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LITERATURE REVIEW

Comparative Effectiveness of AI-Assisted Telerehabilitation Versus Conventional Rehabilitation for Upper Limb Recovery After Stroke: A Systematic Review and Meta-Analysis

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ABSTRACT

Background: Stroke is a leading cause of long-term disability worldwide. Recovery of upper extremity (UE) function remains particularly challenging because persistent arm and hand impairments substantially limit indepence in activities of daily living and quality of life. Advances in artificial intelligence (AI) have enabled AI-assisted telerehabilitation platforms that deliver intensive, task-specific, individualized therapy remotely. However, current evidence remains inconclusive as to whether AI-assisted telerehabilitation provides better UE motor recovery than conventional therapist-led rehabilitation.

Methods: PubMed, Embase, Scopus, Cochrane CENTRAL, and Web of Science were searched from 2014 to June 2025. Randomized controlled trials and quasi-experimental studies enrolling adults with stroke-related upper limb impairment were eligible. Studies compared AI-assisted telerehabilitation with conventional therapist-led or standard remote therapy and reported validated outcomes, including the Fugl-Meyer Assessment for Upper Extremity (FMA-UE) and Motor Activity Log (MAL). Risk of bias was assessed using the Cochrane tool, and pooled mean differences were calculated using random-effects models.

Result: Five studies, including 339 participants, met the inclusion criteria. Meta-analysis demonstrated no statistically significant difference between AI-assisted telerehabilitation and conventional therapy. The pooled mean difference for FMA-UE was 0.55 (95% CI: -0.60 to 1.08; $p=0.38$; $I^2=89\%$), and for MAL was 0.36 (95% CI: -0.45 to 1.17; $p=0.39$). Both groups achieved clinically meaningful improvements, with no serious adverse events reported.

Conclusion: AI-assisted telerehabilitation is acceptable to conventional post-stroke upper limb rehabilitation.

Keywords: artificial intelligence, motor recovery, stroke, telerehabilitation, upper limb

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INTRODUCTION

Stroke is a leading cause of long-term disability worldwide and remains a major public health challenge.[1] Motor impairment of the upper extremities is among the most common and persistent consequences of stroke, significantly limiting functional independence, participation in daily activities, and decreasing quality of life.[2,3] While many stroke survivors regain ambulatory function, recovery of upper limb motor control—particularly fine hand movements—often remains incomplete, making upper extremity rehabilitation a central focus of neurorehabilitation practice.[3]

Conventional stroke rehabilitation emphasizes repetitive, task-specific training delivered under direct therapist supervision.[3] Although effective, access to such therapy is frequently limited by geographical barriers, transportation difficulties, availability of trained professionals, and financial constraints.[3,4] These challenges become more pronounced after hospital discharge, when continuity of care is often disrupted and therapy intensity declines.[3,4]

Recent advances in artificial intelligence (AI) have driven the development of AI-assisted telerehabilitation platforms that integrate virtual reality, motion tracking, adaptive feedback, and remote monitoring.[5-8] These systems enable home-based delivery of structured rehabilitation programs while preserving fundamental principles of motor learning and neuroplasticity, including repetition, task specificity, and feedback-driven practice.[9] As a result, AI-assisted telerehabilitation has been proposed as a scalable and accessible solution to extend rehabilitation services beyond traditional clinical settings.[5-8]

Despite increasing adoption, the clinical effectiveness of AI-assisted telerehabilitation compared with conventional therapy remains uncertain.[7,8] Individual studies have reported mixed findings, and heterogeneity in intervention design, patient characteristics, and outcome measures complicates interpretation.[7,8] Moreover, previous reviews often included heterogeneous neurological populations or lacked quantitative synthesis focused specifically on stroke-related upper limb recovery.[7,10]

Therefore, this systematic review and meta-analysis aimed to evaluate the comparative effectiveness of AI-assisted telerehabilitation versus conventional therapy for improving upper limb motor function in adult stroke survivors, using standardized outcome measures and rigorous methodological assessment.

METHODS

This systematic review and meta-analysis was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.

Literature Search Strategy

A comprehensive literature search was performed in PubMed/MEDLINE, Embase, Scopus, Cochrane Central Register of Controlled Trials (CENTRAL), and Web of Science from 2014 to June 2025. The search strategy combined controlled vocabulary (e.g., MeSH terms) and free-text keywords related to "stroke", "artificial intelligence", "telerehabilitation", "virtual reality", "robotics", "rehabilitations", "motor recovery", and "conventional therapy". Boolean operators and database-specific filters were used to maximize sensitivity and specificity.

