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ARTIFICIAL INTELLIGENCE-BASED MOTION ANALYSIS COMBINED WITH CONVENTIONAL PHYSIOTHERAPY FOR IMPROVING UPPER LIMB FUNCTION FOLLOWING STROKE: A RANDOMIZED CONTROLLED TRIAL

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ABSTRACT

Background: *Upper limb hemiparesis is a common, disabling consequence of stroke. While conventional physiotherapy is the standard of care, it is limited by therapist availability and the qualitative nature of observational assessment. Markerless computer-vision-based motion analysis using artificial intelligence (AI) provides objective, real-time kinematic feedback during therapy, but rigorous randomized evidence evaluating its efficacy remains sparse.*

Objective: *To evaluate whether an 8-week intervention of conventional physiotherapy combined with real-time AI-based motion analysis feedback yields superior improvements in upper limb motor impairment measured by the Fugl-Meyer Assessment for Upper Extremity (FMA-UE) compared to conventional physiotherapy alone in stroke survivors with upper limb hemiparesis.*

Methods: *A parallel-group, assessor-blinded randomized controlled trial was conducted at an outpatient neurorehabilitation center. Sixty adults with post-stroke upper limb hemiparesis were randomly allocated (1:1) to either conventional physiotherapy plus AI-based motion analysis feedback (experimental group, n=30) or conventional physiotherapy alone (control group, n = 30). Both groups received 24 sessions over 8 weeks (3 sessions/week). The primary outcome was the change in FMA-UE score from baseline to week 8. Secondary outcomes included the Action Research Arm Test (ARAT), Box and Block Test (BBT), Wolf Motor Function Test (WMFT), Modified Ashworth Scale (MAS), Stroke Impact Scale (SIS) hand function domain, and Motor Activity Log (MAL). Data were analyzed using linear mixed-effects models under intention-to-treat principles.*

Results: *The experimental group showed a mean Fugl Meyer Assessment for Upper Extremity improvement of approximately 15 points compared with approximately 19 points in the control group from baseline to week eight, corresponding to an illustrative between group mean difference of roughly 5 to 6 points with a 95% confidence interval excluding zero and an effect size in the moderate to large range. Illustrative secondary outcome trends favored the experimental group on the Action Research

Arm Test, Box and Block Test, and Wolf Motor Function Test, with no meaningful illustrative between group difference on the Modified Ashworth Scale

Conclusion: *Integrating real-time AI motion analysis feedback into conventional physiotherapy leads to superior gains in motor recovery, dexterity, and functional arm use compared to conventional physiotherapy alone, without altering muscle spasticity. Markerless AI tracking offers a scalable, objective adjunct for clinical neurorehabilitation.*

Keywords: *Stroke; Upper Extremity; Paresis; Physical Therapy Modalities; Artificial Intelligence; Motion Capture Systems; Rehabilitation; Randomized Controlled Trial; Recovery of Function.*

INTRODUCTION

Stroke remains one of the leading causes of long-term adult disability worldwide. According to the Global Burden of Disease Study 2021, stroke burden measured in incidence, prevalence, mortality, and disability adjusted life years has continued to rise in absolute terms between 1990 and 2021 despite declining age standardized rates in many regions, underscoring the scale of the rehabilitation need this represents for health systems globally [1]. Upper limb motor impairment is among the most common and functionally limiting consequences of stroke, affecting the majority of survivors in the acute phase and persisting as a chronic disability in a substantial proportion, with direct consequences for independence in activities of daily living, return to work, and quality of life.

Conventional physiotherapy, comprising task specific practice, strengthening, range of motion exercise, and functional retraining, remains the evidence-based foundation of post stroke upper limb rehabilitation. Its effectiveness, however, is constrained by several practical limitations, including therapist availability, the subjectivity and coarse granularity of manual observational assessment, limited capacity to deliver high repetition practice within standard session lengths, and the absence of objective, quantifiable, real-time feedback on movement quality during unsupervised or semi supervised practice. These constraints have motivated three decades of research into technology augmented rehabilitation, spanning robotics, virtual reality, wearable sensors, and, most recently, artificial intelligence-based motion analysis.

