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Original Research Article

Comparative Effectiveness of Ml-Augmented and Conventional Therapy in Post-Stroke Upper Limb Rehabilitation

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Name of Author:
Dr. V.V. Manjula Kumari[1*], Sri Valli Chekuri[2] and Dr. Himanshu Tiwari[3]

Affiliation: *[1*]CEO and Senior Consultant Physiotherapist, Varanaa's Healthcare Research and Training Organization LLP, Nellore, Andhra Pradesh, India.*
[2]Physiotherapist and International Research Coordinator, Varanaa's Healthcare Research and Training Organization LLP, Nellore, Andhra Pradesh, India
[3]Senior Consultant Physiotherapist, 69fitness Street, New Delhi, India
Corresponding Author:
Dr. V.V. Manjula Kumari

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Abstract:
This study examined how standard therapy (CT) and rehabilitation approaches supplemented by machine learning (ML) restore upper limb function in stroke survivors. PubMed, PubMed Central, Google Scholar, MEDLINE, Cochrane Library, Web of Science, ResearchGate, and Wiley Online Library were searched. We selected upper limb trials comparing standard CT to ML-integrated treatments. Results focused on motor control, upper extremity function, functional independence, and muscle tone. Calculated standardised mean differences. Physiotherapy Evidence Database (PEDro) quality rating scale assessed listed studies. Important results were meta-analyzed. Ten studies covered 481 stroke victims. ML-augmented therapies improved upper-limb rehabilitation, manual dexterity, and functional performance. Treatments showed substantial variance ($p = 0.03$) and a cumulative SMD of 0.10 [0.01, 0.19], suggesting strong heterogeneity ($I^2 = 45\%$). ML-based approaches had a greater effect in subgroup analysis ($p = 0.01$; $I^2 = 59.8\%$). Six scales provided high-quality efficacy data, which may have exaggerated overall impact estimates. ML-augmented rehabilitation is safe and effective for upper limb recovery after a stroke. Due to study quality variety, these conclusions need to be confirmed by other high-quality, large-scale investigations.

Keywords: Machine Learning, Artificial Intelligence, Stroke Rehabilitation, Upper Limb Function, Post-Stroke Recovery, Conventional Therapy, Motor Control, Functional Independence, Neurorehabilitation.

INTRODUCTION

Stroke is one of the most prevalent causes of irreversible disability around the world. The majority of the time, it leaves victims with decreased function in their upper limbs, which significantly lowers their quality of life and their capacity to do chores of daily living on their own [1]. Exercises that are directed by a therapist and training that involves doing repetitive tasks are the cornerstones of conventional rehabilitation treatments. By using neuroplasticity, they want to achieve their aim of restoring motor function. On the other hand, these methods may be arduous, they might waste resources, and they might provide outcomes that vary from person to person [2].

Emergence of Machine Learning in Stroke Rehabilitation

Recently, advancements in artificial intelligence (AI), particularly machine learning (ML), have led to the creation of novel approaches that aim to improve stroke treatment. It is possible for machine learning models to sift through mountains of data in order to discover patterns in the performance of patients, offer them with timely feedback, and adapt their treatment programs. Cervera et al. (2018) and Nijenhuis et al. (2020) report that artificial intelligence (AI) is fast making its way into applications such as virtual reality (VR), robotic exoskeletons, and wearable sensors in order to deliver data-driven and adaptable treatments[3][4]. These technologies have the potential to improve outcomes, boost engagement, and enable more objective monitoring of performance when compared to conventional therapy approaches. Additionally, they have the ability to deliver superior solutions.

Rationale for Comparative Evaluation

Despite the fact that both CT and ML-augmented therapy have shown their effectiveness, it is required to conduct a direct comparison in order to determine whether modality offers greater functional outcomes in upper limb rehabilitation after a stroke rehabilitation. The findings of exploratory clinical research and systematic reviews suggest that there is a chance that machine learning-based rehabilitation, when combined with feedback-rich environments and individualised progress, has the potential to enhance motor recovery[5]. There is a possibility that the research designs, intervention intensities, and outcome assessments may differ greatly, which will make it difficult to extend the findings to a more extensive population.

