Attention-Adaptive BCI-AOT System Enhances Motor Recovery and Neural Engagement After Stroke

Hyunmi Lim, Hyoseon Choi, Bilal Ahmed, Yoonghil Park, and Jeonghun Ku

***Abstract*— Stroke frequently results in long-term motor deficits that impair quality of life. Action observation therapy (AOT) has shown promise for motor recovery through engagement of the mirror neuron system (MNS), yet its passive nature and lack of attentional tracking limit its neuroplasticity efficacy. To address these limitations, we developed a closed-loop Brain-Computer Interface-integrated AOT (BCI-AOT) system employing real-time Steady-State Visual Evoked Potential (SSVEP)-based attention monitoring to dynamically control therapy delivery. In a within-subject crossover study, 22 individuals with hemiplegic stroke completed both BCI-AOT and conventional AOT conditions, each consisting of five daily sessions and separated by a one-week washout. In BCI-AOT, video playback depended on sustained attentional engagement detected via SSVEPs. Behavioral outcomes (Box and Block Test [BBT], Action Research Arm Test [ARAT]) and physiological measures (Motor Evoked Potential [MEP] amplitude and latency, EEG power) were assessed pre- and post-intervention. Significant Condition × Day interactions were found for both BBT and ARAT, indicating greater functional gains over time in the BCI-AOT condition. Both conditions showed increased corticospinal excitability over time, while BCI-AOT additionally exhibited distinct mu and theta modulation over time. Participants also reported greater motivation and attention after BCI-AOT compared to conventional AOT. These results suggest that BCI-AOT elicits stronger neuroplasticity responses and user engagement than standard AOT. This study supports the feasibility and clinical potential of closed-loop, attention-adaptive neurorehabilitation for stroke recovery.**

***Index Terms*— Action observation therapy (AOT), brain-computer interface (BCI), attention feedback, steady-state visual evoked potentials (SSVEP), stroke rehabilitation.**

I. Introduction

STROKE remains one of the leading causes of long-term disability worldwide [1]. More than 60% of stroke survivors experience persistent motor deficits, particularly in the upper limbs, which substantially impair quality of life and functional independence [2]. Conventional rehabilitation approaches, such as physiotherapy, repetitive task training, and constraint-induced movement therapy, rely heavily on therapist supervision and patient compliance and often yield limited efficacy in individuals with severe impairment or fatigue [3], [4]. In unsupervised or home-based settings, these methods are associated with poor adherence and reduced neural engagement, potentially compromising therapeutic outcomes [5].

Action observation therapy (AOT) has emerged as an effective method to enhance motor recovery by activating the mirror neuron system (MNS), a cortical network engaged during both observation and execution of goal-directed actions [6], [7]. AOT enables motor system activation even in the absence of physical movement, which is particularly advantageous for patients with severe impairments [8]. However, conventional AOT is inherently passive and lacks mechanisms to ensure sustained attentional engagement, which may limit its neuroplasticity benefits [9], [10].

To address these limitations, brain-computer interface (BCI)-guided rehabilitation has been proposed as a means to personalize therapy delivery through real-time monitoring of brain activity [11], [12], [13]. Among various BCI paradigms, steady-state visual evoked potentials (SSVEPs) offer a reliable, low-training alternative for capturing visual attention by detecting neural responses to flickering visual stimuli at specific frequencies [14], [15]. Notably, SSVEP responses are

Received 15 August 2025; revised 14 November 2025 and 12 December 2025; accepted 5 January 2026. Date of publication 19 January 2026; date of current version 23 January 2026. This work was supported in part by the National Research Foundation of Korea (NRF) Grant funded by Korean Government through Ministry of Science and ICT (MSIT), Republic of Korea, under Grant NRF-2022R1A2B5B01001443, Grant RS-2024-00397674, Grant RS-2025-00561764, and Grant 2022R1G1A1011574; and in part by Eulji University in 2020. *(Hyunmi Lim and Hyoseon Choi contributed equally to this work.) (Corresponding author: Jeonghun Ku.)*

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Institutional Review Board (IRB) of Eulji Hospital, Seoul, South Korea, under Application No. 2024-07-009.

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This article has supplementary downloadable material available at https://doi.org/10.1109/TNSRE.2026.3654935, provided by the authors.

