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REVIEW

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Effects of brain-computer interface based training on post-stroke upper-limb rehabilitation: a meta-analysis

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Abstract

Background Previous research has used the brain-computer interface (BCI) to promote upper-limb motor rehabilitation. However, the results of these studies were variable, leaving efficacy unclear.

Objectives This review aims to evaluate the effects of BCI-based training on post-stroke upper-limb rehabilitation and identify potential factors that may affect the outcome.

Design A meta-analysis including all available randomized-controlled clinical trials (RCTs) that reported the efficacy of BCI-based training on upper-limb motor rehabilitation after stroke.

Data sources and methods We searched PubMed, Cochrane Library, and Web of Science before September 15, 2024, for relevant studies. The primary efficacy outcome was the Fugl-Meyer Assessment-Upper extremity (FMA-UE). RevMan 5.4.1 with a random effect model was used for data synthesis and analysis. Mean difference (MD) and 95% confidence interval (95%CI) were calculated.

Results Twenty-one RCTs ($n = 886$ patients) were reviewed in the meta-analysis. Compared with control, BCI-based training exerted significant effects on FMA-UE (MD = 3.69, 95%CI 2.41–4.96, $P < 0.00001$, moderate-quality evidence), Wolf Motor Function Test (WMFT) (MD = 5.00, 95%CI 2.14–7.86, $P = 0.0006$, low-quality evidence), and Action Research Arm Test (ARAT) (MD = 2.04, 95%CI 0.25–3.82, $P = 0.03$, high-quality evidence). Additionally, BCI-based training was effective on FMA-UE for both subacute (MD = 4.24, 95%CI 1.81–6.67, $P = 0.0006$) and chronic patients (MD = 2.63, 95%CI 1.50–3.76, $P < 0.00001$). BCI combined with functional electrical stimulation (FES) (MD = 4.37, 95%CI 3.09–5.65, $P < 0.00001$), robots (MD = 2.87, 95%CI 0.69–5.04, $P = 0.010$), and visual feedback (MD = 4.46, 95%CI 0.24–8.68, $P = 0.04$) exhibited significant effects on FMA-UE. BCI combined with FES significantly improved FMA-UE for both subacute (MD = 5.31, 95%CI 2.58–8.03, $P = 0.0001$) and chronic patients (MD = 3.71, 95%CI 2.44–4.98, $P < 0.00001$), and BCI

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combined with robots was effective for chronic patients (MD = 1.60, 95%CI 0.15–3.05, P = 0.03). Better results may be achieved with daily training sessions ranging from 20 to 90 min, conducted 2–5 sessions per week for 3–4 weeks.

Conclusions BCI-based training may be a reliable rehabilitation program to improve upper-limb motor impairment and function.

Trial registration PROSPERO registration ID: CRD42022383390.

Keywords Brain-computer interface, Stroke, Upper-limb, Motor impairment, Rehabilitation

Introduction

Stroke is the leading cause of long-term adult disability worldwide, leading to an estimated cost burden [1]. Survivors of stroke frequently suffer from hemiplegia, often characterized by motor impairment (e.g., abnormal movement patterns and abnormal reflexes), poor motor function, spasticity in affected limbs, and muscle weakness, presenting a significant challenge in stroke rehabilitation [2–4]. Despite active treatment, 80% of people with stroke failed to achieve full recovery of motor function and disabilities of the upper limb, affecting their activities of daily living and overall quality of life substantially [5]. Various rehabilitation approaches employed nowadays have some limitations [6]. For example, constraint-induced movement therapy (CIMT), is often suitable for individuals with residual movement capability, and robotic therapy and neuromuscular electrical stimulation, often rely on fixed programs without brain activity significant recovery [7]. Hence, finding a more effective method for upper-limb recovery after stroke remains a challenge.

Recently several studies [8–11] have reported upper-limb benefits through BCI-based training. BCI, a novel technology in neurological rehabilitation, facilitates bidirectional communication between the brain and the environment by utilizing recorded brain activity [12]. BCI systems can be categorized as invasive or non-invasive, depending on the location of signal acquisition. The non-invasive BCI is widely adopted due to its safety, portability, and cost-effectiveness [13]. Non-invasive BCI methods for recording brain signals include electroencephalogram (EEG), magnetoencephalogram (MEG), functional near-infrared spectroscopy (fNIRS), and functional magnetic resonance imaging (fMRI), with EEG being the most commonly utilized [14]. Motor imagery (MI), steady-state visual evoked potential (SSVEP), and P300 are common sources of EEG signals [15]. In contrast to common rehabilitation strategies for post-stroke upper-limb motor dysfunction, BCI-based training employs a closed-loop approach called "central-peripheral-central", offering the benefits of real-time feedback that enables self-regulation of neurophysiological activities [16].

BCI is often combined with various feedback methods such as functional electrical stimulation (FES) [8, 9, 17–21], robotic assistance [10, 11, 22–31], and visual feedback [32, 33]. Although benefits for post-stroke upper-limb motor impairment have been reported, debates persist due to variations in training protocol. Recent systematic reviews mostly focused on the impact of different external feedback types or stroke phases [34, 35] without analysis of the efficacy of specific external feedback across different phases. Moreover, the impact of several key clinical issues, such as the training intensity (time, sessions, and duration) was not considered appropriately. The optimal scheduling for BCI-based training has not been systematically analyzed. Addressing these aspects is essential for developing personalized training programs and enhancing the recovery of upper-limb function, daily activities, and overall quality of life in stroke patients.

The primary objectives of this meta-analysis are as follows: (1) to investigate the clinical effects of BCI-based training on improving upper-limb motor impairment, motor function, and activities of daily living following a stroke, (2) to identify potential factors that may impact the outcomes, including stroke phases, external feedback, external feedback across stroke phases, training intensity (time, sessions, and duration) and (3) to try to determine optimal BCI-based training protocol for stroke patients.

Methods

We followed the guidelines provided by the Meta-Analysis of Observational Studies in Epidemiology Group, the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) 2020 guidelines [36], the PRISMA checklist (Supplementary Table S1), and the Cochrane Collaboration definition for systematic review and meta-analysis. The review protocol was registered with the International Prospective Register of Systematic Reviews (PROSPERO: CRD42022383390).

Search strategy

We conducted a systematic search for articles on PubMed, Cochrane Library, and the Web of Science published before September 15, 2024. The search strategy included the terms: ("stroke"[Mesh] OR cerebrovascular accident OR apoplexy OR brain vascular accident OR cerebral vascular accident OR hemiplegia) AND ("Brain-Computer Interfaces"[Mesh] OR Brain Computer

Interfaces OR Brain-Computer Interface OR Brain-Machine Interfaces OR Brain-Machine Interface). The detailed search strategy is presented in Supplementary Table S2.

Eligibility criteria and study selection

We included studies that met predefined criteria, encompassing (1) RCTs, (2) All the participants included in the studies meeting the clinical diagnostic criteria of stroke or were diagnosed as having stroke by MRI or CT, and suffering from upper-limb motor dysfunction, (3) The experimental group received BCI-based training, including BCI-FES, BCI-robot, BCI-visual feedback training, (4) Control groups received sham BCI training or conventional rehabilitation training (e.g. motor therapy, occupational therapy, physical factor therapy, coordination, etc.), (5) The outcomes of these studies must include FMA-UE. The exclusion criteria included: (1) Second-hand unoriginal research (reviews, meta-analysis, letters, reports, conference abstracts), (2) Duplicated studies, (3) Studies lacking baseline data, (4) Studies with incomplete original data or data that could not be extracted, and no response from authors upon contact, (5) Studies without FMA-UE. In cases of multiple articles using the same data, the one published earlier will be selected. Two reviewers (RL and WQ) independently evaluated the eligibility of the included articles, and disagreements were resolved through consensus during a meeting.

Data extraction

Data extraction was conducted by two independent reviewers (DL and YB). The extracted information from each study included the first author's name, year of publication, participant age, stroke phases, interventions and control details, outcome measures, external feedback, sample size, and follow-up evaluation after interventions. If the mean and SD of change scores were shown in the articles, they were extracted. If not explicitly stated, change scores were calculated using the following formula based on the principles of the Cochrane Handbook for Systematic Reviews of Interventions [37]. In cases where studies reported median and interquartile range, we converted these values to mean and SD estimates using the transformations: mean ≈ median and standard deviation = IQR × 1.35.

$$\mathrm{Mean}_{change} = \mathrm{Mean}_{final} - \mathrm{Mean}_{baseline};$$

$$SD_{change} = \sqrt{SD^2_{baseline} + SD^2_{final} - (2 \times \mathrm{Corr} \times SD_{baseline} \times SD_{final})}$$

Quality assessment

The quality and risk of bias for included studies were independently assessed by two reviewers (GS and YL). The tool chosen for the quality appraisal of this meta-analysis was the Physiotherapy Evidence Database (PEDro) scale since it is an effective and reliable scoring tool for evaluating methodological quality within the physiotherapy profession and has been used frequently in systematic reviews and meta-analysis [38]. The PEDro scale comprises 11 items, addressing aspects including the risk of bias in randomization, allocation concealment, blinding, dropout rate, intention to treat, and data reporting. Except for the first item, each of the remaining 10 items receives 1 point if a clinical controlled trial fulfills the criterion, and the final score is determined by summing these points. Studies with a PEDro score of 9–10 are classified as "excellent" quality, 6–8 as "good" quality, 4–5 as "fair" quality, and below 4 as "poor" quality [38, 39]. Additionally, the risk of bias in included studies was assessed using the items of the Cochrane Risk of Bias tool (ROB) and recorded in Review Manager 5.4.1, consisting of random sequence generation, allocation concealment, blinding of participants and personnel, blinding of outcome assessment, incomplete outcome data, and selective reporting. The Grading of Recommendations Assessment, Development, and Evaluation (GRADE) guidelines for systematic reviews were used to evaluate the quality of outcomes [40]. In instances of disagreement, a third reviewer (YS) was consulted, and consensus was reached.