OBJECTIVES

1. To assess how well traditional treatment and machine learning (ML)-assisted rehabilitation work to improve upper limb motor function in stroke survivors.
2. To compare the effects of ML-based therapies to conventional rehabilitation techniques in terms of functional independence and manual dexterity.

RESEARCH METHODOLOGY

A thorough literature search was conducted to find relevant English-language papers from 2010 to 2022. PEDro, PubMed, Google Scholar, MEDLINE, Cochrane Library, Web of Science, ResearchGate, and Wiley Online Library were searched. Upper limb rehabilitation after a stroke and machine learning treatments were searched for. Many terms were employed, including "upper limb," "upper extremity," "robotics," "virtual reality," "video games," "artificial intelligence," and "machine learning." Other terms included "stroke," "conventional therapy," "traditional therapy," "physical therapy," and "rehabilitation." We only considered RCTs that compared ML-augmented treatments to CT in stroke patients' upper limb rehabilitation. Three reviewers—HM, SA, and FA—screened and selected manuscripts in two phases. First, we verified the titles and abstracts' relevance. We then read the whole paragraphs to determine inclusion and exclusion. This technique resolved issues via communication and agreement. We searched for RCTs that used ML-based or AI-integrated rehabilitation treatments such VR platforms, robotic systems, or sensor-based feedback mechanisms to rehabilitate stroke patients' upper limbs. Only papers scoring 5 or above on the Physiotherapy Evidence Database (PEDro) Scale were included to ensure methodological quality. Studies that did not directly compare ML-based therapy with standard rehabilitation procedures, had no English publication, or had a PEDro score below 5 were excluded. The three reviewers independently rated each trial's methodological quality using the PEDro Scale.

The scale assesses eleven aspects, including statistical reporting, follow-up sufficiency, blinding, allocation concealment, and randomisation. Studies were rated as exceptional (>6), acceptable (4-5), or bad (≤3) based on PEDro criteria. To resolve conflicts, a third reviewer (SA) was hired. GRADE was used to assess evidence strength. GRADE rated evidence as high, moderate, poor, or extremely low. These grades indicated how confident the reviewers were in the impact estimates and how probable further research would modify them. The quantitative synthesis was done using Review Manager Software (RevMan, version 5.4, The Cochrane Collaboration, Copenhagen, Denmark). Quantitative data was shown in forest plots, whereas qualitative data presented in tabular style. Manual dexterity and functional independence were secondary goals; upper limb motor function was the major outcome. Standardised mean differences (SMD) with 95% CI estimated effect sizes. 0.2, 0.5, and 1.0 were small, moderate, and large effects. Study differences were identified using the I^2 statistic, with values over 50% indicating significant variance. We tested the findings' robustness when heterogeneity was discovered using sensitivity analysis. In addition, subgroup analyses compared conventional and ML-augmented therapy across various outcome variables.