Eligibility Criteria

Studies were eligible for inclusion if they: (1) were randomized controlled trials (RCTs) or quasi-experimental studies; (2) enrolled adult participants (≥18 years) with a clinical diagnosis of ischemic or hemorrhagic stroke and upper limb motor impairment; (3) compared AI-assisted telerehabilitation interventions (including platforms incorporating machine learning, adaptive algorithms, or virtual reality with intelligent feedback) to conventional rehabilitation delivered in-person or via standard remote care; and (4) reported quantitative outcomes assessing upper limb motor function, such as the Fugl-Meyer Assessment for Upper Extremity (FMA-UE), Motor Activity Log (MAL). Studies were excluded if they were non-comparative, enrolled pediatric populations, were not available in English, or did not report sufficient data for effect size calculation.

Study Selection and Data Extraction

Following de-duplication, all identified records were independently screened by two reviewers (initially by title and abstract, then by full text) to assess eligibility. Discrepancies were resolved through discussion or consultation with a third reviewer. Data were extracted using a standardized, pre-piloted form and included study characteristics (author, year, country, design), participant demographics (age, sex, stroke type and phase, baseline motor status), intervention and comparator details (modality, dose, duration, setting), outcome measures, follow-up duration, and relevant numeric results (sample size, means, standard deviations, effect sizes, and attrition rates).

Risk of Bias Assessment

Risk of bias was assessed using the Cochrane Risk of Bias tool for randomized trials (RoB 2) or the ROBINS-I tool for non-randomized studies, evaluating the randomization process, deviations from intended interventions, missing outcome data, outcome measurement, and selective reporting.

Data Synthesis and Statistical Analysis

Meta-analyses were performed using RevMan 5.4.1 (The Cochrane Collaboration 2008, Copenhagen) software. For continuous outcomes measured on the same scale (e.g., FMA-UE), mean differences (MD) with 95% confidence intervals (CIs) were calculated. If different scales were used for the same construct, standardized mean differences (SMD) were computed. When studies reported medians and interquartile ranges, means and standard deviations were estimated using established formulas. Heterogeneity across studies was assessed using the I^2 statistic and Cochran's Q test. A random-effects model was employed if substantial heterogeneity ($I^2 > 50\%$) was present; otherwise, a fixed-effects model was used. Sensitivity analyses were conducted by excluding studies at high risk of bias and by analyzing only randomized trials. Publication bias was evaluated using funnel plots and Egger's regression test when at least ten studies were available for a given outcome. Where meta-analysis was not feasible due to data heterogeneity or insufficient reporting, results were summarized narratively.

RESULTS

Search Results and Study Selection

The study selection process is illustrated in the PRISMA flow diagram (**Figure 1**). The comprehensive literature search identified 349 records, of which five studies met all eligibility criteria and were included in the final quantitative synthesis.[11–15] The timeline of the studies was from 2014 to 2023. The studies were conducted across diverse healthcare settings in North America and Europe. Collectively, the studies enrolled 339 adult stroke survivors with upper limb motor impairment, representing a broad range of ages, clinical characteristics, and time since stroke onset. Most participants were in the subacute or chronic phase of recovery, reflecting typical populations encountered in outpatient and home-based rehabilitation services.[11–15] All included studies specifically targeted upper extremity rehabilitation because arm and hand dysfunction remains one of the most disabling sequelae of stroke, substantially affecting functional independence and activities of daily living.[11–15]

Study Characteristics

The key characteristics of the included studies are summarized in **Table 1.** Considerable clinical and methodological heterogeneity was observed across trials.[11–15] AI-assisted telerehabilitation interventions employed a range of technological platforms, including virtual reality–based training systems, adaptive feedback-driven computer programs, and home-based gaming applications.[11–15] These interventions were designed to deliver task-specific upper limb training in the home environment, often incorporating real-time performance feedback and individualized progression. Intervention duration ranged from four to twelve weeks, with training frequencies of three to five sessions per week, closely mirroring the structure and intensity of conventional rehabilitation programs. Control groups across all studies received therapist-guided in-person therapy or supervised home exercise programs with comparable treatment doses, thereby minimizing treatment intensity bias.[11–15]