Digital Object Identifier 10.1109/TNSRE.2026.3654935

strongly modulated by whether an individual is focused or distracted, making them a powerful approach for monitoring attention in real-time during rehabilitation [16], [17], [18].

Sustained attention is a critical driver of neuroplasticity and functional recovery, as attentional lapses are associated with reduced motor cortex activity and may disrupt optimal motor learning [19], [20], [21], [22]. In conventional rehabilitation, feedback is typically performance-based and often fails to detect subtle cognitive disengagement during training [23], [24], [25]. By contrast, SSVEP-based BCI systems can complement these approaches by directly monitoring attentional state and providing timely feedback to re-engage the patient, thereby supporting adaptive learning and promoting cortical reorganization [17], [18], [26], [27], [28], [29].

Our previous studies have shown that integrating SSVEP-based feedback into motor rehabilitation, including action observation training, can strengthen activation in motor cortical areas, improve motor control, and increase patient motivation compared to traditional approaches [27], [29], [30], [31].

Although evidence indicates that attention modulates observational motor learning, few studies have implemented closed-loop AOT systems that dynamically adapt based on real-time attentional engagement [15], [27], [32]. This represents a critical gap in neurorehabilitation, where both cognitive and motor engagement are essential for driving neuroplasticity and optimizing functional outcomes [33].

This study introduces a novel closed-loop BCI-AOT system that integrates real-time SSVEP-based attention monitoring into AOT. The system continuously tracks attentional engagement and delivers immediate, adaptive feedback, such as pausing video playback during lapses and resuming upon re-engagement, to maintain optimal cognitive and motor involvement throughout training. We aim to evaluate whether this approach can enhance upper limb motor recovery and promote neurophysiological changes in individuals with stroke.

We hypothesize that (H1) participants receiving BCI-AOT will demonstrate significantly greater improvement in upper limb function, as measured by the Box and Block Test (BBT) and Action Research Arm Test (ARAT), compared with those receiving conventional AOT; (H2) EEG data will show distinct neural activation patterns and favorable trends in corticospinal excitability, as reflected in motor evoked potential (MEP) amplitude and latency; and (H3) BCI-AOT participants will report higher motivation, attention, and satisfaction than in the conventional AOT condition.

II. Methods

A. Proposed BCI-AOT System

To improve motor recovery in patients with stroke, the proposed rehabilitation system was developed by combining AOT with a closed-loop BCI system. The system monitors real-time attentional engagement through SSVEPs and dynamically controls the playback of AOT videos. It consists of six gamified AOT videos depicting specific hand movements, grasping, gripping, and pinching from the ARAT. These movements are embedded within everyday scenarios, such as placing a cake on a plate or feeding a bird, and are accompanied by virtual cues and animations to simulate functional daily activities.

A flickering square, slightly larger than the hand performing the action in the AOT video, was overlaid on the video and programmed to follow the hand's movements throughout each action sequence to elicit SSVEP responses. This design encouraged participants to naturally direct their gaze toward the flickering region while observing the hand. The flickering square overlaid on the hand region alternated between black and white at 15 Hz with a 75% duty cycle, providing reliable visual stimulation for SSVEP-based attention tracking.

The flickering square overlaid on the hand region alternated at 15 Hz with a 75% duty cycle. A stimulation frequency of 15 Hz was selected to avoid overlap with dominant mu-band activity (8–13 Hz) while remaining in a range that reliably elicits SSVEPs and is generally well tolerated by users. A 75% duty cycle was used to increase the effective luminance contrast per cycle and thereby improve the SSVEP signal-to-noise ratio without excessively increasing high-frequency visual load. In our previous study with stroke participants and healthy adults using a similar AOT-flicker paradigm, 15-Hz stimulation produced stable SSVEP responses and was well tolerated, which motivated the use of the same parameters in the present clinical protocol [27], [29], [31].

Through this closed-loop mechanism, patients remain cognitively engaged and actively involved in therapy sessions, as videos continue only when sustained attentional engagement is detected via a positively classified SSVEP signal. The system employs a trained Support Vector Machine (SVM) classifier that continuously analyzes real-time EEG input to detect sustained visual attention. When the classifier identifies a disengaged attentional state, video playback stops, and an auditory stimulus alerts the participant to maintain attention. Once attention is re-established and confirmed by the classifier, the video resumes seamlessly from the paused frame.