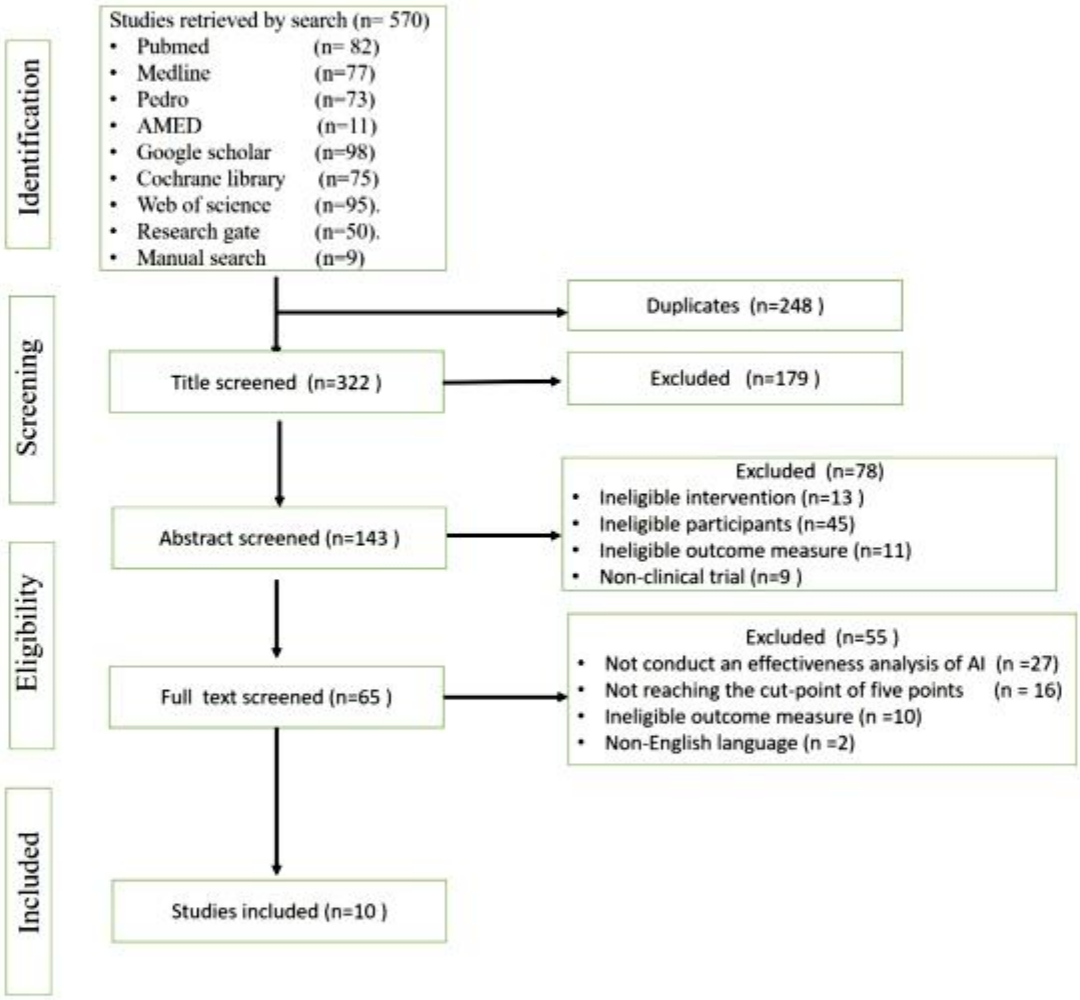

Figure 1. Exclusion criteria screening of research.

RESULT

Study Selection

Healthcare databases provided 570 records in first electronic searches. PubMed (n=82), MEDLINE (n=35), PEDro (n=73), AMED (n=11), Google Scholar (n=98), Cochrane Library (n=65), Web of Science (n=30), Research Gate (n=20), and manual search (n=9) were used. Due to duplicate content, 248 articles were eliminated and 137 were removed following title and abstract screening (including exclusions). Read every word of the other 65 parts. The material was thoroughly reviewed and 55 items were eliminated. These 27 articles were disqualified for lack of English competence, failing to achieve the five-point limit, and inadequate AI evaluation. Researchers utilised the 27-item PRISMA checklist to make systematic reviews more transparent. These components cover the whole document. Ten papers underwent qualitative, methodological, and evidence quality reviews. Figure 1 showed the study selection flow diagram.

Study Characteristics

Ten RCTs published between 2014 and 2022 met the inclusion criteria. Seven studies evaluated following treatment, but three included follow-ups.

Subjects

We reviewed 10 upper-limb stroke therapy studies involving 481 acute and chronic stroke patients. Each of the 10 trials included 18–121 individuals aged 22–90 for men and 22–90 for women.