Baseline demographic and clinical characteristics were generally well balanced between intervention and control groups within each study.[11–15] No significant between-group differences were reported for age, sex distribution, stroke severity, or time since stroke onset. All studies employed standardized and validated outcome measures, most commonly the Fugl-Meyer Assessment for Upper Extremity (FMA-UE) as the primary outcome, with secondary outcomes including the Motor Activity Log (MAL) and other measures of upper limb function.[11–15]

Primary Outcome: Upper Limb Motor Function (FMA-UE)

For the primary outcome, pooled analysis of FMA-UE change scores demonstrated no statistically significant difference between AI-assisted telerehabilitation and conventional therapy (mean difference 0.55; 95% CI −0.60 to 1.08; $p = 0.38$).[11–15] The corresponding forest plot is presented in **Figure 2**. Although both groups showed improvements from baseline, the incremental benefit of AI-assisted interventions was not superior to conventional therapy. Effect estimates were consistent across studies, and no single trial disproportionately influenced the pooled result. Substantial heterogeneity was observed in the FMA-UE analysis ($I^2 = 89\%$), reflecting variability in participant characteristics, intervention design, and technological complexity.[11–15] Sensitivity analyses excluding individual studies or restricting analysis to randomized controlled trials did not materially alter the pooled effect size or reduce heterogeneity, suggesting that between-study differences were largely driven by contextual and clinical factors.

Secondary Outcome: Functional Arm Use (MAL)

Secondary analysis of MAL outcomes included three studies with extractable data.[11–13] The pooled mean difference was 0.36 (95% CI −0.45 to 1.17; $p = 0.39$), indicating no statistically significant difference between intervention groups. The forest plot for MAL is shown in **Figure 3**, reinforcing the finding that both rehabilitation approaches yielded comparable improvements in patient-reported arm use.

Risk of Bias Assessment

Risk of bias assessment is summarized in **Table 2**. Two studies were rated as having low overall risk of bias, two had some concerns, and one was judged to have high risk due to selective outcome reporting.[11–15] Overall, methodological quality was considered acceptable for meta-analysis.

Adverse Events

No serious adverse events related to AI-assisted telerehabilitation were reported across the included studies.[11–15] Minor issues such as transient fatigue or technical difficulties were infrequent and self-limited.

DISCUSSION

Summary of Main Findings

This systematic review and meta-analysis demonstrates that AI-assisted telerehabilitation produces upper limb motor outcomes comparable to those achieved with conventional therapy in adult stroke survivors.[11–15] Across five controlled studies, both intervention approaches were associated with meaningful improvements from baseline; however, no statistically significant superiority of AI-assisted telerehabilitation was observed for either impairment-based outcomes measured by the Fugl-Meyer Assessment for Upper Extremity (FMA-UE) or patient-reported outcomes assessed using the Motor Activity Log (MAL).

Interpretation of Findings

The absence of significant pooled effects should be interpreted in the context of the substantial clinical and methodological heterogeneity observed across included studies, as summarized in **Table 1.** AI-assisted interventions differed considerably in technological platforms, treatment content, duration, and level of therapist involvement.[11–15] In addition, participant characteristics varied across trials, particularly with respect to stroke phase and baseline impairment severity. Importantly, most studies employed dose-matched control interventions, which enhances internal validity but inherently limits the likelihood of detecting large between-group differences.[3,4,9] These findings support the notion that treatment intensity and task specificity—rather than the mode of delivery alone—remain the primary determinants of motor recovery after stroke.[3,9]

Methodological Considerations and Risk of Bias

Risk of bias assessment **Table 2**. indicated generally acceptable methodological quality across studies, although selective outcome reporting in one trial may have contributed to heterogeneity.[11–15] Nevertheless, the consistency of outcome patterns across trials strengthens confidence in the overall conclusions and aligns with findings from previous systematic reviews evaluating AI-based rehabilitation technologies.[7,8,10]

Clinical Implications

Although AI-assisted telerehabilitation did not demonstrate superior motor outcomes, it offers several clinically relevant advantages. Home-based delivery may reduce transportation barriers, support continuity of care following hospital discharge, and improve access to rehabilitation services for patients in rural or underserved areas.[4,19] Several studies also reported high levels of patient satisfaction and engagement with AI-based platforms, suggesting potential benefits in adherence and long-term participation that may not be fully captured by short-term motor outcome measures.[11–13]