This adaptive AOT platform delivers rehabilitative content in a personalized, engagement-driven manner and is therefore suitable for evaluating attention-driven motor recovery in patients with stroke. Figure 1 illustrates the BCI-AOT system pipeline, Figure 2 presents the six gamified AOT video tasks, and Table I summarizes the task types and therapeutic focus.

B. Participants

The inclusion criteria were: (1) diagnosis of unilateral stroke confirmed by MRI or CT, (2) stroke onset at least 6 months before enrollment, (3) age >30 years, (4) mild to moderate motor impairment, defined as a Fugl-Meyer Assessment (FMA) upper extremity score of 23 or higher, (5) medically stable condition, and (6) ability to understand and follow task instructions. Participants were excluded if they (1) had a history of epilepsy or other neurological disorders, (2) exhibited severe cognitive impairment (Mini-Mental State Examination score <24), (3) had contraindications for EEG or TMS use, including metal implants, pacemakers, or scalp conditions that could interfere with EEG signal acquisition, (4) had significant visual field defects, visual impairments, or hemispatial neglect that could interfere with task

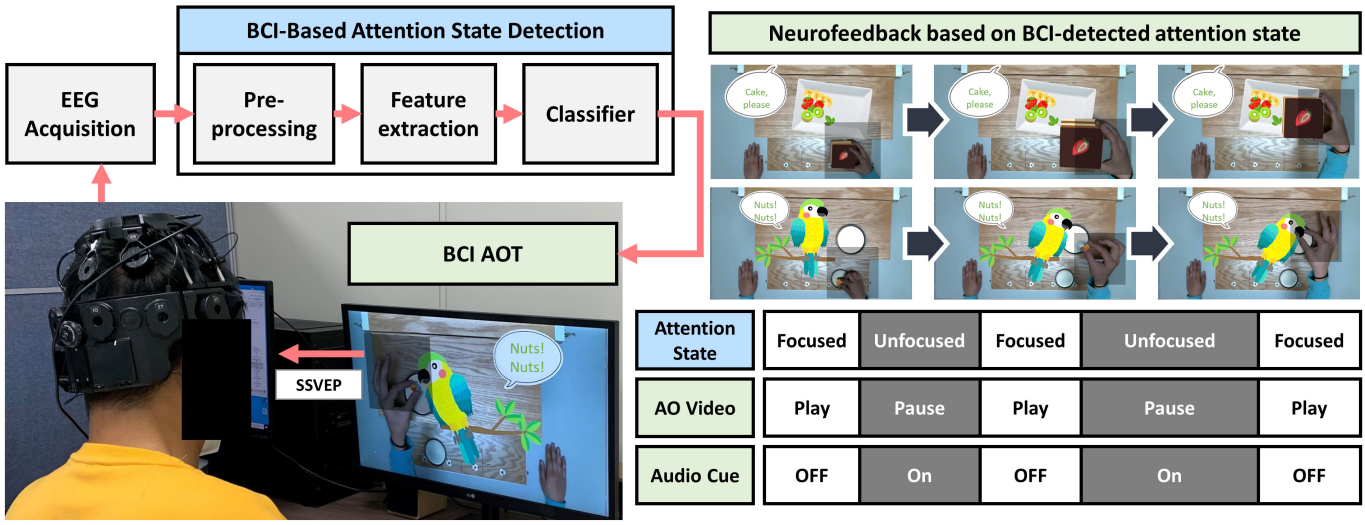

Fig. 1. Overview of the closed-loop BCI-AOT system integrating real-time attention state detection and neurofeedback. EEG signals elicited by SSVEP are acquired and processed through a BCI pipeline, including preprocessing, feature extraction, and binary classification of attention state (Focused vs. Unfocused). The classified attention state dynamically controls AOT video playback and auditory cues. Neurofeedback is delivered such that AOT content is played only during periods of sustained attention, aiming to enhance engagement and MNS activation during rehabilitation.