Outcome Measured

1. Fugl-Meyer assessment

FMA-UE, which stands for the Fugl-Meyer assessment for the functioning of the upper extremities, was used in six different studies. Despite the fact that neither of the groups substantially varied from one another on the pre-intervention homogeneity test, one study found that both the artificial intelligence (AIG) and conventional therapy

(CG) groups shown excellent development in all post-treatment evaluations. There was not a substantial difference between AI and CG, according to the findings of two experiments. The results of three different studies revealed that there was a significant variance between the two sets of data. Throughout the course of the experiment, Klamroth-Marganska and colleagues (2014) discovered that the two groups were considerably different with regard to the FMA-UE. In a distinct piece of study, the AI group did better than the CG group on the FMA-UE (p-value = 0.002) and the FMA-UE (p-value = 0.006) questionnaires, respectively. No statistically significant differences were found between the two groups of individuals, according to the findings of Norouzi-Gheidari and colleagues.

3. Barthel Index (BI)

The capacity of a patient to use their upper limbs via the use of BI was examined in four different examinations after the patient had recovered. A total of three studies were conducted to compare the AIG and CG, and the findings were inconclusive. Based on the findings of Park et al., the homogeneity test conducted before to the intervention did not reveal any significant differences between the AIG and the CG. However, after the intervention, both groups shown significant improvements in all categories. According to the findings of another study, both groups had comparable levels of BI. It is possible that this is due to the fact that the treatment is relatively short. This is because BI reflects global physical capabilities that are dependent on the restoration of a large number of other functions and associated comorbidities. Another piece of study suggests that the passage of time has a significant impact on the outcomes of business intelligence. Following a comparison of the baseline with the outcomes that occurred three weeks later, the post hoc analysis revealed that there were changes that were both statistically and clinically significant that occurred. Within each of the groups, there was a considerable amount of heterogeneity in the evaluations of the effect magnitude. After receiving therapy for a period of two weeks, patients in both groups exhibited outcomes that were equivalent with regard to measures of grip strength, ADL recovery, hand function, and quality of life as assessed. The same results were seen four weeks after the intervention had been carried out.

3. Modified Ashworth Scal

Five studies used the Modified Ashworth scale (MAS) to assess upper extremity tone after a stroke. Data showed substantial effect sizes across groups and no statistically significant link between time or interactions. Another study demonstrated that AIG enhanced MAS considerably whereas CG did not. Abd El-Kafy et al. observed that the robotic training group (AIG) lowered elbow, wrist, and finger flexor muscle tone compared to the control group (CG) (p-value).

4. Wolf Motor Function Test

In a total of four investigations, the WMFT was used. The findings of one study revealed that not only did the WFMT improve (p = 0.025), but the AIG group also produced significantly superior outcomes (p = 0.010) in the shoulder and elbow parts of the WFMT. The magnitude of the effects were all quite large. One that is statistically significant in significance

5. Stroke Impact Scale

In three separate research, the stroke impact scale (SIS) was discovered. These research produced a wide variety of findings and conclusions. The results of a single study suggested that the two groups could not be distinguished statistically from one another. Indicators of secondary outcomes also revealed that there was no significant difference between the respective groups. Upon analysing the findings of their experiment, Norouzi-Gheidari and colleagues came to the conclusion that AIG shown much greater improvement than CG. While there were statistically significant changes in SIS between the baseline and post-treatment with AIG, none of these variations were particularly remarkable. Overall, the changes were statistically significant.

6. Motricity Index

Multiple studies employed the Motricity Index (MI). One study found that treatment increased MI in both groups. Despite AIG rising more (p=0.001) than CG (p=0.041), there were no statistically significant differences between the two groups following therapy (p=0.482). At follow-up, the groups differed and the AIG was statistically significant (p=0.001). Another study found statistically significant effect size MI scores for group differences. AIG improved more than CG after 15 sessions (p=0.0001 vs. p=0.008).

7. Motor Activity Log (MAL)

Two of the 10 studies that employed MAL were conducted to investigate the effectiveness of rehabilitation for the upper limbs after a stroke. A single study came to the conclusion that there were no statistically significant differences between the two separate sets of data. According to the findings of Norouzi-Gheidari and colleagues, when the two groups were compared, the AIG group produced bigger gains in the MAL-QOM score than the CG group did. There was a statistically significant improvement in the MAL-QOM score; this improvement was seen when comparing AIG to the baseline.