Beyond motor rehabilitation, artificial intelligence–based interventions have also been explored in other post-stroke domains, such as aphasia assessment and management, highlighting the broader potential of AI to support comprehensive neurorehabilitation beyond motor recovery.[20]

Study Limitations

The favorable safety profile observed across studies supports the feasibility of AI-assisted telerehabilitation as a complementary rehabilitation strategy.[11–15] However, the current evidence base remains limited by small sample sizes, short follow-up durations, and variability in intervention design. Moreover, few studies incorporated formal economic evaluations or long-term functional outcomes, which are essential for informing large-scale implementation and policy decision-making .[7,10]

Future Research Directions

Future research should prioritize multicenter randomized controlled trials with standardized intervention protocols, extended follow-up periods, and robust cost-effectiveness analyses.[19] Identifying patient subgroups most likely to benefit from AI-assisted approaches will also be critical, particularly given the marked inter-individual variability in stroke recovery trajectories demonstrated through longitudinal machine learning analyses.[18]

CONCLUSION

In summary, this systematic review and meta-analysis of five controlled studies demonstrates that AI-assisted telerehabilitation is both safe and effective for improving upper limb motor function in adult stroke survivors but does not confer a statistically significant advantage over conventional therapy in terms of standardized motor recovery or self-reported arm use. While both modalities yield meaningful gains from baseline, the substantial heterogeneity observed and the equivalence of outcomes highlight the importance of individualizing therapy choices based on patient preferences, access, and context. Further large-scale, methodologically rigorous studies with long-term follow-up and economic evaluation are warranted to fully elucidate the potential of AI-driven telerehabilitation to transform post-stroke rehabilitation and address persistent gaps in care accessibility and resource optimization.

CONFLICT OF INTEREST

The authors declared there is no conflict of interest.

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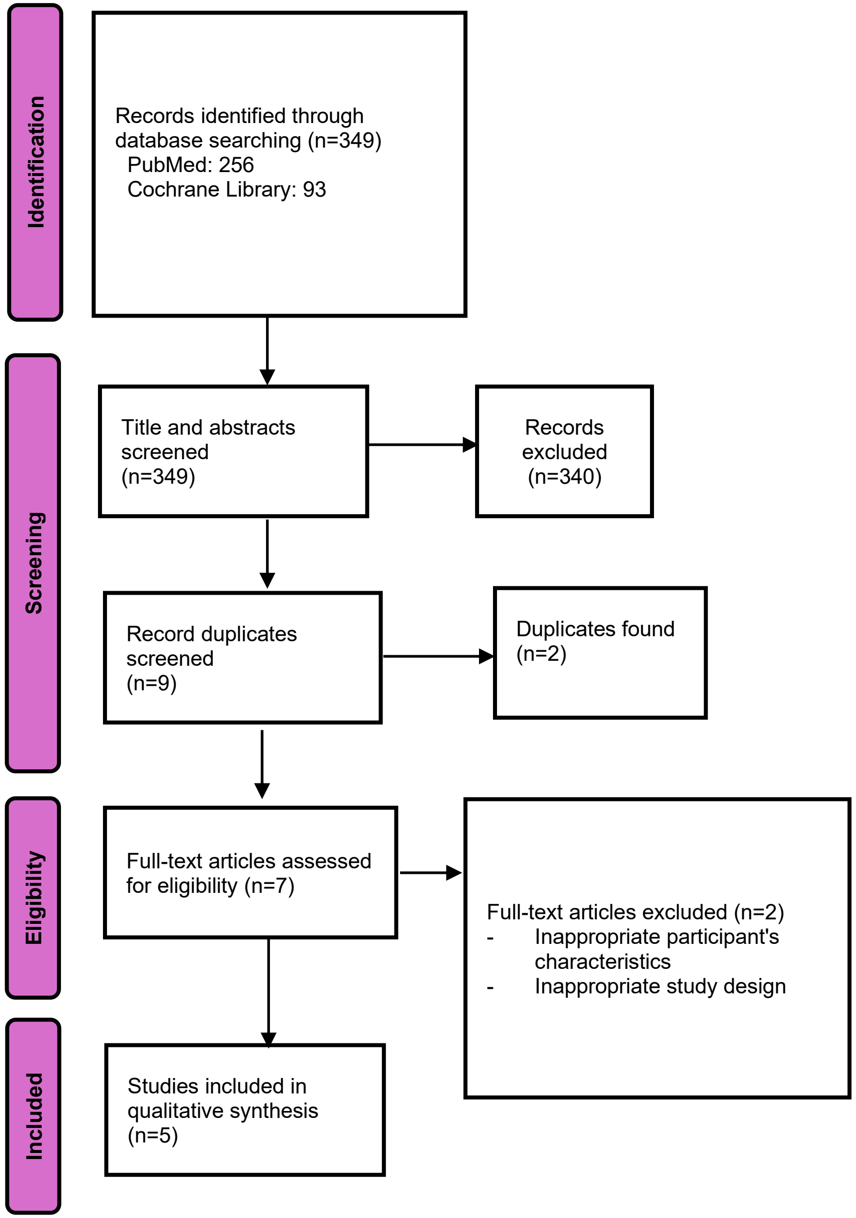