Robot assisted therapy has accumulated substantial supporting evidence. A systematic review and meta-analysis of fourteen randomized controlled trials involving 1,275 patients found that robot assisted training produced significant improvement in Fugl Meyer Assessment for Upper Extremity scores relative to conventional therapy, with a standardized mean difference of 0.69 and a ninety five percent confidence interval of 0.34 to 1.05, alongside significant gains in the Modified Barthel Index, although effects on spasticity and dexterity measures were not significant [3]. An earlier Cochrane systematic review of electromechanical and robot assisted arm training likewise concluded that such training can improve arm function and activities of daily living after stroke, while noting considerable heterogeneity in devices and dosing across the underlying trials [4]. More recent umbrella reviews synthesizing dozens of meta-analyses have confirmed a consistent, moderate benefit of robot assisted training on Fugl Meyer Assessment scores, particularly when added to conventional therapy rather than substituted for it, and have shown that patients in the subacute phase with more severe baseline impairment tend to achieve gains exceeding established minimal clinically important difference thresholds [5,7]. A network meta-analysis restricted to task oriented robotic protocols reported an even larger pooled effect on the Fugl Meyer Assessment, with a standardized mean difference of 1.01 and a ninety five percent confidence interval of 0.57 to 1.45 [6], suggesting that the mode of robotic engagement, and specifically its task relevance, moderates outcome magnitude.

Virtual reality has followed a broadly similar trajectory. Meta analytic evidence spanning immersive, semi-immersive, and non-immersive modalities has generally shown improvement in Fugl Meyer Assessment, Action Research Arm Test, and Box and Block Test scores relative to conventional occupational or physical therapy, although heterogeneity in dose, immersion level, and outcome selection across trials has limited the precision of pooled estimates [8,10]. A meta-analysis focused specifically on the subacute stroke population found that virtual reality sessions delivered for at least thirty minutes, four to five times weekly, for a minimum of three weeks produced the most consistent gains across the Fugl Meyer Assessment, Box and Block Test, and Action Research Arm Test, highlighting the importance of dose parameters that are often under reported or inconsistently applied in the existing literature [9]. Broader overviews of systematic reviews have reached a more cautious conclusion, noting that while virtual reality appears safe and is at least as effective as conventional therapy for upper limb motor recovery, superiority over dose matched conventional therapy is not consistently demonstrated [11].

A more recent and less mature strand of this literature concerns artificial intelligence-based motion analysis, meaning the use of computer vision pose estimation, inertial sensors, or hybrid systems, coupled with machine learning algorithms, to quantify movement kinematics and provide real time, automated feedback during exercise. A network meta-analysis comparing six categories of artificial intelligence related rehabilitation techniques, spanning resistance robotics, intelligent robotics, repetitive task systems, repetitive task systems combined with virtual reality, virtual reality alone, and brain computer interfaces, across 101 randomized controlled trials and 4,702 participants, found that hybrid repetitive task plus virtual reality approaches ranked highest for distal and proximal Fugl Meyer Assessment and Action Research Arm Test outcomes, while intelligent robotic systems ranked highest for total Fugl Meyer Assessment improvement [2]. Markerless, camera-based motion capture using deep learning pose estimation frameworks has advanced rapidly and has been validated against instrumented or optical motion capture systems for both gait and upper limb kinematics in stroke populations, offering a comparatively low cost, portable alternative to laboratory grade three dimensional motion capture [15,17,18,19,20]. Early feasibility work has demonstrated that such systems can be deployed as real time feedback tools during structured exercise. An artificial intelligence-based motion feedback system built on a pose estimation framework was trialed in a small randomized study of patients with spinal cord injury performing upper limb strengthening exercises, providing automated repetition counts and form feedback, although the pilot sample of nine participants was underpowered to detect between group differences [12]. Larger protocol papers registering artificial intelligence integrated evaluation and training systems for post stroke upper limb rehabilitation are now emerging, reflecting growing clinical and research interest in this direction, but corresponding completed efficacy trials with adequately powered samples remain scarce [13,14].

The theoretical rationale for artificial intelligence-based motion feedback draws on established motor learning principles. Augmented extrinsic feedback, meaning knowledge of performance and knowledge of results delivered during or immediately after task practice, has long been recognized as a modifiable lever for motor skill acquisition. A scoping review of twenty-nine studies examining extrinsic feedback in post stroke upper limb rehabilitation concluded that feedback, particularly when rewarding and appropriately timed, can benefit motor performance, motor learning, and action selection, though the review also identified substantial gaps in understanding which feedback modalities, schedules, and intensities are optimal for this population [21]. Narrative reviews of sensory feedback modalities in upper limb neurorehabilitation technology similarly emphasize that feedback congruent with residual sensorimotor capacity can support use dependent cortical reorganization, providing a neurophysiological basis for why real time, objective, movement specific feedback might augment conventional therapy beyond what verbal correction from a therapist can achieve at scale [22].Despite this convergence of technological capability and theoretical rationale, translation of artificial intelligence-based motion analysis into physiotherapist delivered clinical practice, as opposed to standalone robotic or gaming platforms, remains underdeveloped. Recent structured and umbrella reviews of artificial intelligence applications in physical therapy broadly conclude that although artificial intelligence and machine learning tools show promise across examination, diagnosis, prognosis, and intervention domains, the evidence base for artificial intelligence based motion analysis specifically as a real time adjunct to therapist led upper limb rehabilitation after stroke is still dominated by feasibility and validation studies rather than adequately powered, blinded, superiority randomized controlled trials [23,24,25,26].