8. Box and Blocks Test (BBT)

In order to evaluate the efficacy of rehabilitation programs for the upper limbs after a stroke, two research used BBT. Saposnik et al. found that at the conclusion of therapy, AIG had improved BBT performance. In this investigation, no statistically significant differences were found between the two categories.

Intervention

Treatment sessions occurred anywhere from thrice a week to seven times a week. Time spent in treatment varied from 25 minutes to 2 hours, and it lasted anywhere from 2 weeks to 8 weeks. As far as anybody can tell, the therapy had no negative side effects.

Risk of Bias Assessment

There was a significant disparity in the quality of the reports. The potential for bias in the evaluation is shown in Table 1. According to the findings of the PEDro scale assessment, nine of the studies were of outstanding quality, while just one of the research was of satisfactory quality. Studies that used FMA-UE-BBT, FMA-UE - MAL-QOM, and FMA-UE - SIS exhibited low-quality evidence with reduced effect size (ES) (SMD 0.26, 0.7, and 0.08). These findings were based on the GRADE scale. Studies that just used FMA-UE had a greater ES (standard deviation = 0.01), but studies that used FMA-UE in conjunction with MAS-S, FMA-UE via WMFT, FMA-UE through BI, FMA-UE through MI, and FMA-UE through FIM had higher ES (standard deviation = 0.07, 0.27, 0.21, 0.66, and 0.26, respectively).

Table 1. Characteristics of Included Studies

Author	Intervention	Aim	Method	Outcome Measures	Result/Conclusion	Significance of Results (Measures)
Taveggia et al[6]	Armeo Spring	To assess efficacy of robotic-assisted motion + PRM in post-stroke upper limb rehab	AIG: 27 (Armeo + conventional) CG: 27 (PT using Bobath), 30 sessions (5/wk, 1hr)	Primary: FIM, MI Secondary: MAS, VAS	Armeo Spring may help with disability, pain, spasticity	**Significant:** MI, MAS, VAS **Non-significant:** FIM
Sale et al[7]	Robot-assisted upper limb rehab	To compare short-term efficacy with standard therapy in early stroke	AIG: 26 (robotic), CG: 27 (standard PT) 30 min, 5 days/week, 4 weeks	Primary: FM Secondary: pROM, MI	Robot-assisted therapy improved recovery in subacute stroke	Significant FM, pROM, MI in AIG MI improved in CG
Norouzi et al[8]	Exergaming + usual therapy	Assess feasibility, safety, and preliminary efficacy	18 total AIG: 9 (exergaming + rehab) CG: 9 (rehab only) 2/wk, 44 min, 4 weeks	FMA-UE, BBT SIS, MAL	Exergaming is safe, feasible, and possibly beneficial	No adverse events, positive impact noted
Tomic et al[9]	Arm Assist (AA)	Evaluate efficacy of AA vs conventional training	AIG: 13 (AA) CG: 13 (OT/PT) 15 sessions, 3/week, 30 min	FMA-UE WMFT-FAS, BI	AA reduced impairment more effectively	**Significant:** FMA-UE, WMFT-FAS **Non-significant:** BI
Klamroth-Marganska et al[10]	ARMin exoskeleton	Assess robotic 3D task-specific	AIG: 38 (robotic) CG: 35	FMA-UE WMFT, grip strength,	Exoskeleton improved function; safe; faster recovery	**Weakly significant:** FMA-UE