Figure 1. Diagram flow of literature search strategy for this systematic review

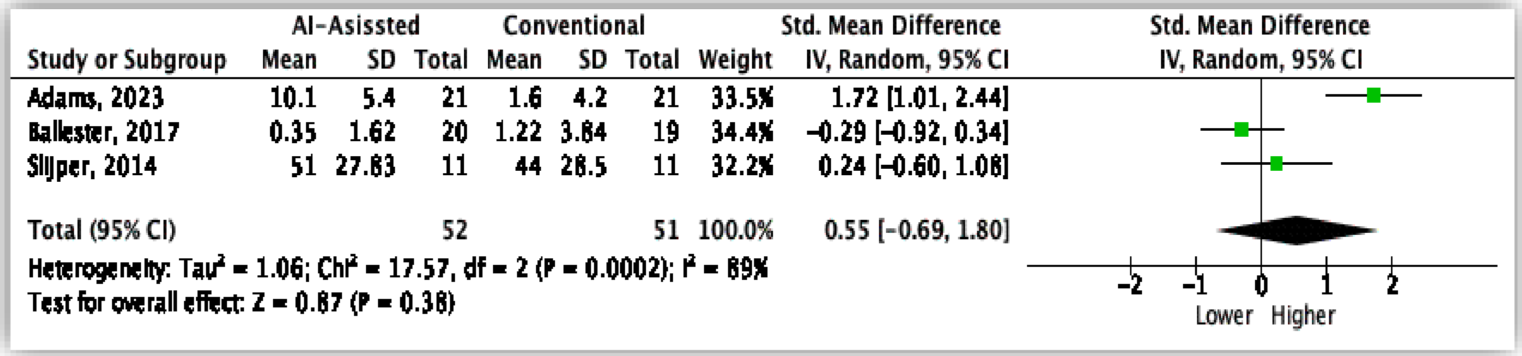

Figure 2. Pooled result of FMA-UE between intervention and control group

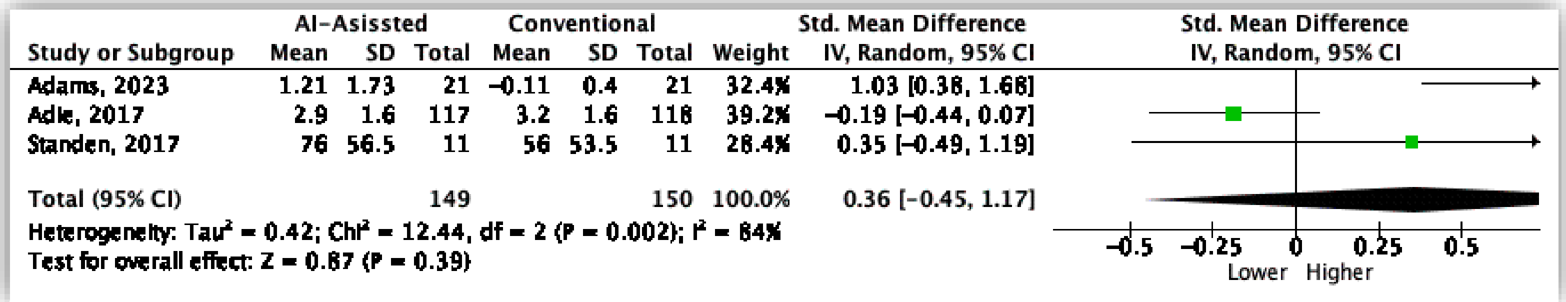

Figure 3. Pooled result of MAL between intervention and control group

Supplementary Tables and Figures

Table 1. Characteristics of Included Studies

Study (Year)	Country	n (Interv/Ctrl)	Population/Stroke Phase	Intervention (Type, Dose, Duration)	Comparator	Primary Outcome(s)	Main Results (FMA-UE, MAL, ARAT/BBT)	Key Findings/Notes
Adams et al (2023)[11]	USA	21 / 21	Chronic UE dysfunction	Home-based VR (GRASP), 45min, 4x/wk, 8wks	Usual care	FMA-UE, MAL, WMFT	FMA-UE: +10.1 (VR), +1.5 (UC)	Significant FMA-UE ↑ in VR group (P<0.001)
Ballester et al (2017)[12]	Spain	20 / 19	Chronic, MRC>2, 45–85y	RGS VR, 20min, 5x/wk, 3wks	Occupational therapy	FMA-UE, CAHAI, BI	Both improved (no mean given)	No group difference, moderate impairment
Adie et al (2017)[13]	UK	117 / 118	Subacute, MRC<5	Wii Sports, 45min/day, 6wks	Arm exercises	ARAT, FMA-UE, SIS	ARAT: −1.7 (NS), FMA-UE: NS	No group difference at 6wks, large sample
Standen et al (2017)[14]	UK	13 / 14	Chronic, residual UE	VR glove, 20min, 3x/day, 8wks	Usual care	FMA-UE, MAL, WMFT	Sig. ↑, no mean given	Sig. improvement in MAL (Amount of Use)
Slijper et al (2014)[15]	Sweden	11 / -	Chronic, 26–66y	Home game training, 5wks	None	FMA-UE, ARAT, Grip	Sig. ↑ in FMA-UE, ARAT	Single group, no comparator

Study (Year)	FMA-UE				MAL			
	Intervention	SD	Control	SD	Intervention	SD	Control	SD
Adams et al (2023)[11]	10.1	5.4	1.6	4.2	1.21	1.73	-0.11	0.4
Ballester et al (2017)[12]	0.35	1.62	1.22	3.84				