Statistical analysis

Effect size calculation

Upper-limb motor impairment, motor function, and activities of daily living were the focused outcomes in our meta-analysis. The FMA-UE is the most frequently utilized clinical measurement for detecting the recovery of motor impairments in the paretic upper limbs of stroke patients [41], and it was adopted as the primary outcome measure in this study. Assessments of upper-limb motor function included WMFT [42] and ARAT [43]. Modified Barthel Index (MBI) was used to assess activities of daily living [44]. MD and 95%CI for each statistical analysis were calculated to assess the efficacy of BCI-based training, and the difference was significant when the test level was $P < 0.05$. RevMan 5.4.1 was used for data synthesis and analysis.

Heterogeneity analysis

The chi-square test and I^2 test were used to estimate statistical heterogeneity between trials. The statistical heterogeneity was categorized as negligible or small heterogeneity (0-40%), moderate heterogeneity (30-60%), substantial heterogeneity (50-90%), and considerable heterogeneity (>75%) [45]. If the chi-square test was $P>0.1$ or $I^2<50\%$, the studies were assessed as having high homogeneity, and the fixed-effects model was used for meta-analysis. If the chi-square test was $P<0.1$ or $I^2>50\%$, the studies were assessed as having significant heterogeneity, and the random-effects model was used for meta-analysis. A subgroup or sensitivity analysis was conducted to explore the potential sources of clinical heterogeneity within the included studies and verify the reliability of the results. Leave-one-out sensitivity analysis was performed.

Publication bias

A funnel plot analysis was performed to assess the potential for publication bias in the meta-analysis, applicable when the number of included studies exceeded ten. In the event of symmetry in the distribution of effect sizes around the pooled mean effect size, this would indicate an absence of publication bias, assuming that any observed variability is attributable to random sampling error.

Subgroup analysis

Subgroup analysis was performed based on different follow-up (≤3 months vs.>3 months), stroke phases (subacute: 7 days to 6 months from stroke onset vs. chronic: >6 months from stroke onset [46]), external feedback combined with BCI (BCI-FES vs. BCI-robot vs. BCI-visual feedback), external feedback and stroke phases (BCI-FES on subacute vs. BCI-FES on chronic, BCI-robot on subacute vs. BCI-robot on chronic). Additionally, to provide a reference for clinical training intensity settings for BCI-based training, we have subdivided the intervention intensity into the following categories: training time per day (<20 min vs. 20 min vs. 30–40 min vs. 60 min vs. 60–90 min vs. 90 min), training sessions per week (2–3 sessions vs. 5 sessions), total training sessions (≤10 sessions vs. 10–20 sessions vs. ≥20 sessions), training duration (2 weeks vs. 3–4 weeks vs. > 4 weeks). The outcome measure for all subgroup analysis was the FMA-UE.

Results

Search results

The search strategy yielded 3773 articles from various sources: 1092 from PubMed, 272 from Cochrane Library, 2409 from Web of Science, and 1 from other sources. After removing duplicates, patents, books, and conference proceedings, the titles and abstracts of 2192 articles were screened for possible inclusion. Subsequently, 409 articles were assessed for eligibility through full-text screening. Finally, 21 articles, involving 886 patients were included in the meta-analysis. The flowchart of the search strategy and selection steps is presented in Fig. 1, and the main characteristics of the included studies are detailed in Table 1 and Supplementary Table S3-S4.