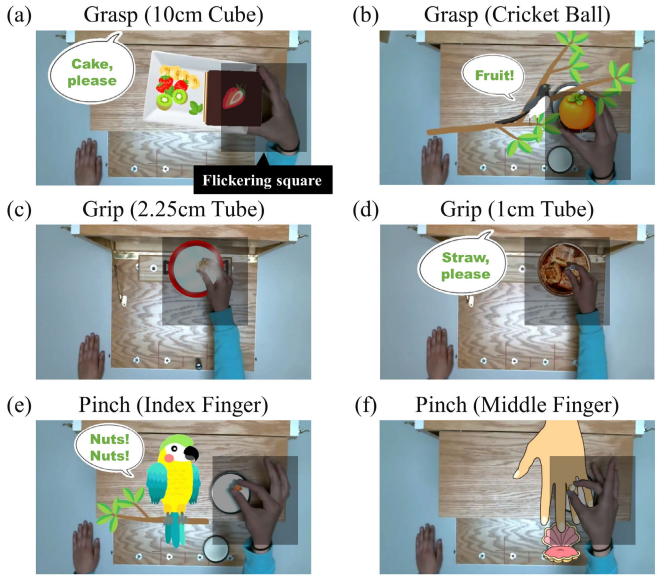

Fig. 2. Six gamified AOT video frames used in the BCI-AOT system, each representing distinct hand movements derived from the ARAT: (a) Grasping a 10cm cube–"placing a cake on a plate"; (b) Grasping a cricket ball–"feeding a bird"; (c) Gripping a 2.25cm tube–"transferring noodles"; (d) Gripping a 1cm tube–"inserting a straw"; (e) Pinching with index finger–"feeding a parrot"; and (f) Pinching with middle finger–"placing a pearl on a ring". Each task is visually enhanced with context-relevant animations to facilitate motor engagement and MNS activation.

performance [34], or (5) had a history of neurological or musculoskeletal injuries involving the upper limb. All participants provided informed consent to participate in this research and to publish their data, in accordance with the Declaration of Helsinki [35].

The required sample size was determined based on effect size estimates from a prior study [36], examining the change in BBT scores following AOT-based interventions. Sample size calculation was conducted using G* Power for a two-tailed paired t-test, assuming an effect size of dz = 0.65, $\alpha = 0.05$, and power of 0.80. The analysis indicated that a minimum of 19 participants was required for adequate statistical power. To account for potential dropouts and incomplete data, the target sample size was increased by approximately 25%, resulting in an intended enrollment of 24 participants.

TABLE I
OVERVIEW OF GAMIFIED REHABILITATION TASKS USED IN THE AOT INTERVENTION

Video Exercise Types	Tasks	Game Scenarios	Therapeutic Focus
Grasp	Lifting a 10cm cube (a)	Placing a cake on a plate	Hand strength & coordination
	Picking up a cricket ball (Fruit) (b)	Feeding a bird with fruit	Round object grasping
Grip	Moving a 2.25cm alloy tube (c)	Transfer noodles to a boiling pot	Controlled object transfer
	Moving a 1cm alloy tube (d)	Inserting a straw into a cup	Small object grip
Pinch	Picking up a nut (Index & Thumb) (e)	Feeding a parrot	Finger dexterity
	Picking up a pearl (Middle & Thumb) (f)	Placing a pearl on a ring	Pinch grip strength

Baseline impairment level was assessed using the Fugl-Meyer Assessment of the Upper Extremity (FMA-UE) to confirm comparable motor deficits across participants. Post-training FMA-UE data were not collected in this pilot study due to time constraints and to minimize participant fatigue.

C. Behavioral Outcome Measures

Manual dexterity of the affected upper limb was assessed using the BBT and ARAT. The BBT is a standardized,