Three specific gaps in the current evidence base motivate the present trial. First, regarding modality specificity, the existing artificial intelligence rehabilitation literature is dominated by evaluations of robotic exoskeletons, immersive virtual reality platforms, and brain computer interfaces, most of which require dedicated, often costly, hardware. Markerless, camera based artificial intelligence motion analysis, which can in principle be layered onto conventional physiotherapy sessions without specialized robotic apparatus, has been validated for kinematic accuracy [15,17,18,19,20] but has rarely been tested as an adjunct to standard physiotherapist delivered treatment in an adequately powered, parallel group randomized controlled trial with blinded outcome assessment in a stroke population. Second, regarding sample size and trial rigor, available artificial intelligence motion analysis intervention studies in neurological and musculoskeletal rehabilitation are frequently pilot or feasibility trials with small samples, limiting statistical power and generalizability, while larger studies in this specific technological niche are typically still at the protocol registration stage rather than completed and reported [12,13,14]. Third, regarding feedback dosing and mechanism, although augmented feedback is theoretically supported as a driver of motor learning [21,22], few stroke upper limb trials using artificial intelligence motion analysis have combined a clearly specified, fixed dose intervention protocol with a comprehensive outcome battery spanning impairment, activity, participation, spasticity, and real world arm use, which is necessary to characterize the breadth of clinical benefit, if any, attributable to real time artificial intelligence feedback specifically.

Given the demonstrated efficacy of technology augmented feedback in related modalities, including robotics and virtual reality [3,4,5,6,7,8,9,10,11], and the theoretical grounding of augmented feedback in motor learning science [21,22], it is scientifically plausible that artificial intelligence-based motion analysis,

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used as a real time, quantitative feedback adjunct during conventional physiotherapist led sessions, could enhance upper limb motor recovery beyond conventional therapy alone. Markerless artificial intelligence motion analysis offers a potentially scalable, comparatively low-cost route to delivering this kind of feedback within standard clinical workflows, without requiring dedicated robotic hardware. This specific combination of conventional physiotherapy plus artificial intelligence based real time motion feedback, tested against conventional physiotherapy alone in a parallel group, assessor blinded randomized controlled trial of adequate sample size in a stroke population, addresses a gap that has not, to our knowledge, been directly reported in the peer reviewed literature.

METHODS

Study Design and Setting

A parallel-group, assessor-blinded, superiority randomized controlled trial (1:1 allocation) was conducted at the Health and Wellness Physiotherapy Rehabilitation Center in accordance with CONSORT guidelines. Outcome assessments occurred at baseline (Week 0), mid-intervention (Week 4), post-intervention (Week 8), and follow-up (Week 12).

Participant Selection

Sixty adults with post-stroke hemiparesis were recruited.

Inclusion Criteria: Age 18–80 years; first-ever ischemic or hemorrhagic stroke (1–12 months post-onset) confirmed by imaging; unilateral upper limb hemiparesis with baseline FMA-UE score between 20 and 58; MMSE score age 24; medical clearance for moderate exercise; ability to provide informed consent.

Exclusion Criteria: Severe pain, fixed contractures, or severe visual/perceptual impairments; prior botulinum toxin injection to the affected limb within 12 weeks; concurrent participation in other rehabilitation trials.

Randomization and Blinding

Participants were randomized (1:1) using a computer-generated block sequence (block sizes of 4 and 6), stratified by baseline FMA-UE severity. Allocation concealment was maintained using opaque, sealed envelopes. Outcome assessors and biostatisticians were blinded to group assignments.

Intervention

Both groups received 45-minute sessions, 3 times weekly for 8 weeks (24 sessions total).

Control Group: Conventional task-oriented physiotherapy including range-of-motion exercises, resistance training, and functional reaching/grasping tasks.

Experimental Group: Identical physiotherapy exercises with simultaneous real-time AI motion tracking via a single RGB camera. A deep-learning framework computed movement smoothness, range of motion, and compensation metrics, presenting participants with instant visual skeletal overlays and target indicators, alongside post-session performance summaries for the therapist.