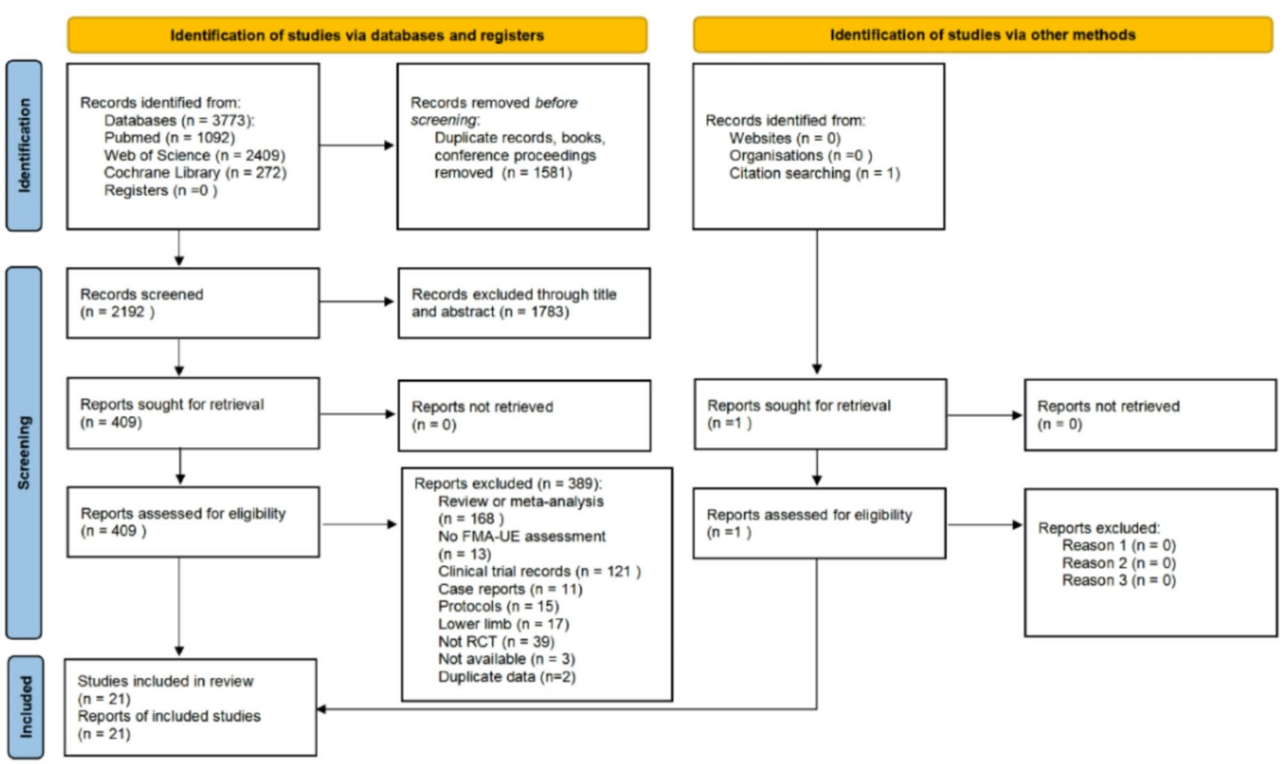

Fig. 1 PRISMA flow chart of study selection

Table 1 Characteristics of the included studies

Study	Time from stroke onset	Stroke phases	Experimental interventions	Control interventions	BCI training intensity	Outcome measures	Follow-up	Sample size	PEDro
Ang, 2014	E: 285.7 ± 64.0 d C: 454.4 ± 109.6 d	chronic	BCI-HK + con-rehab	HK: HK + con-rehab SAT: con-rehab	60 min /d, 3 d/wk, 6 wks, 18 sessions	FMA-UE	6 wks 18 wks	E: 6 C: 8/7	7
Ang, 2015	E: 383.0 ± 290.8 d C: 234.7 ± 183.8 d	chronic	BCI-Manus robot	Manus robot	90 min/d, 3 d/wk, 4 wks,12 sessions	FMA-UE	8 wks	E: 11 C: 14	7
Biasiucci, 2018	E: 39.8 ± 45.9 m C: 33.5 ± 30.5 m	chronic	BCI-FES + con-rehab	sham FES + con-rehab	60 min/d, 2 d/wk, 5 wks, 10 sessions	FMA-UE MRC MAS ESS	6–12 m	E: 14 C: 13	8
Chen, 2020	E: 3.1 ± 1.7 m C: 3.9 ± 1.5 m	subacute	BCI-exoskeleton + con-rehab	sham BCI + con-rehab	19.5 min/d, 3 d/wk, 4 wks, 12 sessions	FMA-UE	—	E: 7 C: 7	6
Cheng, 2020	E: 476.8 ± 302.0 d C: 890.2 ± 257.2 d	chronic	BCI-SRG + con-rehab	SRG + con-rehab	90 min /d, 3 d/ wk, 6 wks, 18 sessions	FMA-UE ARAT	6 wks 18 wks	E: 5 C: 5	6
Curado, 2015	E: 5.6 ± 3.9 y C: 5.5 ± 6.1 y	chronic	BCI-orthosis + con-rehab	sham BCI + con-rehab	60 min/d, 5 d/wk, 4 wks, 20 sessions	FMA-UE	—	E: 16 C: 14	6
Frolov, 2017	E: 8.4 ± 6.9 m C: 10.9 ± 7.9 m	subacute and chronic	BCI-exoskeleton + con-rehab	sham BCI	30 min/d, 5 d/wk, 2 wks, 10 sessions	FMA-UE, ARAT	—	E: 55 C: 19	6
Fu, 2023	E: 77.5 (33.8, 175.3) d C: 64.0 (37.0, 150.0) d	unclear	BCI-hand robot + con-rehab	con-rehab	30 min/d, 5 d/wk, 4 wks, 20 sessions	FMA-UE	—	E: 30 C: 31	6
Guo, 2022	E: 12.5 ± 7.1 m C: 10.9 ± 7.9 m	chronic	BCI-SRG + con-rehab	Robotic: SRG control: con-rehab	60 min/d, 5 d/wk, 2 wks, 10 sessions	FMA-UE WMFT MAS	12 wks	E: 10 C: 10/10	5
Kim, 2016	E: 8.3 ± 2.0 m C: 7.8 ± 1.8 m	chronic	BCI-FES + con-rehab	con-rehab	30 min/d, 3 d/wk, 4 wks, 12 sessions	FMA-UE MAL MBI ROM	—	E: 15 C: 15	7
Lee, 2020	E: 7.5 ± 1.6 m C: 8.3 ± 2.0 m	chronic	BCI-FES + con-rehab	FES + con-rehab	30 min/d, 5 d/wk, 4 wks, 20 sessions	FMA-UE WMFT MAL MBI	—	E: 13 C: 13	7
Li, 2014	E: 2.2 ± 1.8 m C: 2.8 ± 2.0 m	subacute	BCI-FES + con-rehab	FES + con-rehab	60–90 min/d, 3 d/wk, 8 wks, 24 sessions	FMA-UE ARAT	—	E: 7 C: 7	7

Table 1 (continued)

Study	Time from stroke onset	Stroke phases	Experimental interventions	Control interventions	BCI training intensity	Outcome measures	Follow-up	Sample size	PEDro
Li, 2022	E: 4.0 (2.0, 11.3) m C: 4.3 ± 2.60 m	subacute	BCI-exoskeleton + con-rehab	con-rehab	60 min/d, 5d/wk, 2 wks, 10 sessions	FMA-UE WMFT MBI	2 wks	E: 12 C: 12	5
Liu, 2023	E: 52.5 (45.0, 59.3) d C: 18.0 (9.8, 23.0) d	subacute	BCI-FES + con-rehab	FES + con-rehab	20 min/d, 5d/wk, 3wks, 15 sessions	FMA-UE WMFT MBI	—	E: 30 C: 30	8
Ma, 2023	E: 5.90 ± 2.99 m C: 6.45 ± 3.38 m	unclear	BCI-exoskeleton + con-rehab	con-rehab	40 min/d, 5d/wk, 2 wks, 10 sessions	FMA-UE	—	E: 20 C: 20	7
Miao, 2020	E: 18.3 ± 10.9 m C: 11.1 ± 5.0 m	chronic	BCI-FES + con-rehab	con-rehab	16 min/d, 3 d/wk, 4 wks, 12 sessions	FMA-UE	—	E: 8 C: 8	5
Mihara, 2013	E: 146.6 ± 36.2 d C: 123.4 ± 38.3 d	subacute	BCI-visual feedback + con-rehab	sham BCI + con-rehab	20 min/d, 3 d/wk, 2 wks,6 sessions	FMA-UE ARAT	2 wks	E: 10 C: 10	8
Pichiorri, 2015	E: 2.7 ± 1.7 m C: 2.5 ± 1.2 m	subacute	BCI-virtual feedback + con-rehab	MI + con-rehab	60 min/d, 3 d/wk, 4 wks, 12 sessions	FMA-UE NIHSS MRC MAS	—	E: 14 C: 14	7
Ramos-Murguialday, 2013	E: 66.0 ± 45.0 m C: 71.0 ± 72.0 m	chronic	BCI-orthosis + con-rehab	sham BCI + con-rehab	60 min/d, 5 d/wk, 4 wks, 20 sessions	FMA-UE MAL AS GAS	6 m	E: 16 C: 16	8
Wang, 2024	E: 15 (8–21) d C: 13 (8 – 1) d	subacute	BCI-FES + con-rehab	con-rehab	30 min/d, 5 d/wk, 4 wks, 20 sessions	FMA-UE ARAT WMFT MAS IADL	2 m	E: 150 C: 146	7
Wu, 2020	E: 2.1 ± 0.3 m C: 2.0 (1.5, 3.0) m	subacute	BCI-exoskeleton + con-rehab	con-rehab	60 min/d, 5 d/wk, 4 wks, 20 sessions	FMA-UE ARAT WMFT	—	E: 14 C: 11	6

Abbreviations: E: Experimental group, C: Control group, BCI: Brain-Computer interface, FES: Functional electric stimulation, con-rehab: Conventional rehabilitation, m: Months, d: Days, SAT: Standard Arm Therapy, FMA-UE: Fugl-Meyer assessment-upper extremity, ARAT: Action research arm test, WMFT: Wolf motor function Test, MBI: modified Barthel index, NIHSS: National Institutes of Health Stroke Scale, IADL: Instrumental Activity of Daily Living, MAS: modified Ashworth scale, AS: Ashworth scale, MRC: Medical Research Council Scale, MAL: Motor Activity Log, GAS: Goal Attainment Scale, ESS: European Stroke Scale

Methodological quality and risk of bias

According to the PEDro scale (Supplementary Table S5), quality assessment was conducted for the included RCTs. Eighteen RCTs (85.7%) were classified as "good" quality studies, while five RCTs (14.3%) were classified as fair quality studies, with no studies identified as "poor" quality. Figures 2 and 3 show the results of the RoB evaluation. The qualitative assessment showed a low risk of missing outcome data and selection of the reported results. Moreover, studies showed some concerns in the randomization process, allocation concealment, and measurement of outcomes. As blinding of participants and intervention providers was not feasible, the studies mainly focused on blinding outcome assessors, which might cause a high risk of performance bias (2).

Effects on upper-limb motor impairment

FMA-UE

The findings indicated that BCI-based training significantly improved FMA-UE scores (random, MD = 3.69, 95%CI 2.41–4.96, $P < 0.00001$) (Fig. 4). There was substantial heterogeneity among the included studies ($I^2 = 70\%$, $P < 0.00001$). Leave-one-out sensitivity analysis revealed 2 studies contributing most to heterogeneity

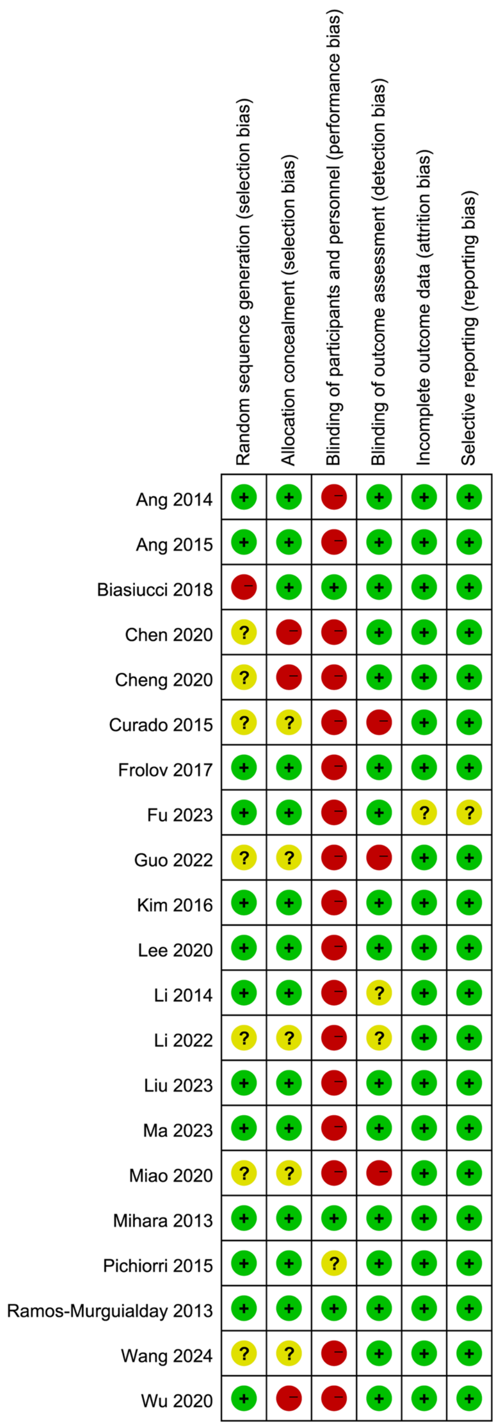

Fig. 2 Risk of bias summary

[11, 31]. The heterogeneity was reduced significantly after excluding the two studies ($I^2 = 46\%$). The results also showed that BCI-based training significantly improved FMA-UE scores (random, MD = 3.16, 95%CI 2.10–4.22, $P < 0.00001$) (Supplementary Fig S1-S4). In addition, In case of excluding studies with PEDro score < 6 [18, 21, 29], the results also favored the benefits of BCI-based training (random, MD = 3.91, 95%CI 2.53–5.30, $P < 0.00001$) (Supplementary Fig S5-S6).