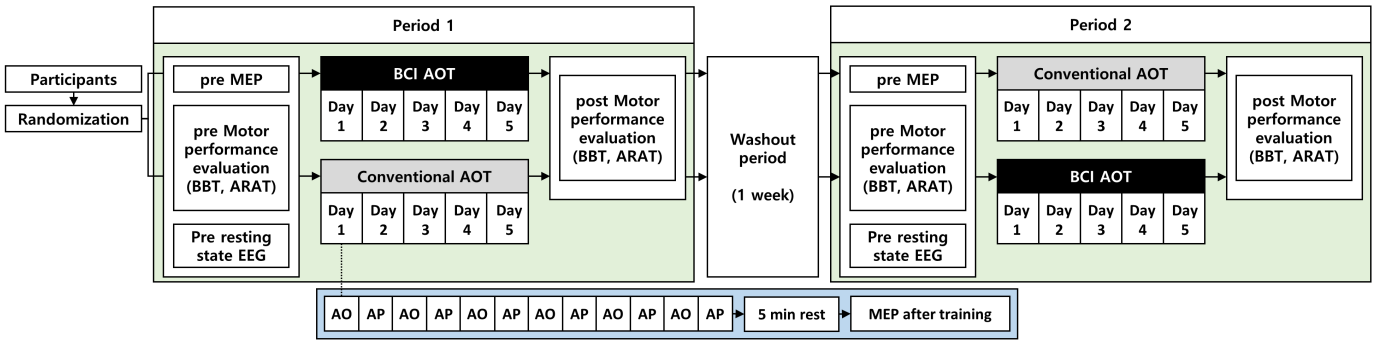

Fig. 3. The experimental protocol illustrates the randomized crossover design. Participants completed two intervention phases—BCI-AOT and conventional AOT, each lasting five consecutive days and separated by a one-week washout period. Pre-intervention assessments included resting-state EEG, motor performance evaluations (BBT and ARAT), and MEPs. Post-intervention assessments included MEP and motor performance evaluations. Each daily session alternated between AOT and AP to promote neuroplasticity and enable assessment of attention-modulated recovery.

validated test in which participants are instructed to move as many blocks as possible from one compartment to another within a single box in 60 s using the affected hand [37]. The ARAT is a standardized assessment of upper limb function that evaluates grasp, grip, pinch, and gross movement, with higher scores indicating better motor performance [38]. Both the BBT and ARAT were administered twice, before and after each of the two phases of the intervention program (BCI-AOT, conventional AOT). The primary outcome was the change in test scores across conditions to evaluate motor function improvement.

D. Experimental Design

The experiment employed a within-subject crossover design, with each participant receiving both BCI-AOT and conventional AOT in random order. Randomization was conducted using the order of entry into the study and a computerized research randomizer with random blocks. The study consisted of two phases, each comprising five consecutive days of intervention and separated by a one-week washout period to minimize potential carryover effects. This duration aligns with previous motor-learning and stroke rehabilitation crossover studies demonstrating that a one-week interval is sufficient to prevent residual intervention effects [39], [40]. This design enabled a direct within-subject comparison of EEG-guided BCI-AOT and conventional AOT. Participants were randomly assigned to begin with either BCI-AOT or conventional AOT in Period 1, followed by the alternate intervention in Period 2.

Participants were randomly assigned to start with either the BCI-AOT or conventional AOT condition in Period 1, followed by the alternate intervention in Period 2. Both phases included a detailed assessment protocol, resting-state EEG, MEP acquisition, and behavioral evaluations of motor function before and after training. EEG signals were recorded during every training session to track real-time brain engagement and evaluate differences in neural responsiveness between active (BCI-guided) and passive (non-feedback) therapy conditions. MEPs were measured daily, approximately 5 min after each training session, to assess changes in corticospinal excitability across the intervention period.

Figure 3 presents the experimental timeline and methodological framework, outlining participant randomization, intervention phases, assessment time points, and washout periods. The figure also illustrates the daily training sessions in which AOT and ARAT performance (AP) are alternated, as well as the collection of EEG data, tracking of motor performance, and measurement of MEPs to demonstrate the systematic capture of information.

Order (sequence) effects were evaluated to ensure that the one-week washout period sufficiently prevented carryover between intervention phases. For behavioral outcomes (BBT, ARAT), mixed-effects models including Condition, Time, and Order were used. For neurophysiological measures (MEP and EEG), Condition $\times$ Day $\times$ Order interactions were tested using mixed-effects models.

E. Implementation of AOT Conditions: BCI-AOT (EEG-Guided) Vs. Conventional AOT

This study included two conditions: BCI-AOT (EEG-guided AOT) and conventional AOT, both experienced by all participants. The primary difference between these conditions was the presence of attention-based feedback.