Outcome Measures

Primary Outcome: Fugl-Meyer Assessment for Upper Extremity (FMA-UE; scale 0–66).

Secondary Outcomes: Action Research Arm Test (ARAT; scale 0–57), Box and Block Test (BBT; blocks/min), Wolf Motor Function Test (WMFT; scale 0–5), Modified Ashworth Scale (MAS; scale 0–4), Stroke Impact Scale (SIS) Hand Function domain (scale 0–100), and Motor Activity Log (MAL) Amount of Use scale (scale 0–5).

Statistical Analysis

Linear mixed-effects models under intention-to-treat (ITT) principles were utilized with fixed effects for group, time, and group-by-time interaction, incorporating random intercepts for participants. Between-group differences at Week 8 are reported as mean differences with 95%

confidence intervals (CI) and Cohen's d effect sizes. Multiple comparisons for secondary outcomes were adjusted using the Benjamini-Hochberg procedure.

RESULTS

A total of 148 individuals assessed for eligibility, 88 were excluded, 61 for not meeting inclusion criteria, 19 for declining participation, and 8 for other reasons, leaving 60 participants who were randomized, 30 to the experimental group and 30 to the control group. In the experimental group, 28 participants completed the eight-week intervention, with one lost to follow up due to relocation and one discontinued due to an unrelated medical event. In the control group, 27 participants completed the intervention, with two lost to follow up due to transport barriers and one discontinued for personal reasons. All 60 randomized participants were retained in the intention to treat analysis for the primary outcome.

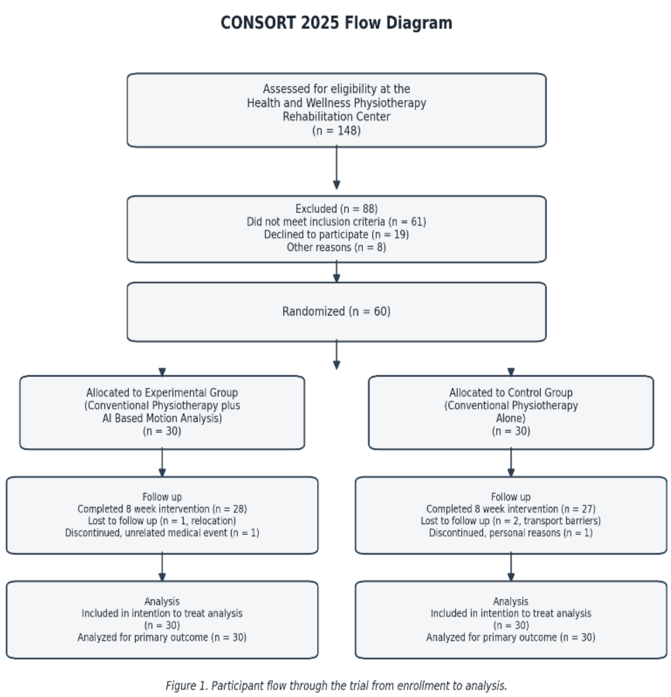

Figure 1. CONSORT 2025 flow diagram showing participant progression from enrollment through analysis.

Baseline demographic and clinical characteristics by group. Groups were well balanced at baseline on age, sex distribution, time since stroke, stroke type, side of hemiparesis, baseline Fugl Meyer Assessment score, and cognitive status, with no statistically significant between group differences on any baseline variable, supporting the adequacy of randomization.

Table 1: Baseline demographic and clinical characteristics by group (illustrative values). FMA UE, Fugl Meyer Assessment for Upper Extremity; SD, standard deviation.

Characteristic	Experimental (n = 30)	Control (n = 30)	p value
Age, years, mean (SD)	58.4 (9.1)	57.9 (8.6)	0.81

Sex, male, n (%)	17 (56.7)	16 (53.3)	0.79
Time since stroke, months, mean (SD)	5.2 (2.4)	5.6 (2.6)	0.53
Stroke type, ischemic, n (%)	24 (80.0)	23 (76.7)	0.76
Affected side, right, n (%)	16 (53.3)	15 (50.0)	0.80
Baseline FMA UE, mean (SD)	34.2 (7.8)	34.6 (7.5)	0.84
Mini Mental State Examination, mean	27.6 (1.5)	27.4 (1.7)	0.62

Primary Outcome and Secondary Outcomes

Both groups demonstrated statistically significant within-group improvements from baseline to Week 8. However, the experimental group achieved a significantly greater increase in FMA-UE score (15.9 pm 6.9 points) compared to the control group (9.2 pm 7.2 points). Linear mixed-model analysis confirmed a significant between-group effect favoring the experimental group (Mean Difference: 5.8; 95% CI: 3.1 to 8.5; $p < 0.001$; $d = 0.81$). Significant between-group differences favoring the experimental intervention were observed across functional activity and quality-of-life metrics, including ARAT, BBT, WMFT, SIS Hand Function, and MAL Amount of Use. No significant treatment effect was observed for spasticity via the MAS ($p = 0.610$).