Furthermore, BCI-based training not only showed better effects compared to sham BCI (random, MD = 2.92, 95%CI 1.51–4.33, $P < 0.0001$), with moderate heterogeneity ($I^2 = 52\%$, $P = 0.01$) but compared to conventional rehabilitation (random, MD = 5.03, 95%CI 3.12–6.94, $P < 0.00001$), with considerable heterogeneity ($I^2 = 75\%$, $P < 0.0001$) (Supplementary Fig S7-S8). Besides, 5 of the 21 studies used the MAS or AS to assess spasticity [8–10, 29, 33] and consistently reported that BCI-based training did not improve MAS or AS scores compared with control interventions.

Effects on upper-limb motor function

WMFT

The WMFT scores of the affected side were significantly longer in the intervention group than in the control group (random, MD = 5.00, 95%CI 2.14–7.86, $P = 0.0006$), with considerable heterogeneity ($I^2 = 79\%$, $P = 0.0002$). Leave-one-out sensitivity analysis revealed 2 studies contributing most to heterogeneity [11, 20]. The heterogeneity was decreased significantly after excluding the two studies ($I^2 = 0\%$). The results also showed that BCI-based training significantly improved WMFT scores (random, MD = 2.96, 95%CI 2.06–3.87, $P < 0.00001$) (Fig. 4 and Supplementary Fig S9-S10).

ARAT

The pooled results showed that BCI-based training exhibited significant improvements in ARAT scores (fixed, MD = 2.04, 95%CI 0.25–3.82, $P = 0.03$), with small heterogeneity ($I^2 = 35\%$, $P = 0.18$) (Fig. 4 and Supplementary Fig S11).

Effects on activities of daily living

MBI

We found no statistically significant improvement in MBI scores (random, MD = 7.46, 95%CI -0.29-15.22, P = 0.06), with considerable heterogeneity (I2 = 94%, P < 0.00001). Sensitive exclusion analysis indicated that BCI-based training produced a statistically significant improvement in MBI after excluding the studies of Liu et al. [20] (random, MD = 3.60, 95%CI 0.17–7.03, P = 0.04), with moderate heterogeneity (I2 = 55%, P = 0.11). (Fig. 4 and Supplementary Fig S12-S Table 2

Subgroup analysis

Follow-up

The aggregated findings from follow-up assessments demonstrated that the effects of BCI-based training on FMA-UE could be sustained for both a short time (random, MD = 3.22, 95%CI 1.10–5.34, $P = 0.003$) with moderate heterogeneity ($I^2 = 46\%$, $P = 0.09$) and a longer

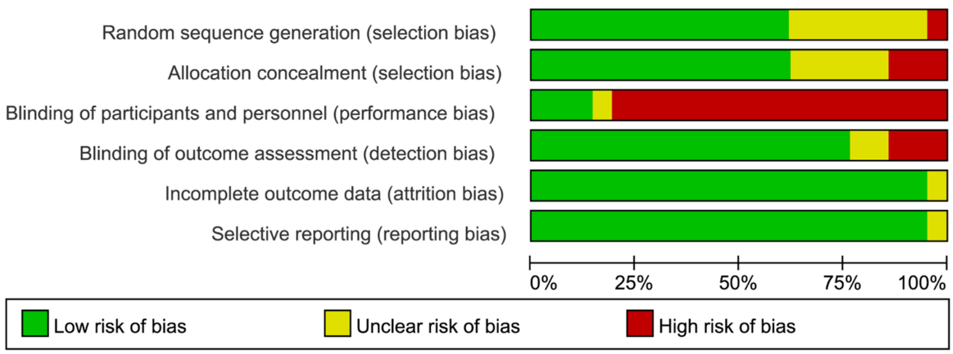

Fig. 3 Risk of bias graph

Table 2 GRADE quality of evidence assessment of individual outcome measures for the efficacy of BCI-based training in the improvement of upper-limb recovery

Outcome measure	Number of participants	Heterogeneity		Model of analysis	Group effect value		MD	95%CI	Grade
		I^2	*P*		Z	*P*			
FMA-UE	886 (21 RCT)	70%	< 0.00001	Random effect	5.65	< 0.00001	3.69	[2.41, 4.96]	Moderate
WMFT	451 (6 RCT)	79%	0.0002	Random effect	3.43	0.0006	5.00	[2.14, 7.86]	Low
ARAT	412 (6 RCT)	38%	0.18	Fixed effect	2.23	0.03	2.04	[0.25, 3.82]	High
MBI	140 (4 RCT)	94%	< 0.00001	Random effect	1.89	0.06	7.46	[-0.29, 15.22]	Low

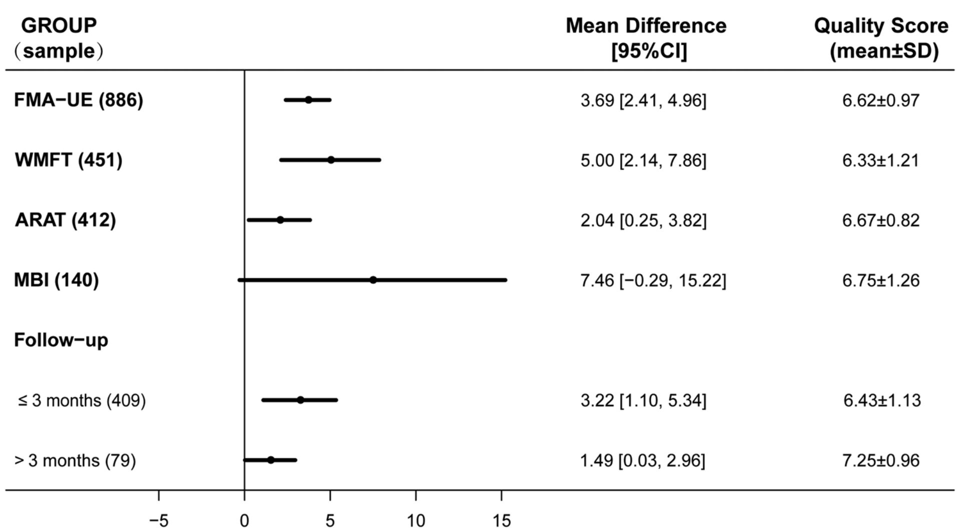

Fig. 4 Evaluating effects of BCI-based training in improving upper-limb rehabilitation after stroke compared to control interventions. The analysis includes assessments of FMA-UE, WMFT, ARAT, and MBI, and the follow-up of FMA-UE after finishing the intervention

duration after intervention (random, MD = 1.49, 95%CI 0.03–2.96, $P = 0.05$) with small heterogeneity ($I^2 = 23\%$, $P = 0.27$) (Fig. 4 and Supplementary Fig S14-S15).

Stroke phases

Compared with control interventions, our analysis demonstrated that BCI-based training significantly impacted FMA-UE for subacute patients (random, MD = 4.24, 95%CI 1.81–6.67, $P = 0.0006$) with considerable heterogeneity ($I^2 = 77\%$, $P < 0.0001$) and chronic patients (random, MD = 2.63, 95%CI 1.50–3.76, $P < 0.00001$) with small heterogeneity ($I^2 = 26\%$, $P = 0.20$) (Fig. 5 and Supplementary Fig S16-S17).