In the BCI-AOT condition, participants watched AOT videos featuring daily functional movements designed to activate the MNS. Video playback was controlled by the SSVEP-based BCI classifier, playing when attention was detected and pausing otherwise. Following the AOT phase, participants completed the AP session, replicating the observed movements with their paretic hand.

In the conventional AOT condition, participants watched the same pre-recorded AOT videos as in the BCI-AOT condition. However, these videos played continuously in a loop without neurofeedback. After the AOT phase, participants performed the same AP session as in the BCI-AOT condition, replicating the observed movements with their paretic hand. EEG was recorded continuously during the AOT session to analyze brain activity and assess neural responses, but no real-time feedback was provided.

Each daily training session consisted of six gamified AOT video tasks, which were each performed once per session. Each AOT task lasted 2 min, and each AP task lasted 1 min,

with a 3-min rest period between tasks. Across both conditions, continuous EEG monitoring was performed during AOT phases to evaluate neural responses and cognitive engagement. However, only the BCI-AOT condition incorporated real-time SSVEP-based attentional tracking and adaptive video playback.

To ensure within-subject comparability, the number of ME task repetitions was identical across conditions for each participant. All interventions were administered by experienced therapists, and outcome assessments were conducted by a blinded assessor.

F. EEG Acquisition and Processing

EEG data were acquired using a DSI-24 EEG headset (Wearable Sensing, San Diego, CA, USA) with 19 electrodes positioned according to the International 10–20 system. A signal quality check was performed before the experiment to confirm that the impedance values of all EEG channels met the manufacturer's criteria, as verified through the system's built-in software. A 27-inch LCD screen displaying AOT videos was positioned 60 cm from the participant's eyes to minimize postural strain while maintaining eye level. EEG signals were recorded at a 300 Hz sampling rate.

A rigorous preprocessing pipeline was applied to ensure high-quality EEG data. First, raw EEG signals were filtered using a 1–50 Hz bandpass filter to remove low-frequency drifts and high-frequency noise. To reduce spatially distributed artifacts and improve inter-channel consistency, common average referencing (CAR) was applied. Following CAR, independent component analysis (ICA) was performed to identify and remove artifacts caused by eye blinks, muscle activity, and environmental noise. ICA components were visually inspected, and those corresponding to non-neural sources were removed to enhance signal clarity. Independent component analysis (ICA) with visual inspection was applied only for offline preprocessing of EEG data used for group-level spectral analyses and topographic mapping. ICA was not used in the online BCI pipeline.

G. Classifier Design and Real-Time Detection

The BCI system implemented a real-time classification framework to detect attentional engagement based on SSVEP responses. Prior to the BCI-AOT sessions, each participant completed an individualized calibration procedure. EEG data were recorded under two alternating conditions: (1) flicker-present trials, in which participants fixated on the 15-Hz flickering square overlaid on an AOT video (attention-present), and (2) flicker-absent trials, in which a non-flickering fixation screen was shown and participants were allowed to relax (attention-absent). Each condition consisted of 15 trials of 6 s (total $\approx$ 3 min), and the two conditions were alternated to minimize adaptation.

For feature extraction, EEG signals were segmented into 1.0-s analysis windows with a 0.1-s update interval (90% overlap). Each window was band-pass filtered in the SSVEP band (14.5–15.5 Hz) and the mu band (8–13 Hz), and the filtered signals were projected through band-specific Common Spatial Pattern (CSP) filters computed from the calibration data. CSP has been widely used to enhance discriminability of EEG features in attention and motor-related paradigms [27]. Log-variance features from the CSP-projected signals were then concatenated across bands to form the final feature vector. This CSP-based approach was selected over canonical correlation analysis (CCA) and task-related component analysis (TRCA) because the present paradigm required binary discrimination of attentional state rather than multi-frequency SSVEP target identification. CSP provides high discriminability for two-class problems and offers computational efficiency with low latency, making it suitable for real-time closed-loop feedback in rehabilitation settings. ICA was applied only offline (for group-level EEG analysis) and was not used in the real-time pipeline to avoid latency and stability issues.