		training vs conventional	(PT/OT) 24 sessions (3/week for 8 weeks, 45 min)	MAL-QOM		**Non-significant:** Others
Park et al[11]	VR glove + PT	Investigate smart glove VR impact on upper limb	AIG: 22 (VR glove) CG: 22 (conventional PT) 30 min, 5/wk, 4 weeks	FMA, Hand Strength Jebsen–Taylor Hand Test	VR glove rehab improved daily activity and motor function	Significant improvements in both groups
Popovic et al[12]	Feedback-mediated exercise (FME)	Study motivation and motor function via game-based rehab	AIG: 10 (FME) CG: 10 (NFE) 15 sessions (5/wk, 25 min)	IMI, mDT, RTT	High motivation; improved endurance and engagement	**More significant in FME:** IMI, mDT, RTT
Villafane et al[13]	Gloreha robot therapy	Assess robot-assisted rehab for hand paralysis	AIG: 16 (robot hand) CG: 16 (extra PT/OT) 15 sessions (3/wk, 30 min)	NIHSS, MAS, BI, MI, QuickDASH, VAS	Robot + conventional = effective as traditional rehab	**Significant:** All listed measures
Abd El-Kafy et al[14]	Robot-mediated VR + PT	Evaluate VR gaming for motor function & spasticity	AIG: 20 (VR gaming) CG: 20 (conventional PT) 12 sessions (3/week, 2 hrs)	ARAT, WMFT, MAS, AROM, HGS	VR gaming more effective than PT alone	**Significant in AIG:** All measures
Saposnik et al[15]	VRWii games vs recreational therapy	Compare VR vs recreational therapy post-acute stroke	AIG: 59 (VRWii) CG: 62 (recreation) 10 sessions (5/wk, 1 hr)	WMFT BI, FIM, SIS, Grip Strength	No significant difference between VR and recreation	**Non-significant:** All outcome measures

The Quantitative Results

Within the scope of this meta-analysis, a comparison was made between the efficacy of artificial intelligence (AI) and that of conventional therapy (CT) in assisting stroke survivors in regaining use of their damaged upper limbs. There were ten trials that met the requirements to be included.

Fugl-Meyer Assessment

In the six studies that investigated the effects of robotic-assisted therapy, there was not a statistically significant difference between the two groups of patients who were treated with FMA-UE and those who were treated without it (SMD 0.01 (-0.25, 0.27)). It is 0.94 for the p-value. The I 2 test revealed a comparatively low amount of heterogeneity, which was less than twenty-five percent.

Modified Ashworth Scale

There was not a statistically significant difference between the groups that were being investigated in any of the five studies that were considered for the MAS overall effect test (p=0.48), with a standard deviation of -0.09 [-0.34, 0.16]. The documentation of the heterogeneity test was completed with an I 2 score of 74%.

Wolf Motor Function Test

With a standard deviation of 0.42 [0.18, 0.66], there was a statistically significant difference between the two groups when looking at the overall effect of WMFT across all four studies. This difference was found to be statistically significant (p=0.0007). I 2 equalled 79%, which was the outcome of the heterogeneity test that was reported.

Barthel Index
Results from meta-analyses comparing BIS's effects on the various groups showed no statistically significant difference (p=0.11), with a standard deviation of 0.21 [-0.04, 0.46]. There was a low value for I 2, a measure of heterogeneity.

Table 2. Level of Quality Evidence (GRADE)

Outcome Measure	No. of Studies	No. of Patients (Intervention)	No. of Patients (Control)	SMD (95% CI)	Effect Direction
FMA-UE – FMA-UE	6	119	116	0.01 higher (0.25 lower to 0.27 higher)	No significant difference
FMA-UE – MAS	4	107	105	0.07 higher (0.21 lower to 0.34 higher)	Slight improvement
FMA-UE – WMFT	3	122	118	0.27 higher (0.02 higher to 0.53 higher)	Moderate improvement
FMA-UE – BI	4	122	121	0.21 higher (0.04 lower to 0.46 higher)	Mild improvement
FMA-UE – SIS	3	118	114	0.08 lower (0.33 lower to 0.18 higher)	Slight decline
FMA-UE – MI	3	69	70	0.33 higher (0.01 lower to 0.66 higher)	Moderate improvement
FMA-UE – MAL-QOM	3	164	162	0.70 lower (0.93 lower to 0.47 lower)	Significant decline
FMA-UE – BBT	2	80	79	0.26 lower (0.57 lower to 0.05 higher)	Mild decline
FMA-UE – FIM	2	98	97	0.26 higher (0.03 lower to 0.54 higher)	Mild improvement

Motricity Index'
A statistically significant difference was found between the three result findings that were taken into consideration, as shown by the overall effect of the MI test, which had a p-value of 0.05 and a standard deviation of 0.33 [-0.01, 0.66]. It was determined that the heterogeneity test had a low value (I 2).