External feedback

Compared with control interventions, the subgroup analysis revealed that BCI combined with FES (random, MD = 4.37, 95%CI 3.09–5.65, $P < 0.00001$), BCI combined with robots (random, MD = 2.87, 95%CI 0.69–5.04, $P = 0.010$), and BCI combined with visual feedback (random, MD = 4.46, 95%CI 0.24–8.68, $P = 0.04$) exhibited significant effects on FMA-UE (Fig. 4). The three subgroups

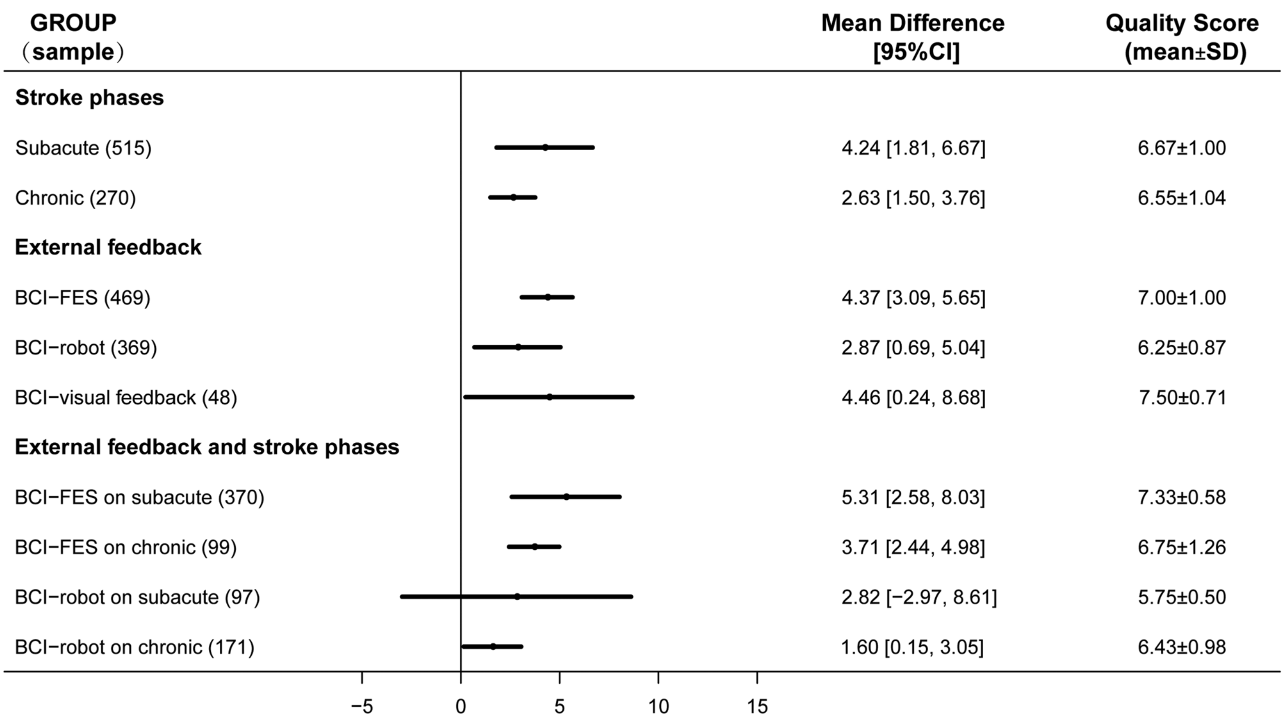

Fig. 5 Subgroup meta-analysis assessing the effectiveness of BCI-based training in enhancing FMA-UE across distinct stroke phases and comparing the efficacy of BCI combined with different external devices in post-stroke upper-limb motor recovery

had small heterogeneity ($I^2 = 36\%$, $P = 0.15$), considerable heterogeneity ($I^2 = 81\%$, $P < 0.00001$), and small heterogeneity ($I^2 = 27\%$, $P = 0.24$), respectively (Fig. 5 and Supplementary Fig S18-S19).

Further analysis indicated that BCI combined with FES was superior to both sham BCI (random, MD = 4.94, 95%CI 2.73–7.15, $P < 0.0001$), with moderate heterogeneity ($I^2 = 58\%$, $P = 0.07$) and conventional rehabilitation (random, MD = 3.81, 95%CI 2.30–5.32, $P < 0.00001$), with negligible heterogeneity ($I^2 = 0\%$, $P = 0.49$). BCI combined with robots was superior to both sham BCI (random, MD = 1.58, 95%CI 0.31–2.85, $P = 0.01$), with negligible heterogeneity ($I^2 = 0\%$, $P = 0.44$) and conventional rehabilitation (random, MD = 5.73, 95%CI 3.13–8.33, $P < 0.0001$), with considerable heterogeneity ($I^2 = 78\%$, $P = 0.004$) (Supplementary Fig S20-S22).

External feedback across stroke phases

Compared with control interventions, further analysis indicated significant improvement in FMA-UE through the combination of BCI and FES both for subacute patients (random, MD = 5.31, 95%CI 2.58–8.03, $P = 0.0001$), with substantial heterogeneity ($I^2 = 60\%$, $P = 0.08$) and chronic patients (random, MD = 3.71, 95%CI 2.44–4.98, $P < 0.00001$) with negligible heterogeneity ($I^2 = 0\%$, $P = 0.54$). Compared with control interventions, the combination of BCI and robots improved FMA-UE for chronic patients (random, MD = 1.60, 95%CI 0.15–3.05, $P = 0.03$), with small heterogeneity ($I^2 = 10\%$, $P = 0.35$), but not subacute patients (random, MD = 2.82, 95%CI -2.97-8.61, $P = 0.34$), with considerable heterogeneity ($I^2 = 89\%$, $P < 0.00001$) (Fig. 5 and Supplementary Fig S23-S25).

Training time per day

Compared with control interventions, subgroup analysis of < 20 min per day, there was no significant improvement in FMA-UE (random, MD = 2.87, 95%CI -0.19-5.92, $P = 0.07$) with negligible heterogeneity ($I^2 = 0\%$, $P = 0.77$). In the subgroup of 20 min per day, a significant improvement in FMA-UE was shown (random, MD = 5.30, 95%CI 1.17–9.42, $P = 0.01$) with substantial heterogeneity ($I^2 = 65\%$, $P = 0.09$). In the subgroup of 30–40 min, a significant improvement in FMA-UE was shown (random, MD = 3.92, 95%CI 2.18–5.66, $P < 0.0001$) with substantial heterogeneity ($I^2 = 65\%$, $P = 0.010$). In the subgroup of 60 min per day, a significant improvement in FMA-UE was shown (random, MD = 4.06, 95%CI 1.40–6.71, $P = 0.0003$) with considerable heterogeneity ($I^2 = 80\%$, $P = 0.0001$). Only one study [18] reported a training time of 60–90 min per day, which showed a significant improvement in FMA-UE (random, MD = 5.94, 95%CI 0.38–11.50, $P = 0.04$). In the subgroup of 90 min per day (random, MD = -1.80, 95%CI -5.42-1.82, $P = 0.33$) with negligible heterogeneity ($I^2 = 0\%$, $P = 0.81$) per day, there was no significant improvement in FMA-UE (Fig. 6 and Supplementary Fig S28-S29).

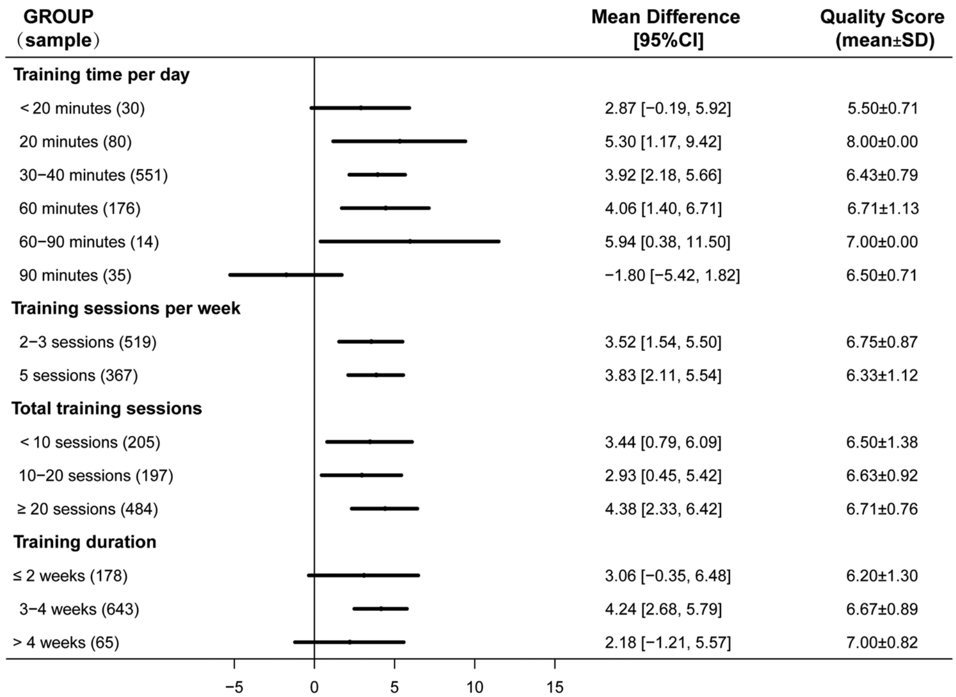

Fig. 6 Subgroup meta-analysis of the efficacy of BCI-based training in improving FMA-UE with varying training intensity

Training sessions per week

Compared with control interventions, the findings revealed that BCI-based training was effective in improving FMA-UE for 2–3 sessions per week (random, MD = 3.52, 95%CI 1.54–5.50, $P = 0.0005$), with substantial heterogeneity ($I^2 = 73\%$, $P < 0.0001$) and 5 sessions per week (random, MD = 3.83, 95%CI 2.11–5.54, $P < 0.00001$), with substantial heterogeneity ($I^2 = 70\%$, $P = 0.0008$) (Fig. 6 and Supplementary Fig S24-S25).