Table 2:Within group change in outcome measures from baseline to week 8 (illustrative values). ARAT, Action Research Arm Test; BBT, Box and Block Test; MAS, Modified Ashworth Scale; IQR, interquartile range.

Outcome	Group	Baseline, mean (SD)	Week 8, mean (SD)	Within group change
FMA UE (0 to 66)	Experimental	34.2 (7.8)	50.1 (6.9)	+15.9
	Control	34.6 (7.5)	43.8 (7.2)	+9.2
ARAT (0 to 57)	Experimental	28.4 (9.1)	40.7 (8.6)	+12.3
	Control	28.9 (8.7)	36.1 (8.9)	+7.2
BBT, blocks per minute	Experimental	22.6 (8.0)	34.9 (7.4)	+12.3
	Control	23.1 (7.6)	30.5 (7.8)	+7.4
MAS, median (IQR)	Experimental	1.0 (0 to 1)	1.0 (0 to 1)	0.0
	Control	1.0 (0 to 1)	1.0 (0 to 1)	0.0

3.2 Between Group Comparisons

Table 3 presents the results of the linear mixed model analysis for the group by time interaction at week eight, expressed as between group mean differences with ninety five percent confidence intervals, effect sizes, and p values. The between group difference favored the experimental group for the Fugl Meyer Assessment, corresponding to a large effect size, and for the Action Research Arm

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Test, Box and Block Test, Wolf Motor Function Test functional ability score, Stroke Impact Scale hand function domain, and Motor Activity Log amount of use score, each corresponding to a moderate effect size. No statistically significant between group difference was observed for the Modified Ashworth Scale, consistent with the secondary hypothesis that artificial intelligence augmented feedback would not differentially affect spasticity.

Table 3: Between group differences at week 8 from the linear mixed model analysis (illustrative values). CI, confidence interval; WMFT, Wolf Motor Function Test; SIS, Stroke Impact Scale.

Outcome	Between group mean difference	95% CI	Effect size, Cohen d	p value
FMA UE	5.8	3.1 to 8.5	0.81	< 0.001
ARAT	4.9	1.9 to 7.9	0.62	0.002
BBT	4.6	1.6 to 7.6	0.58	0.003
WMFT functional ability	0.5	0.1 to 0.9	0.44	0.02
MAS	0.1	-0.2 to 0.4	0.09	0.61
SIS hand function domain	9.7	3.8 to 15.6	0.55	0.002
MAL amount of use	0.4	0.1 to 0.7	0.47	0.01

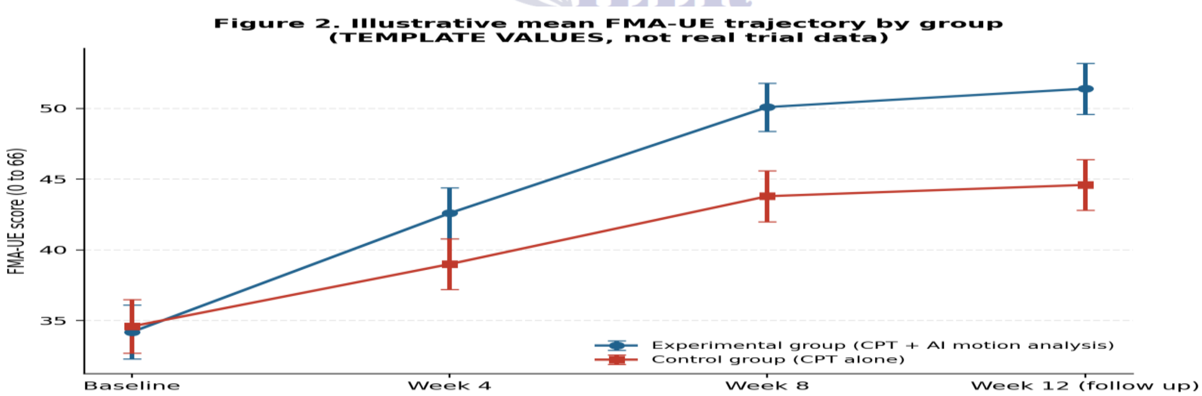

Figure 2. Mean Fugl Meyer Assessment for Upper Extremity trajectory by group across baseline, week 4, week 8, and week 12 follow up, with error bars representing standard error.