Adie et al (2017)[13]					2.9	1.6	3.2	1.6
Standen et al (2017)[14]					76	56.5	56	53.5
Slijper et al (2014)[15]	51	27.83	44	28.5				

ARAT, Action Research Arm Test; BI, Barthel Index; CAHAI, Chedoke Arm and Hand Activity Inventory; FMA-UE, Fugl-Meyer Assessment for Upper Extremity; GRASP, Graded Repetitive Arm Supplementary Program; MAL, Motor Activity Log; MRC, Medical Research Council; NS, Non-Significant; RGS, Rehabilitation Gaming System; SIS, Stroke Impact Scale; UC, Usual Care; UE, Upper Extremity; VR, Virtual Reality; WMFT, Wolf Motor Function Test;

Table 2. Results of Risk-Bias Assessment

Study ID	Experimental	Comparator	Outcome	D1	D2	D3	D4	D5	Overall
Adams et al (2023)[11]	Home-based VR (GRASP), 45min, 4x/wk, 8wks	Usual care	FMA-UE, MAL, WMFT	+	+	!	+	+	+
Ballester et al (2017)[12]	RGS VR, 20min, 5x/wk, 3wks	Occupational therapy	FMA-UE, CAHAI, BI	!	+	+	+	+	!
Adie et al (2017)[13]	Wii Sports, 45min/day, 6wks	Arm exercises	ARAT, FMA-UE, SIS	+	+	+	+	-	+
Standen et al (2017)[14]	VR glove, 20min, 3x/day, 8wks	Usual care	FMA-UE, MAL, WMFT	!	+	+	+	+	!
Slijper et al (2014)[15]	Home game training, 5wks	None	FMA-UE, ARAT, Grip	+	+	+	+	+	+

+	Low risk
!	Some concerns
-	High risk
D1	Randomisation process
D2	Deviations from the intended interventions
D3	Missing outcome data
D4	Measurement of the outcome
D5	Selection of the reported result

ARAT, Action Research Arm Test; BI, Barthel Index; CAHAI, Chedoke Arm and Hand Activity Inventory; FMA-UE, Fugl-Meyer Assessment for Upper Extremity; GRASP, Graded Repetitive Arm Supplementary Program; MAL, Motor Activity Log; RGS, Rehabilitation Gaming System; SIS, Stroke Impact Scale; VR, Virtual Reality; WMFT, Wolf Motor Function Test