Total BCI-based training sessions

Subgroup analysis of total training sessions ≤ 10 sessions, a significant improvement in FMA-UE was shown (random, MD = 3.44, 95%CI 0.79–6.09, $P = 0.01$), with substantial heterogeneity ($I^2 = 65\%$, $P = 0.01$). In the subgroup of 10–20 sessions, a significant improvement in FMA-UE was shown (random, MD = 2.93, 95%CI 0.45–5.42, $P = 0.02$), with substantial heterogeneity ($I^2 = 70\%$, $P = 0.001$). In the subgroup of ≥ 20 sessions, a significant improvement in FMA-UE was shown (random, MD = 4.38, 95%CI 2.33–6.42, $P < 0.0001$), with considerable heterogeneity ($I^2 = 80\%$, $P < 0.0001$) (Fig. 6 and Supplementary Fig S30-S31).

Training duration

Compared with control interventions, subgroup analysis of training duration < 2 weeks, showed no significant improvement in FMA-UE (random, MD = 3.06, 95%CI -0.35-6.48, $P = 0.08$), with substantial heterogeneity ($I^2 = 72\%$, $P = 0.006$). Subgroup analysis of 3–4 weeks showed that BCI-based training could significantly improve FMA-UE (random, MD = 4.24, 95%CI 2.68–5.79, $P < 0.00001$), with substantial heterogeneity ($I^2 = 74\%$, $P < 0.00001$). However, in the subgroup of > 4 weeks, a significant improvement in FMA-UE was not observed (random, MD = 2.18, 95%CI -1.21-5.57, $P = 0.21$), with substantial heterogeneity ($I^2 = 60\%$, $P = 0.06$) (Fig. 6 and Supplementary Fig S32-S33).

Discussion

The meta-analysis explored the efficacy of BCI-based training on upper-limb function in stroke patients, revealing significant enhancements in upper-limb motor impairment and function, and this improvement can be maintained or continued to increase after intervention. Besides, the efficacy of BCI-based training varied with stroke phases, external feedback types, and training intensity. Our present work could give a new insight into BCI-based training for stroke survivors.

Subgroup analysis revealed the effectiveness of BCI-based training for both subacute and chronic stroke patients. The initial six months post-stroke play a crucial role in shaping the recovery trajectory [47]. However, many stroke patients miss that time window and only obtain limited functional gains during the chronic phase [48]. Patients in the chronic phase can still exhibit enduring and extensive cortical reorganization through reinforcement learning and programmed memory, leading to positive prognostic outcomes [49]. BCI-based training facilitates safe and repetitive rehabilitation training, allowing for maximum patient participation [50, 51], enhancing early recovery, and overcoming later functional plateaus.

Clinically, different studies have used different types of external feedback to apply to stroke patients. Our results showed that BCI-FES, BCI-robot, and BCI-visual feedback can significantly improve motor impairment. These findings underscored the distinctive benefits of the active closed-loop feedback inherent to the "central-peripheral-central" paradigm of BCI-based training. The enduring benefits of BCI-based training are likely due to its capacity to enhance motor recovery, cortical reorganization, and functional restoration, resulting in long-term improvements in motor impairment [8, 52]. During BCI-based training, patients develop movement intentions to move the paralyzed limb, and the coupling of external feedback devices completes the loop between cortical activity and movement [10, 53, 54]. This process enables participants to consciously regulate sensorimotor oscillations, generating afferent feedback activity that may restore corticospinal and corticomuscular connections, fostering neuroplasticity and improving motor impairment [25, 55, 56].

In addition, subgroup analysis revealed that BCI-FES is effective for both subacute and chronic stroke patients, whereas BCI-robot is beneficial exclusively for the chronic phase and not for subacute patients. This suggested that for subacute stroke patients, BCI-FES may be more potent in enhancing upper-limb motor impairment compared to BCI-robot. Furthermore, in chronic stroke patients, BCI-FES yielded a higher improvement than BCI-robot. This disparity may arise from FES facilitating voluntary muscle contraction, providing rich proprioceptive and somatosensory information feedback, and increasing perfusion to the sensory-motor cortex [57–59]. The efficacy of BCI-robot may also be influenced by the type of robot used, as differences in materials, joints, and training protocols can affect joint mobility, proprioceptive stimuli, and patient experience [60–62]. The robots used in these studies included end-effector [22, 23], hand exoskeleton [11, 24, 26, 28, 30], arm and hand orthosis [10, 27], and soft robotic gloves [25, 29]. While the pooled results from our studies leaned towards BCI combined with visual feedback, some researchers, such as Ono et al. [63] have posited that proprioceptive feedback generated by real motion is more advantageous. Therefore, FES may be more favorable external feedback for BCI in upper-limb recovery following a stroke. Combining BCI with FES may be a more favorable option for patients in both the subacute and chronic phase.

Regarding training intensity, the majority of researchers opted for a training frequency of 3–5 sessions per week. Moreover, a training duration of 3–4 weeks appeared to be optimal. In general, more intense exercise is associated with more benefits [64]. However, our analysis showed that training for less than 20 min or up to 90 min per day and training 2 weeks or longer than 4 weeks did not significantly improve motor impairment. On the one hand, inadequate daily training durations may preclude meaningful improvement, whereas excessively long sessions could precipitate fatigue and distraction [26], on the other hand, the small number of included studies and the high heterogeneity caused the bias of the results [25]. More high-quality studies are needed to bring more reliable results. Drawing from the subgroup analysis, we can offer tentative recommendations on training intensity: daily training sessions ranging from 20 to 90 min, conducted 2–5 sessions per week for 3–4 weeks, may yield the most favorable results.

MBI scores were not improved compared with the control group after BCI-based training in our analysis. MBI focuses on independence from the activities of daily living, rather than on a single motor function. The functional improvement observed may have not yet been translated into the practical use of the upper limbs for activities of daily living. It is noteworthy to highlight that spasticity is a prevalent complication among stroke survivors, with a notable impact on upper-limb recovery. Interestingly, 5 studies [8–10, 29, 33] consistently demonstrated that BCI-based training did not confer greater improvements in MAS or AS scores compared with control interventions. This observation suggests that BCI-based training may not substantially influence spasticity associated with stroke. More effective rehabilitation strategies for spasticity need further exploration.

Conventional rehabilitation therapies also play a key role in clinical recovery. The studies included in our analysis predominantly encompassed conventional rehabilitation programs that involved physical therapy (e.g. exercise therapy, passive mobilization, stretching, and physical factor therapy) [8–11, 17–22, 24–33] and more than half of the studies also incorporated occupational therapy [9–11, 20, 24, 28–33]. A few studies mentioned acupuncture [18] and cognitive therapy [33]. Overall, conventional rehabilitation pathways were generally consistent across the studies.

BCI-based training holds promise for patients with motor impairment, bridging the gap between motor intention and actual movement. Beyond stroke phases, external feedback, and training intensity, BCI accuracy is always crucial for the efficiency of BCI-based training. Considering moderate to severe brain deficits of stroke patients, motor-related cortical activities may be decreased or even hindered [65], which causes difficulties in detecting motor intention. Much effort has been made to solve the problem, including sophisticated algorithms [66], user training [67], and sensor fusion [68]. Recently, non-invasive brain stimulation techniques, such as anodal transcranial direct current stimulation (tDCS) [69] and repetitive transcranial magnetic stimulation (rTMS) [70], have been considered to be feasible in enhancing BCI performance. These approaches offer novel solutions to address BCI inefficiency, potentially advancing the clinical application of BCI-based stroke rehabilitation.

Finally, given the current findings and the PEDro scale assessment in our analysis, future studies should explore the dose-response relationship of BCI-based training, optimize treatment regimens, and incorporate long-term follow-up to assess the sustainability of the benefits of BCI-based training. Secondly, an individualized BCI-based training program should be developed according to the characteristics and rehabilitation stage of the patient. In addition, the high methodological quality of the study design was ensured by clear criteria, randomization, blinding, and adequate sample size. These recommendations aim to advance the research and application of BCI in stroke rehabilitation.