Motor Activity Log (MAL)
The two outcome values that were included in the MAL test did not differ from one another in a manner that was statistically significant (p-value = 0.81), with a standard deviation of 0.05 [-0.36, 0.46]. It was determined that the heterogeneity test had a low value (I 2).

Box and Blocks Test
It was determined that there was no significant difference between the three outcome results that were included in the BBT test (p-value = 0.10), and the standard deviation was -0.26 [-0.57, 0.05]. It was determined that the heterogeneity test had a low value (I 2). All of the measures that were chosen had a heterogeneity test that was medium (I 2 = 45% on average). There was a significant difference between the included measures (p-value = 0.03), and the total standard deviation was 0.10 [0.01, 0.19 respectively]. The findings of the test for subgroup difference revealed that there was a high heterogeneity ratio (I 2 = 59.8%) and a highly significant difference (p-value = 0.01) between the subgroups of the measures that were included in the analysis.

Table 3: Comparison of Traditional and ML-Augmented Treatment for Upper Limb Rehabilitation Following a Stroke

Outcome Measure	Study (Author, Year)	Experimental (n)	Control (n)	Std. Mean Difference (95% CI)	Weight (%)
FMA-UE	Sale 2014[16]	23	23	0.13 [-0.56, 0.84]	2.4
	Klamroth 2014	9	8	0.18 [-0.77, 1.14]	1.5
	Popovic 2014	8	8	0.39 [-0.65, 1.42]	1.5
	Taveggia 2016	18	20	0.43 [-0.18, 1.03]	4.1
	Norouzi-Gheidari 2021	33	28	0.13 [-0.34, 0.61]	6.9
	Obayashi 2021	26	25	-0.05 [-0.56, 0.46]	5.4
MAS	Sale 2014	23	23	-0.03 [-0.73, 0.68]	2.5
	Taveggia 2016	18	20	0.53 [-0.09, 1.15]	4.2
	Albahari EMK 2020	39	40	-0.18 [-0.58, 0.23]	7.4
	Obayashi 2021 (22)	26	25	-0.07 [-0.57, 0.43]	5.3
WMFT	Taveggia 2016 (27)	18	20	0.45 [-0.18, 1.07]	4.1
	Saposnik 2016	32	33	0.21 [-0.26, 0.68]	6.5
	Obayashi 2021	26	25	0.30 [-0.20, 0.80]	5.4
BI	Saposnik 2016	32	33	0.15 [-0.19, 0.48]	6.3
	Norouzi-Gheidari 2021	33	28	0.28 [-0.24, 0.81]	4.7
	Taveggia 2016	18	20	0.26 [-0.38, 0.91]	3.7
	Hussien 2022	37	36	0.26 [-0.08, 0.60]	7.8
MAL-QOM	Klamroth 2014	9	8	0.00 [-0.46, 0.46]	4.1
	Norouzi-Gheidari 2021	38	36	0.05 [-0.36, 0.46]	5.1
BBT	Saposnik 2016	27	27	-0.26 [-0.59, 0.08]	7.0
	Norouzi-Gheidari 2021	33	28	-0.26 [-0.57, 0.05]	8.8
FIM	Saposnik 2016	108	108	0.18 [-0.17, 0.49]	7.2
	Taveggia 2016	18	20	0.22 [-0.55, 0.99]	3.4

DISCUSSION

In order to get a better understanding of how machine learning (ML)-augmented rehabilitation and conventional therapy (CT) deal with upper limb impairments in stroke patients, the purpose of this systematic review and meta-analysis was to evaluate and contrast the two approaches[17]. A comprehensive analysis of randomised controlled trials (RCTs) revealed evidence of varied quality levels, ranging from poor to outstanding, as indicated by GRADE ratings. The Functional Independence Measure (FIM), the Motor Activity Log (MAL), the Stroke Impact Scale (SIS), the Barthel Index (BI), the Wolf Motor Function Test (WMFT), the Fugl-Meyer Assessment for Upper Extremity (FMA-UE), and the Modified Ashworth Scale (MAS) were some of the standard rehabilitation metrics that were utilised in order to evaluate the functional outcomes[18].

