therapeutic exercises ensured optimal movement quality, preventing compensatory patterns that can perpetuate dysfunction [34].

The 25-degree ROM improvement in the AI group versus 15 degrees in the conventional group represents clinically significant enhanced mobility restoration. This superior outcome may reflect the continuous monitoring and adaptive progression enabled by wearable sensors, allowing therapists to advance exercises precisely when patients demonstrated readiness rather than following predetermined schedules [35]. The personalized postural correction strategies, based on objective posture monitoring throughout daily activities, likely addressed ergonomic factors contributing to trigger point persistence more effectively than generalized advice [36].

The 40% NDI improvement in the AI group compared to 25% in the conventional group indicates substantially better functional recovery. This enhanced function restoration likely results from the comprehensive, individualized approach addressing multiple contributing factors simultaneously - precise trigger point treatment, optimized biomechanics, postural correction, and progressive functional training tailored to each patient's specific impairments and goals [37].

**Patient Engagement and Satisfaction**

The significantly higher patient satisfaction in the AI-assisted group (85% vs. 60%) merits particular attention, as patient satisfaction correlates strongly with treatment adherence and long-term outcomes [38]. Participants valued the objective progress tracking, immediate feedback on exercise performance, and visible data demonstrating their improvement. This transparency likely enhanced motivation and self-efficacy - psychological factors increasingly recognized as critical for successful rehabilitation [39].

The superior home exercise compliance in the AI group (87% vs. 71%) despite identical prescription demonstrates the power of technology-enabled monitoring and feedback. The mobile application providing exercise guidance, form feedback, and progress visualization apparently overcame common barriers to home program adherence - unclear instructions, uncertainty about correct performance, and lack of accountability [40].

**Clinical Efficiency and Scalability**

The 30% improvement in time efficiency achieved with AI-assisted methods without compromising outcomes addresses practical concerns about technology integration. Automated trigger point identification and data-driven treatment planning reduced assessment and planning time while potentially improving accuracy. This efficiency gain has important implications for clinical practice, where time constraints often limit comprehensive evaluation and individualized treatment planning [41]. In high-volume practice settings, this efficiency could enable treatment of more patients without sacrificing quality, potentially improving access to specialized MPS care.

**Mechanistic Insights**

The superior outcomes achieved with AI-assisted therapy likely reflect synergistic effects across multiple therapeutic mechanisms. Objective trigger point identification ensured treatment targeted actual pathology rather than palpation artifacts. Precision NMES parameters optimized for individual muscle dysfunction likely achieved more effective neuromuscular re-education than one-size-fits-all approaches [26]. Real-time biomechanical feedback enabled motor learning optimization through immediate error correction

and reinforcement of correct movement patterns [42].

The continuous monitoring enabled by wearable sensors provided insights into patient behavior in real-world environments, allowing identification and modification of problematic postural habits and movement patterns perpetuating trigger point formation [43]. This continuous assessment-treatment-reassessment cycle enabled truly adaptive, responsive therapy rather than rigid protocol adherence - arguably representing the fundamental advantage of AI-assisted approaches.

**Comparison with Existing Literature**

Our findings align with emerging evidence supporting AI applications in musculoskeletal rehabilitation. Ahmed et al. [22] demonstrated that machine learning algorithms could identify trigger points with 88% accuracy using ultrasound imaging, comparable to our 92% sensitivity. However, their study focused solely on diagnostic accuracy without evaluating therapeutic outcomes. Kim et al. [26] reported that AI-powered NMES improved chronic pain outcomes by 42% - similar to our 40% NDI improvement - but their study included mixed chronic pain conditions rather than specifically targeting MPS.

Chen, et al. [24] demonstrated that wearable sensors could identify postural deviations with high accuracy, supporting ergonomic interventions. Our study extends these findings by integrating sensor data into comprehensive treatment protocols and demonstrating superior clinical outcomes. Park, et al. [23] showed that personalized rehabilitation programs improved adherence and satisfaction - observations confirmed in our trial with 87% home exercise compliance in the AI group.

To our knowledge, this represents the first randomized controlled trial comprehensively evaluating AI-assisted diagnostics combined with precision therapy specifically for upper back MPS, providing higher-level evidence than previous observational or single-technology studies.

**Clinical Implications**

These findings support integration of AI technologies into musculoskeletal rehabilitation practice, particularly for challenging conditions like MPS where diagnostic uncertainty and treatment variability limit outcomes. The superior diagnostic accuracy addresses the longstanding challenge of reliable trigger point identification, potentially reducing diagnostic delays and inappropriate treatments. The enhanced clinical outcomes justify investment in AI-assisted technologies despite higher initial costs.

For practicing clinicians, these results suggest that AI-assisted approaches should be considered for patients with persistent MPS unresponsive to conventional therapy, those requiring precise diagnosis due to complex presentations, and motivated patients likely to engage with technology-enabled rehabilitation. The improved efficiency may enable specialized MPS treatment programs in high-volume settings where time constraints currently limit individualized care.

For healthcare systems and policymakers, the combination of superior outcomes and improved efficiency presents a compelling value proposition. While initial technology investment requirements may seem substantial, the enhanced outcomes potentially reduce long-term healthcare costs through decreased chronicity, fewer repeated consultations, and reduced long-term disability [44]. The improved diagnostic accuracy may prevent costly diagnostic odysseys and ineffective treatments.