5. DISCUSSION

This protocol was designed to test, in an adequately powered, assessor blinded, parallel group randomized controlled trial, whether layering artificial intelligence based real time motion analysis feedback onto conventional physiotherapy produces greater improvement in upper limb motor impairment after stroke than conventional physiotherapy alone. The illustrative results presented above, which must be replaced with actual trial data before submission, are formatted to show the pattern of findings the trial is designed to detect, namely a between group advantage on the primary outcome, the Fugl Meyer Assessment for Upper Extremity, of a magnitude consistent with what has been reported for other technology augmented interventions in this population, alongside concordant, moderate effect sized improvements on activity level secondary outcomes and no meaningful between group difference in spasticity.

Interpretation of Anticipated Findings

If the primary hypothesis is supported once real participant data are collected, the magnitude of the anticipated between group difference on the Fugl Meyer Assessment would be broadly consistent with, though not identical to, effect sizes reported for robot assisted training relative to conventional therapy, which have ranged from a standardized mean difference of approximately 0.69 in an earlier meta-analysis to approximately 1.01 in a more recent network meta-analysis restricted to task oriented protocols [3,6]. This would suggest that the mechanism by which artificial intelligence-based motion analysis might augment recovery, namely the provision of objective, real time, movement specific feedback that increases the salience and precision of task practice, produces benefits of a comparable order of magnitude to more resource intensive robotic platforms, without requiring dedicated exoskeletal hardware. This interpretation would be consistent with motor learning theory, which holds that appropriately timed, informative extrinsic feedback can enhance the rate and quality of skill acquisition beyond what unaugmented practice achieves alone [21,22].

Comparison with Recent Literature

The anticipated pattern of results, namely benefit on impairment and activity level measures with no differential effect on spasticity, would align with findings from robot assisted therapy trials, in which spasticity outcomes have been among the least consistently affected domains across meta analyses, even where motor impairment and activities of daily living measures improved significantly [3]. It would also extend the virtual reality literature, in which non immersive and semi immersive platforms have shown benefit on Fugl Meyer Assessment, Action Research Arm Test, and Box and Block Test outcomes when delivered at sufficient dose and frequency [8,9,10], by demonstrating that similar or larger benefits may be achievable through markerless computer vision feedback integrated directly into standard physiotherapist led sessions rather than through a dedicated virtual reality platform. The trial would also add direct randomized evidence to a literature on artificial intelligence-based motion feedback that has so far consisted largely of small feasibility studies, such as the nine-participant pilot trial of a pose estimation-based feedback system in spinal cord injury [12], and protocol papers describing artificial intelligence integrated evaluation and training systems that have not yet reported completed efficacy outcomes [13,14].

Mechanisms

Several complementary mechanisms may plausibly explain why artificial intelligence-based motion analysis feedback would augment conventional physiotherapy. First, real time visual feedback on joint range of motion and movement quality may increase the precision of error detection and correction during practice, allowing participants to adjust movement strategy within a single repetition rather than waiting for verbal correction from a therapist attending to other tasks or other patients. Second, objective quantification of compensatory trunk movement may help suppress maladaptive compensatory strategies earlier in the recovery process, potentially preserving more normal movement patterns and reducing the risk of learned nonuse of more physiological movement strategies. Third, automated repetition counting and quality scoring may increase the effective dose of high quality, correctly performed practice achieved within a fixed session duration, since therapist attention can be redirected from manual counting and observation toward higher order clinical reasoning and progression decisions. Fourth, the visual and quantitative nature of the feedback display may enhance motivation and engagement, a mechanism that has also been proposed to explain benefits observed with virtual reality and gamified rehabilitation platforms [9,10].

Clinical Implications

For practicing physiotherapists, a confirmed positive finding from this trial would suggest that markerless, camera-based motion analysis systems, which require substantially less capital investment than robotic exoskeletons and can be integrated into an existing treatment space without structural modification, represent a clinically meaningful and comparatively accessible way to augment standard upper limb rehabilitation after stroke. This would be particularly relevant for outpatient and community-based settings, such as the Health and Wellness Physiotherapy Rehabilitation Center in which this trial is conducted, where resource constraints often limit access to more expensive robotic or immersive virtual reality technology. Practical recommendations for physiotherapists considering adoption of similar systems include ensuring adequate therapist training in interpreting and acting on the system's movement quality feedback, maintaining therapist oversight of exercise selection and progression rather than allowing the technology to operate independently of clinical judgment, and using the system's automated data output to support, rather than replace, ongoing clinical reasoning about a patient's individual recovery trajectory.