Limitations: Our study is subject to several limitations. Firstly, the analysis was based on a limited number of randomized clinical trials (21 studies involving 886 patients). Secondly, for a robust subgroup meta-analysis, it is recommended to include at least 5 clinical trials in each subgroup [35]. In some of our subgroup analysis, this criterion was not met. Additionally, this study did not involve the interaction between drug use and BCI-based training. It is suggested that future clinical research should add more details of medication to provide a more meaningful reference for clinical practice. Lastly, as with any meta-analysis, the possibility of publication bias is a concern, as evidenced by the asymmetric appearance of the funnel plot in our analysis.

Conclusion

In summary, BCI-based training emerges as an effective strategy for upper-limb rehabilitation following a stroke. The combination of BCI with FES appears particularly promising, catering to patients in both the subacute and chronic phases. A training intensity of 20 to 90 min per day, 2–5 sessions per week for 3–4 weeks may be most recommended. In both research and clinical contexts, careful consideration of stroke phases and the selection of external feedback is crucial. Future investigations should prioritize enhancing BCI accuracy, and refining and standardizing study designs for BCI-based training.

Supplementary Information

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Supplementary Material 1

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Author contributions
DL, RL, and LJ initiated and organized the project. DL, RL, and WQ reviewed references and conducted this meta-analysis. DL, LL, and GS reviewed references and interpreted data. DL, RL, and YS drafted the manuscript. LJ and LL revised the manuscript. All authors have given final approval for the current version to be published. All authors read and approved the final manuscript.

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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References

1. Global regional. National burden of stroke and its risk factors, 1990–2019: a systematic analysis for the global burden of disease study 2019. Lancet Neurol. 2021;20(10):795–820.
2. Lang CE, Beebe JA. Relating movement control at 9 upper extremity segments to loss of hand function in people with chronic hemiparesis. Neurorehabil Neural Repair. 2007;21(3):279–91.
3. Langhorne P, Coupar F, Pollock A. Motor recovery after stroke: a systematic review. Lancet Neurol. 2009;8(8):741–54.
4. Lai CH, Sung WH, Chiang SL, Lu LH, Lin CH, Tung YC, et al. Bimanual coordination deficits in hands following stroke and their relationship with motor and functional performance. J Neuroeng Rehabil. 2019;16(1):101.
5. Kwakkel G, Veerbeek JM, van Wegen EE, Wolf SL. Constraint-induced movement therapy after stroke. Lancet Neurol. 2015;14(2):224–34.
6. Pollock A, Farmer SE, Brady MC, Langhorne P, Mead GE, Mehrholz J, et al. Interventions for improving upper limb function after stroke. Cochrane Database Syst Rev. 2014;2014(11):Cd010820.

7. Sebastián-Romagosa M, Cho W, Ortner R, Murovec N, Von Oertzen T, Kamada K, et al. Brain computer interface treatment for motor rehabilitation of upper extremity of stroke Patients-A feasibility study. Front NeuroSci. 2020;14:591435.
8. Biasiucci A, Leeb R, Iturrate I, Perdikis S, Al-Khodairy A, Corbet T, et al. Brain-actuated functional electrical stimulation elicits lasting arm motor recovery after stroke. Nat Commun. 2018;9(1):2421.
9. Wang A, Tian X, Jiang D, Yang C, Xu Q, Zhang Y, et al. Rehabilitation with brain-computer interface and upper limb motor function in ischemic stroke: A randomized controlled trial. Med (New York NY). 2024;5(6):559–e694.
10. Ramos-Murguialday A, Broetz D, Rea M, Laer L, Yilmaz O, Brasil FL, et al. Brain-machine interface in chronic stroke rehabilitation: a controlled study. Ann Neurol. 2013;74(1):100–8.
11. Wu Q, Yue Z, Ge Y, Ma D, Yin H, Zhao H, et al. Brain functional networks study of subacute stroke patients with upper limb dysfunction after comprehensive rehabilitation including BCI training. Front Neurol. 2020;10:1419.
12. Wolpaw JR, Birbaumer N, McFarland DJ, Pfurtscheller G, Vaughan TM. Brain-computer interfaces for communication and control. Clin Neurophysiology: Official J Int Federation Clin Neurophysiol. 2002;113(6):767–91.
13. Casimo K, Weaver KE, Wander J, Ojemann JG. BCI use and its relation to adaptation in cortical networks. IEEE Trans Neural Syst Rehabilitation Engineering: Publication IEEE Eng Med Biology Soc. 2017;25(10):1697–704.
14. Lebedev MA, Nicolelis MA. Brain-Machine interfaces: from basic science to neuroprostheses and neurorehabilitation. Physiol Rev. 2017;97(2):767–837.
15. Abiri R, Borhani S, Sellers EW, Jiang Y, Zhao X. A comprehensive review of EEG-based brain-computer interface paradigms. J Neural Eng. 2019;16(1):011001.
16. Cervera MA, Soekadar SR, Ushiba J, Millán JDR, Liu M, Birbaumer N, et al. Brain-computer interfaces for post-stroke motor rehabilitation: a meta-analysis. Ann Clin Transl Neurol. 2018;5(5):651–63.
17. Lee SH, Kim SS, Lee BH. Action observation training and brain-computer interface controlled functional electrical stimulation enhance upper extremity performance and cortical activation in patients with stroke: a randomized controlled trial. Physiother Theory Pract. 2022;38(9):1126–34.
18. Li M, Liu Y, Wu Y, Liu S, Jia J, Zhang L. Neurophysiological substrates of stroke patients with motor imagery-based Brain-Computer interface training. Int J Neurosci. 2014;124(6):403–15.
19. Kim T, Kim S, Lee B. Effects of action observational training plus Brain-Computer Interface-Based functional electrical stimulation on Paretic arm motor recovery in patient with stroke: A randomized controlled trial. Occup Ther Int. 2016;23(1):39–47.
20. Liu X, Zhang W, Li W, Zhang S, Lv P, Yin Y. Effects of motor imagery based brain-computer interface on upper limb function and attention in stroke patients with hemiplegia: a randomized controlled trial. BMC Neurol. 2023;23(1):136.
21. Miao Y, Chen S, Zhang X, Jin J, Xu R, Daly I, et al. BCI-Based rehabilitation on the stroke in sequela stage. Neural Plast. 2020;2020:8882764.
22. Ang KK, Guan C, Phua KS, Wang C, Zhou L, Tang KY, et al. Brain-computer interface-based robotic end effector system for wrist and hand rehabilitation: results of a three-armed randomized controlled trial for chronic stroke. Front Neuroeng. 2014;7:30.
23. Ang KK, Chua KS, Phua KS, Wang C, Chin ZY, Kuah CW, et al. A randomized controlled trial of EEG-Based motor imagery Brain-Computer interface robotic rehabilitation for stroke. Clin EEG Neurosci. 2015;46(4):310–20.
24. Chen S, Cao L, Shu X, Wang H, Ding L, Wang SH, et al. Longitudinal electroencephalography analysis in subacute stroke patients during intervention of Brain-Computer interface with exoskeleton feedback. Front NeuroSci. 2020;14:809.
25. Cheng N, Phua KS, Lai HS, Tam PK, Tang KY, Cheng KK, et al. Brain-Computer Interface-Based soft robotic glove rehabilitation for stroke. IEEE Trans Biomed Eng. 2020;67(12):3339–51.
26. Frolov AA, Mokienko O, Lyukmanov R, Biryukova E, Kotov S, Turbina L, et al. Post-stroke rehabilitation training with a Motor-Imagery-Based Brain-Computer interface (BCI)-Controlled hand exoskeleton: A randomized controlled multicenter trial. Front NeuroSci. 2017;11:400.
27. Curado MR, Cossio EG, Broetz D, Agostini M, Cho W, Brasil FL, et al. Residual upper arm motor function primes innervation of Paretic forearm muscles in chronic stroke after Brain-Machine interface (BMI) training. PLoS ONE. 2015;10(10):e0140161.
28. Fu J, Chen S, Shu X, Lin Y, Jiang Z, Wei D, et al. Functional-oriented, portable brain-computer interface training for hand motor recovery after stroke: a randomized controlled study. Front NeuroSci. 2023;17:1146146.
29. Guo N, Wang X, Duanmu D, Huang X, Li X, Fan Y, et al. IEEE Trans neural Syst rehabilitation engineering: publication IEEE Eng Med Biology Soc. 2022;30:1737–44. SSVEP-Based Brain Computer Interface Controlled Soft Robotic Glove for Post-Stroke Hand Function Rehabilitation.
30. Li X, Wang L, Miao S, Yue Z, Tang Z, Su L, et al. Sensorimotor Rhythm-Brain computer interface with Audio-Cue, motor observation and multisensory feedback for Upper-Limb stroke rehabilitation: A controlled study. Front NeuroSci. 2022;16:808830.
31. Ma ZZ, Wu JJ, Hua XY, Zheng MX, Xing XX, Ma J, et al. Evidence of neuroplasticity with brain-computer interface in a randomized trial for post-stroke rehabilitation: a graph-theoretic study of subnetwork analysis. Front Neurol. 2023;14:1135466.
32. Mihara M, Hattori N, Hatakenaka M, Yagura H, Kawano T, Hino T, et al. Near-infrared spectroscopy-mediated neurofeedback enhances efficacy of motor imagery-based training in poststroke victims: a pilot study. Stroke. 2013;44(4):1091–8.
33. Pichiorri F, Morone G, Petti M, Toppi J, Pisotta I, Molinari M, et al. Brain-computer interface boosts motor imagery practice during stroke recovery. Ann Neurol. 2015;77(5):851–65.
34. Nojima I, Sugata H, Takeuchi H, Mima T. Brain-Computer interface training based on brain activity can induce motor recovery in patients with stroke: A Meta-Analysis. Neurorehabil Neural Repair. 2022;36(2):83–96.
35. Mansour S, Ang KK, Nair KPS, Phua KS, Arvaneh M. Efficacy of Brain-Computer interface and the impact of its design characteristics on poststroke Upper-limb rehabilitation: A systematic review and Meta-analysis of randomized controlled trials. Clin EEG Neurosci. 2022;53(1):79–90.
36. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ (Clinical Res ed). 2021;372:n71.
37. Cumpston M, Li T, Page MJ, Chandler J, Welch VA, Higgins JPT, et al. Updated guidance for trusted systematic reviews: a new edition of the Cochrane handbook for systematic reviews of interventions. Cochrane Database of Systematic Reviews; 2019.
38. Maher CG, Sherrington C, Herbert RD, Moseley AM, Elkins M. Reliability of the PEDro scale for rating quality of randomized controlled trials. Phys Ther. 2003;83(8):713–21.
39. Moseley AM, Herbert RD, Sherrington C, Maher CG. Evidence for physiotherapy practice: a survey of the physiotherapy evidence database (PEDro). Aust J Physiother. 2002;48(1):43–9.
40. Guyatt GH, Oxman AD, Vist GE, Kunz R, Falck-Ytter Y, Alonso-Coello P, et al. GRADE: an emerging consensus on rating quality of evidence and strength of recommendations. BMJ (Clinical Res ed). 2008;336(7650):924–6.
41. Fugl-Meyer AR, Jääskö 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.
42. Wolf SL, Lecraw DE, Barton LA, Jann BB. Forced use of hemiplegic upper extremities to reverse the effect of learned nonuse among chronic stroke and head-injured patients. Exp Neurol. 1989;104(2):125–32.
43. Zhao JL, Chen PM, Li WF, Bian RH, Ding MH, Li H, et al. Translation and initial validation of the Chinese version of the action research arm test in people with stroke. Biomed Res Int. 2019;2019:5416560.
44. Mahoney FI, Barthel DW. Functional evaluation: the barthel index. Maryland State Med J. 1965;14:61–5.
45. Bown MJ, Sutton AJ. Quality control in systematic reviews and meta-analyses. Eur J Vascular Endovascular Surgery: Official J Eur Soc Vascular Surg. 2010;40(5):669–77.
46. Bernhardt J, Hayward KS, Kwakkel G, Ward NS, Wolf SL, Borschmann K, et al. Agreed definitions and a shared vision for new standards in stroke recovery research: the stroke recovery and rehabilitation roundtable taskforce. Neurorehabil Neural Repair. 2017;31(9):793–9.
47. Heller A, Wade DT, Wood VA, Sunderland A, Hewer RL, Ward E. Arm function after stroke: measurement and recovery over the first three months. J Neurol Neurosurg Psychiatry. 1987;50(6):714–9.
48. Duncan PW, Goldstein LB, Horner RD, Landsman PB, Samsa GP, Matchar DB. Similar motor recovery of upper and lower extremities after stroke. Stroke. 1994;25(6):1181–8.
49. Whitall J, Waller SM, Sorkin JD, Forrester LW, Macko RF, Hanley DF, et al. Bilateral and unilateral arm training improve motor function through differing neuroplastic mechanisms: a single-blinded randomized controlled trial. Neurorehabil Neural Repair. 2011;25(2):118–29.
50. Remsik A, Young B, Vermilyea R, Kiekhoefer L, Abrams J, Evander Elmore S, et al. A review of the progression and future implications of brain-computer