A linear-kernel Support Vector Machine (SVM) was trained using the calibration dataset. Classifier performance was evaluated offline using 10-fold cross-validation, and a minimum accuracy threshold of 70% was required to proceed to online training; otherwise, an additional short recalibration block ($\sim$1 min) was recorded and the classifier was retrained.

During therapy sessions, the trained classifier operated continuously, generating an attentional decision every 100 ms based on the 1.0-s sliding window. These outputs were used to dynamically modulate video playback in real time, thereby enabling the closed-loop attention-contingent feedback mechanism.

H. Spectral Power Analysis

Changes in mu and theta band power were computed to assess motor system activation and attentional engagement, respectively. Power change (%) was calculated using the following formula:

$$(Power_{base} - Power_{AOT})/Power_{base} \times 100 \quad (1)$$

Baseline power refers to the EEG signal power recorded during the pre-resting-state session, whereas task power refers to the power recorded during AOT. Negative values indicate power decreases (i.e., suppression) during task performance.

EEG analysis focused on the ipsilesional sensorimotor areas (C3/C4) and parietal regions (P3/P4), from which mu band activity (8–13 Hz) and theta band activity (4–8 Hz) were extracted for statistical analysis. These regions were selected due to their established relevance to motor and cognitive processing during AOT.

To ensure hemispheric consistency, topomaps were adjusted based on lesion laterality: for participants with right hemisphere lesions, EEG maps were flipped left-to-right so that the left side of each topomap uniformly represented the ipsilesional hemisphere. Condition-wise averages were computed after this correction across all participants.

I. MEP Analysis

MEP performance, along with MEP amplitude and latency, was used to assess changes in motor performance in relation to corticospinal excitability, identifying MEP changes associated with AP performance. To evaluate corticospinal excitability,

MEPs were recorded using a D702 coil connected to a Magstim 2002 transcranial magnetic stimulator. A trained physician administered TMS in a controlled electrodiagnostic laboratory setting. The coil was positioned at a 45° posterior-lateral angle to the midsagittal plane, and the stimulation site was marked on a swimming cap using a 1 cm grid system to ensure consistent placement across trials.

The resting motor threshold (RMT) was defined as the minimum stimulus intensity required to elicit an MEP of $\geq 50\ \mu$V in at least 5 out of 10 trials. Stimulation intensity was set to 120% of the RMT and remained constant across all experimental tasks. A total of 15 MEPs were collected, with each stimulation delivered at 5–7 s intervals. Average peak-to-peak amplitude and latency values were calculated to assess changes in corticospinal excitability.

The change in MEP amplitude was calculated using:

$$\Delta MEP_{Amp} = MEP_{Amp\_post} - MEP_{Amp\_pre} \tag{2}$$

$\text{MEP}_{\text{Amp\_pre}}$ indicates the baseline amplitude value, and $\text{MEP}_{\text{Amp\_post}}$ is used for post-training amplitude MEP measurement. An increase in $\Delta\text{MEP}_{\text{Amp}}$ means enhanced corticospinal excitability. Moreover, changes in MEP latency were evaluated through the equation:

$$\Delta MEP_{Lat} = MEP_{Lat\_pre} - MEP_{Lat\_post} \tag{3}$$

A positive $\Delta\text{MEP}_{\text{Lat}}$ estimates indicate improvement in the speed of neural conduction, heightened motor responses, cortical excitability, and increased efficiency within motor pathways.

J. J. User Experience Evaluation / Subjective Feedback Assessment

To comprehensively evaluate participants' perceptions of engagement, comfort, fatigue, and overall satisfaction with the interventions, a 13-item Likert scale questionnaire was administered at the end of each intervention phase (BCI-AOT and conventional AOT). Participants rated each statement on a five-point scale ranging from 1 (strongly disagree) to 5 (strongly agree).

The questionnaire included both positively and negatively worded items. Negatively phrased items were reverse-coded during analysis to ensure that higher scores consistently reflected more favorable responses (i.e., greater satisfaction, higher engagement, and lower fatigue).

The questionnaire assessed several key domains, including perceived improvement in motor skills, interest and motivation to participate, sustained attention, levels of fatigue and discomfort, and cues for continuing therapy. Detailed demographic characteristics are provided in Supplementary Table I.