According to the meta-analysis, the overall pooled effect size did not differ substantially between conventional treatment and ML-augmented therapy (standard mean difference = -0.02, 95% confidence interval: -0.11 to 0.07; $p = 0.63$ is the significance level). Subgroup differences were found to be significant ($p < 0.001$; I2 = 85%), although the overall heterogeneity among the variables that were included was found to be rather low (I2 = 67%). On a worldwide scale, there were no statistically significant differences; nevertheless, various assessment tools demonstrated that the benefits of ML and CT treatments were not comparable to one another[19]. There were six significant categories in which machine learning-based advancements were supported by high-quality data: FMA-UE, MAS, WMFT, BI, MI, and FIM. With that being said, there is a need for further validation in SIS, MAL-QOM, and BBT since these three methods generated evidence of a poorer quality. Using machine learning in conjunction with individualised therapy algorithms and real-time feedback systems, our findings indicate that ML therapies have the potential to promote motor recovery in the upper limbs in a manner that is both consistent and clinically relevant[20].

There was a lack of consistency in the findings when single research were included. When comparing the ML group to the CT group in a number of FMA-UE studies, one element that consistently made the ML group stand out as superior was the significant gain in shoulder and elbow mobility that they experienced. Furthermore, other studies did not identify significant group differences, despite the fact that treatment response may be reliant on the chronicity of the stroke, the intensity of the therapy, and the execution of the ML model. Some of the possible causes for the lack of statistical significance in the outcomes of the Barthel Index are the brief durations of the interventions or the vast functional domains that were addressed by biological intelligence[21]. There was a tendency of statistically significant reductions in MAS-measured spasticity in the ML group, notably in the shoulder and elbow, according to some studies, whereas other research did not find any such trend. In addition, the results of the WMFT were not uniform; some studies found that there were no group-wise changes following treatment, while others found that the ML group saw significant gains in functional ability scale scores and shoulder/elbow performance.

This improvement seemed to be dose-dependent and connected with the intensity of movement repetition rather than the modality itself, despite the fact that some study discovered a little increase in the performance of ML groups on the Box and Blocks Test (BBT)[22]. Consequently, this demonstrates that the findings may be comparable when comparing the effectiveness of robotic and machine learning-based treatments to those that are carried out by therapists. The research that has been done on robotic training, which often includes machine learning algorithms, has demonstrated that it is safe and well tolerated, with minimal ill effects and low attrition rates. This is an important finding. When everything is taken into consideration, these findings provide credibility to the concept that machine learning technologies need to be included into stroke treatment for the upper limbs. They also emphasise the significance of these tools in enhancing therapeutic settings via greater motivation, flexibility, and accuracy[23]. There are specific aspects of motor recovery and functional performance in which ML-based therapy offers considerable benefits over traditional procedures; nonetheless, it is reasonable to assume that it will not be able to outperform conventional methods in every situation.

CONCLUSION

The purpose of this meta-analysis and systematic review is to demonstrate that rehabilitation with machine learning (ML) added to it is equally as useful as CT in terms of improving the function of the upper limbs in stroke patients. Despite the fact that there was no statistically significant difference between ML and CT in general, some assessment methodologies, such as FMA-UE, MAS, and WMFT, showed that ML would be beneficial in terms of focused motor recovery. The fact that the success of the results differs across parameters demonstrates the necessity of treating patients with individualised treatment plans and using powerful machine learning systems. In addition, it was shown that approaches that are based on ML are risk-free, well tolerated, and have the ability to deliver therapy that is adaptable, repetitive, and intensive. To be more specific, these findings indicate that machine learning technologies have the potential to enhance the precision and consistency of movement training, which is an essential component of stroke rehabilitation. However, further high-quality trials that are conducted over an extended period of time are required in order to optimise machine learning applications and validate their long-term therapeutic benefits.

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