interface therapies for restoration of distal upper extremity motor function after stroke. Expert Rev Med Dev. 2016;13(5):445–54.
51. Yang W, Zhang X, Li Z, Zhang Q, Xue C, Huai Y. The effect of Brain-Computer interface training on rehabilitation of upper limb dysfunction after stroke: A Meta-Analysis of randomized controlled trials. Front NeuroSci. 2021;15:766879.
52. Ramos-Murguialday A, Curado MR, Broetz D, Yilmaz O, Brasil FL, Liberati G, et al. Brain-Machine interface in chronic stroke: randomized trial Long-Term Follow-up. Neurorehabil Neural Repair. 2019;33(3):188–98.
53. Lucas TH, Fetz EE. Myo-cortical crossed feedback reorganizes primate motor cortex output. J Neuroscience: Official J Soc Neurosci. 2013;33(12):5261–74.
54. Nishimura Y, Perlmutter SI, Eaton RW, Fetz EE. Spike-timing-dependent plasticity in primate corticospinal connections induced during free behavior. Neuron. 2013;80(5):1301–9.
55. Chaudhary U, Birbaumer N, Ramos-Murguialday A. Brain-computer interfaces for communication and rehabilitation. Nat Reviews Neurol. 2016;12(9):513–25.
56. Sitaram R, Ros T, Stoeckel L, Haller S, Scharnowski F, Lewis-Peacock J, et al. Closed-loop brain training: the science of neurofeedback. Nat Rev Neurosci. 2017;18(2):86–100.
57. Christensen MS, Grey MJ. Modulation of proprioceptive feedback during functional electrical stimulation: an fMRI study. Eur J Neurosci. 2013;37(11):1766–78.
58. Eraifej J, Clark W, France B, Desando S, Moore D. Effectiveness of upper limb functional electrical stimulation after stroke for the improvement of activities of daily living and motor function: a systematic review and meta-analysis. Syst Reviews. 2017;6(1):40.
59. Irimia DC, Cho W, Ortner R, Allison BZ, Ignat BE, Edlinger G, et al. Brain-Computer interfaces with Multi-Sensory feedback for stroke rehabilitation: A case study. Artif Organs. 2017;41(11):E178–84.
60. Qu H, Zeng F, Tang Y, Shi B, Wang Z, Chen X et al. The clinical effects of brain-computer interface with robot on upper-limb function for post-stroke rehabilitation: a meta-analysis and systematic review. Disabil Rehabilitation Assist Technol. 2022:1–12.
61. Tyč F, Boyadjian A. Plasticity of motor cortex induced by coordination and training. Clin Neurophysiology: Official J Int Federation Clin Neurophysiol. 2011;122(1):153–62.
62. Veerbeek JM, Langbroek-Amersfoort AC, van Wegen EE, Meskers CG, Kwakkel G. Effects of Robot-Assisted therapy for the upper limb after stroke. Neurorehabil Neural Repair. 2017;31(2):107–21.
63. Ono T, Shindo K, Kawashima K, Ota N, Ito M, Ota T, et al. Brain-computer interface with somatosensory feedback improves functional recovery from severe hemiplegia due to chronic stroke. Front Neuroeng. 2014;7:19.
64. Kruse A, Suica Z, Taeymans J, Schuster-Amft C. Effect of brain-computer interface training based on non-invasive electroencephalography using motor imagery on functional recovery after stroke - a systematic review and meta-analysis. BMC Neurol. 2020;20(1):385.
65. Li C, Jia T, Xu Q, Ji L, Pan Y. Brain-Computer interface Channel-Selection strategy based on analysis of Event-Related desynchronization topography in stroke patients. J Healthc Eng. 2019;2019:3817124.
66. Ang KK, Chin ZY, Wang C, Guan C, Zhang H. Filter bank common Spatial pattern Algosrithm on BCI competition IV datasets 2a and 2b. Front NeuroSci. 2012;6:39.
67. Doud AJ, Lucas JP, Pisansky MT, He B. Continuous three-dimensional control of a virtual helicopter using a motor imagery based brain-computer interface. PLoS ONE. 2011;6(10):e26322.
68. Fazli S, Mehnert J, Steinbrink J, Curio G, Villringer A, Müller KR, et al. Enhanced performance by a hybrid NIRS-EEG brain computer interface. NeuroImage. 2012;59(1):519–29.
69. Wei P, He W, Zhou Y, Wang L. Performance of motor imagery brain-computer interface based on anodal transcranial direct current stimulation modulation. IEEE Trans Neural Syst Rehabilitation Engineering: Publication IEEE Eng Med Biology Soc. 2013;21(3):404–15.
70. Shu X, Chen S, Chai G, Sheng X, Jia J, Zhu X. Neural modulation by repetitive transcranial magnetic stimulation (rTMS) for BCI enhancement in stroke patients. Annual Int Conf IEEE Eng Med Biology Soc IEEE Eng Med Biology Soc Annual Int Conf. 2018;2018:2272–5.

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