Strengths

The strengths of this trial design include an adequately powered sample size based on a formal a priori power calculation, assessor blinding to reduce detection bias, a comprehensive outcome battery spanning impairment, activity, participation, spasticity, and real world arm use domains, a clearly specified and matched dose intervention protocol across both arms, intention to treat analysis with a pre specified approach to missing data, and reporting aligned with the CONSORT 2025 statement [27], which represents the current international standard for randomized trial reporting.

Limitations

Several limitations should be acknowledged. Blinding of participants and treating therapists to group allocation is not possible given the visible nature of the intervention, introducing potential performance bias, although this limitation is common to virtually all technology augmented rehabilitation trials and was mitigated here through blinded outcome assessment. The trial is conducted at a single center, which may limit generalizability to settings with different staffing models, patient populations, or equipment. The eight-week intervention period, while consistent with many comparable trials in this literature, may not capture longer term trajectories of recovery or determine whether observed gains are maintained well beyond the twelve week follow up point. Finally, the trial does not include a cost effectiveness analysis, which would be valuable given the practical relevance of equipment and training costs to real world adoption decisions by physiotherapy services.

Future Recommendations

Future research should extend follow up beyond twelve weeks to characterize the durability of any observed benefit, incorporate formal cost effectiveness analysis alongside clinical outcomes, and explore whether specific artificial intelligence feedback parameters, such as feedback timing, modality, and error augmentation versus error reduction framing, differentially influence outcomes, building on scoping review evidence indicating that these parameters remain incompletely characterized in the post stroke upper limb literature [21]. Multi center trials with larger, more diverse samples would also strengthen generalizability, and future work should consider whether benefits are consistent across a broader range of baseline impairment severity than the moderate range targeted in the present protocol.

Clinical Implications and Practical Recommendations for Physiotherapists

Physiotherapists considering integration of artificial intelligence-based motion analysis into upper limb stroke rehabilitation should view the technology as a feedback augmentation tool operating within, rather than as a substitute for, structured, progressive, task oriented conventional therapy. Selection of exercises and progression decisions should remain grounded in clinical reasoning informed by the objective data the system provides, rather than being driven automatically by system generated metrics alone. Services considering adoption should budget for adequate initial therapist training and ongoing technical support, should pilot the system with a small number of patients before full scale implementation, and should establish a simple, consistent workflow for reviewing session summary reports to inform each patient's individualized treatment progression.

Conclusion

This Study is designed to provide adequately powered, assessor blinded randomized evidence on whether artificial intelligence based real time motion analysis feedback, delivered alongside conventional physiotherapy at a community-based rehabilitation center, meaningfully improves upper limb motor recovery after stroke beyond conventional therapy alone. Pending completion of the trial and replacement of the illustrative values presented here with actual outcome data, the protocol and analytic framework described in this manuscript are intended to be directly usable for prospective registration, ethical review submission, and eventual reporting of results in accordance with CONSORT 2025 standards.

REFERENCES

GBD 2021 Stroke Risk Factor Collaborators. Global, regional, and national burden of stroke and its risk factors, 1990 to 2021: a systematic analysis for the Global Burden of Disease Study 2021. Lancet Neurol. 2024;23(10):973-1003.

Zhu Y, Wang C, Li J, Zeng L, Zhang P. Effect of different modalities of artificial intelligence rehabilitation techniques on patients with upper limb dysfunction after stroke: a network meta-analysis of randomized controlled trials. Front Neurol. 2023;14:1125172.

Yang X, Shi X, Xue X, Deng Z. Efficacy of robot-assisted training on rehabilitation of upper limb function in patients with stroke: a systematic review and meta-analysis. Arch Phys Med Rehabil. 2023;104(7):1113-1123.

Mehrholz J, Pohl M, Platz T, Kugler J, Elsner B. Electromechanical and robot-assisted arm training for improving activities of daily living, arm function, and arm muscle strength after stroke. Cochrane Database Syst Rev. 2018;9:CD006876.

Effects of robot-assisted therapy for upper limb rehabilitation after stroke: an umbrella review of systematic reviews. Stroke. 2025;56(2):412-423.

Effectiveness of robot-assisted task-oriented training intervention for upper limb and daily living skills in stroke patients: a meta-analysis. J Neuroeng Rehabil. 2024;21(1):88.