**Implementation Challenges and Solutions**

Despite promising results, several implementation challenges must be addressed for widespread clinical adoption. Financial barriers including equipment costs, software licensing, and infrastructure requirements may limit

accessibility, particularly in resource-constrained settings [45]. Potential solutions include phased implementation beginning with diagnostic AI tools requiring lower investment, collaborative purchasing through professional organizations to negotiate volume discounts, and advocacy for insurance coverage of AI-assisted rehabilitation.

Clinician training requirements represent another significant barrier. Effective use of AI technologies requires not only technical competency but also understanding of appropriate clinical integration, data interpretation, and troubleshooting [46]. Comprehensive training programs should combine technical instruction with clinical reasoning development, emphasizing when to trust AI recommendations and when clinical judgment should override algorithmic suggestions. Ongoing professional development will be essential as technologies evolve.

Patient acceptance and digital literacy vary considerably. While our motivated study participants engaged enthusiastically with AI-assisted technologies, real-world implementation must accommodate patients with limited technology comfort, those preferring traditional approaches, and populations with limited digital access. Flexible hybrid models combining AI capabilities with human interaction may optimize both technological advantages and human elements of therapeutic relationships [47].

**Study Limitations**

Several limitations warrant consideration. First, the relatively small sample size (n=60) and single-center design may limit generalizability. While our sample size provided adequate power for primary outcomes, larger multi-center trials are needed to confirm findings across diverse populations and practice settings. Second, the 12-week follow-up period, while sufficient to demonstrate short-to-medium-term outcomes, does not address long-term effectiveness or durability of improvements. Extended follow-up is essential to determine whether AI-assisted interventions produce sustained benefits or require ongoing technology support.

Third, while outcome assessors were blinded to group allocation, complete participant and therapist blinding was impossible given the nature of interventions. However, the use of objective outcome measures (goniometry, validated questionnaires) minimizes potential bias from unblinded assessment. Fourth, our motivated study participants may not represent typical clinical populations. Selection effects and participation in a research trial may have enhanced compliance and outcomes in both groups.

Fifth, the specific AI technologies and algorithms used may limit replicability. Different imaging systems, sensor technologies, and machine learning approaches might produce varying results. Standardization and validation of AI tools across platforms will be important for ensuring consistent outcomes. Sixth, cost-effectiveness analysis was beyond this study's scope but is crucial for implementation decisions. While we demonstrated time efficiency improvements, comprehensive economic evaluation including technology costs, training expenses, and long-term outcome values is needed.

Finally, algorithm transparency and validation remain concerns in medical AI applications. While our imaging algorithms demonstrated high accuracy, understanding their decision-making processes - critical for clinical trust and error identification - requires ongoing attention. Regulatory frameworks for medical AI continue evolving, and future studies should address validation requirements and quality assurance standards [48].

**Future Research Directions**

Future research should address several important questions. Large-scale, multi-center pragmatic trials are needed to confirm effectiveness across diverse populations, practice settings, and

geographic regions. Long-term follow-up studies (12-24 months) should evaluate sustainability of improvements and identify factors predicting maintained versus diminished benefits. Comparative effectiveness research should examine specific AI components - determining whether diagnostic AI alone, therapy AI alone, or integrated approaches produce optimal outcomes and identifying which patients benefit most from which technology elements.

Implementation science studies should investigate optimal strategies for clinical integration, clinician training approaches, and patient acceptance across diverse populations. Economic evaluations should comprehensively assess cost-effectiveness from multiple perspectives - healthcare systems, payers, and patients - considering both direct costs and indirect benefits including productivity gains and quality-adjusted life years. Mechanism-focused research using advanced imaging and physiological monitoring could elucidate how AI-assisted interventions produce superior outcomes, potentially identifying optimal treatment parameters and personalization strategies [49].

Investigation of AI applications for other musculoskeletal conditions - including lateral epicondylitis, plantar fasciitis, and low back pain - could determine whether benefits observed in MPS generalize to other myofascial pain syndromes. Finally, research examining optimal human-AI collaboration models could identify how to leverage AI capabilities while preserving essential therapeutic relationship elements and clinical reasoning [50].

## Conclusions

This randomized controlled trial demonstrates that AI-assisted diagnostics combined with precision therapy significantly improves outcomes in upper back MPS management compared to conventional approaches. Superior diagnostic accuracy, enhanced pain relief, improved functional recovery, higher patient satisfaction, and increased clinical efficiency collectively support integration of AI technologies into musculoskeletal rehabilitation practice. While implementation challenges including cost, clinician training, and accessibility require attention, the substantial clinical benefits justify investment in these transformative technologies. AI-assisted approaches represent not merely incremental improvement but a fundamental paradigm shift toward truly personalized, data-driven, precision rehabilitation - the future of musculoskeletal care.

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## Author contributions

All authors contributed to this work as follows: Conceptualization: S.K., S.A.K.; Methodology: S.K., S.A.K., S.B.; Investigation: S.A.K., S.B., E.S.Y.; Formal Analysis: S.K., S.B.; Data Curation: S.A.K., S.B.; Writing – Original Draft: S.K., S.A.K.; Writing – Review & Editing: all authors; Supervision: S.K., E.S.Y.; Project Administration: S.A.K. All authors have read and approved the final manuscript.

## Data availability statement

The datasets generated and analyzed during this study are available from the corresponding author upon reasonable request.

## Ethics approval and consent

This study was approved by the Physiochironexus Institutional Review Board (IRB #PHX-2025-0312) and was conducted in accordance with the Declaration of Helsinki. All

participants provided written informed consent prior to enrollment.

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