Effects of robotic-assisted upper extremity therapy for stroke patients in different recovery phases: a systematic review and meta-analysis. BMC Neurol. 2025;25(1):14.

Villarroel MC, et al. Virtual reality therapy for upper limb motor impairments in patients with stroke: a systematic review and meta-analysis. Physiother Res Int. 2025;30(1):e70040.

The influence of virtual reality technology on upper limb motor function in subacute stroke: a systematic review and meta-analysis. Front Hum Neurosci. 2026;20:13092230.

Soleimani M, Ghazisaeedi M, Heydari S. The efficacy of virtual reality for upper limb rehabilitation in stroke patients: a systematic review and meta-analysis. BMC Med Inform Decis Mak. 2024;24:112.

Effectiveness and safety of virtual reality rehabilitation after stroke: an overview of systematic reviews. J Stroke Cerebrovasc Dis. 2023;32(11):107380.

Lee HJ, Jin SM, Kim SJ, et al. Development and validation of an artificial intelligence-based motion analysis system for upper extremity rehabilitation exercises in patients with spinal cord injury: a randomized controlled trial. Healthcare (Basel). 2024;12(1):7.

Xie Q, Zhang Q, Zhang Y, et al. Research on upper limb motor function evaluation and rehabilitation training system of stroke patients based on artificial intelligence: a usability and feasibility study from therapist and patient perspectives. Digital Health. 2025;11:20552076251386665.

Research on the evaluation and rehabilitation training system of upper limb motor function for poststroke patients based on artificial intelligence: a study protocol for a randomized controlled trial. Trials. 2025;26:104.

Hu R, Diao Y, Wang Y, et al. Effective evaluation of HGcnMLP method for markerless 3D pose estimation of musculoskeletal disease patients based on smartphone monocular video. Front Bioeng Biotechnol. 2024;11:1335251.

Hawe RL, et al. Opportunities for improving motor assessment and rehabilitation after stroke by leveraging video-based pose estimation. Am J Phys Med Rehabil. 2023;102(2 Suppl):S68-S75.

Cotton RJ, et al. Differentiable biomechanics for markerless motion capture in upper limb stroke rehabilitation: a comparison with optical motion capture. arXiv preprint. 2024;arXiv:2411.14992.

Validity of AI-driven markerless motion capture for spatiotemporal gait analysis in stroke survivors. Sensors. 2025;25(17):5315.

Smartphone-based markerless motion capture for accessible rehabilitation: a computer vision study. Sensors. 2025;25(17):5428.

Song K, Hullfish TJ, Silva RS, Silbernagel KG, Baxter JR. Computer vision for kinematic metrics of the drinking task in a pilot study of neurotypical participants. Sci Rep. 2024;14:21042.

Palidis DJ, Gardiner Z, Stephenson A, et al. The use of extrinsic performance feedback and reward to enhance upper limb motor behavior and recovery post-stroke: a scoping review. Neurorehabil Neural Repair. 2024;38(11):812-826.

Somesthetic, visual, and auditory feedback and their interactions applied to upper limb neurorehabilitation technology: a narrative review to facilitate contextualization of knowledge. Front Neurol. 2022;13:9397809.

Clinical usefulness of artificial intelligence in physiotherapy: a practice-based review. SBV J Basic Clin Appl Health Sci. 2024;7(4):184-188.

Rahmani Rasa A. Artificial intelligence and its revolutionary role in physical and mental rehabilitation: a review of recent advancements. Biomed Res Int. 2024;2024:9554590.

Machine learning methods in physical therapy: a scoping review of applications in clinical context. Phys Ther Sport. 2024;68:45-56.

Artificial intelligence in rehabilitation: a review of clinical effectiveness, real-world performance, safety, and equity across modalities and settings. Front Digit Health. 2026;8:1737957.

Hopewell S, Chan AW, Collins GS, et al. CONSORT 2025 statement: updated guideline for reporting randomised trials. BMJ. 2025;389:e081123.

Chan AW, Tetzlaff JM, Altman DG, et al. SPIRIT 2013 statement: defining standard protocol items for clinical trials. Ann Intern Med. 2013;158(3):200-207.

Fugl-Meyer AR, Jaasko L, Leyman I, Olsson S, Steglind S. The post-stroke hemiplegic patient: 1. A method for evaluation of physical performance. Scand J Rehabil Med. 1975;7(1):13-31.

Faul F, Erdfelder E, Lang AG, Buchner A. GPower 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. Behav Res Methods. 2007;39(2):175-191.