K. Statistical Analysis

Repeated-measures analysis of variance (RM-ANOVA) was used to analyze behavioral outcomes (BBT and ARAT), MEP amplitude and latency, and EEG spectral power in the theta and mu bands. The statistical models included within-subject factors of Day and Condition (BCI-AOT vs. conventional AOT). For behavioral outcomes (BBT and ARAT), Day referred to pre- versus post-intervention. For EEG and MEP analyses, Day referred to the five consecutive intervention sessions.

Subjective feedback from the 13-item questionnaire was analyzed using paired-sample t-tests. Reverse-coded items (Items 6, 9, and 11) were adjusted so that higher scores consistently reflected more favorable user experiences.

Effect sizes were reported as partial eta squared (η^2) for RM-ANOVA results and Cohen's d for paired comparisons. Normality assumptions were verified prior to all parametric tests. The significance threshold was set at $p < 0.05$ for all analyses. EEG preprocessing, statistical analysis, and data visualization were performed using Python, while SPSS (version 25) was used for RM-ANOVA and t-tests.

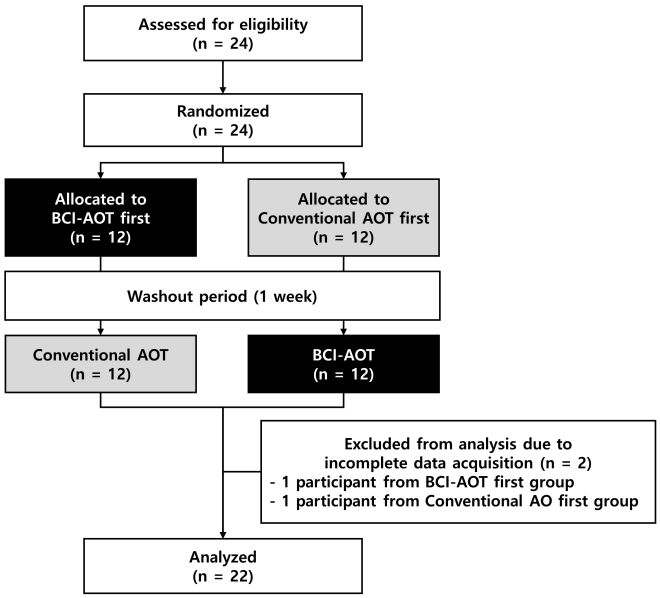

Fig. 4. Participant flow diagram for the randomized crossover trial. A total of 24 patients with stroke were recruited and randomized into two groups: one receiving the BCI-AOT intervention first (n = 12) and the other receiving conventional AOT first (n = 12). After a one-week washout period, each group crossed over to the alternate condition. Two participants were excluded from the final analysis due to incomplete data acquisition, resulting in a total of 22 participants included in the analysis.

III. Results

A. Participants Characteristics

A total of 24 participants were recruited and randomized to the order of conditions (BCI-AOT first or control first) in a crossover design (n = 12 each). All 24 participants completed both intervention conditions with no dropouts during the intervention period. Of these, 2 were excluded from the final analysis due to incomplete data acquisition. Therefore, 22 participants were included in the final analysis (mean age: 59.50 ± 10.96 years; 15 males, 7 females) (Figure 4). Table II summarizes the participants' demographic and clinical characteristics.

B. Real-Time BCI Performance

During the BCI-AOT sessions, the system continuously monitored participants' attentional engagement using an

TABLE II
DEMOGRAPHIC AND CLINICAL CHARACTERISTICS OF PARTICIPANTS

Variable		Value
Age (years)		59.50 ± 10.96
Time Since Stroke (months)		34.64 ± 29.04
Sex	Male	15
	Female	7
Affected Side	Right	12
	Left	10
Stroke Etiology	Infarction	15
	Hemorrhage	7
Lesion Depth	Cortical	3
	Subcortical	18
	Both	1
Lesion Level	Supratentorial	16
	Infratentorial	6
MMSE Score		27.23 ± 2.09
FMA-UE Score		57.86 ± 11.08
TMT-A Time (seconds)		33.35 ± 22.13
TMT-B Time (seconds)		66.01 ± 49.05
MBI Score		96.22 ± 8.00

Values are presented as mean ± standard deviation (SD) or number of participants.

SSVEP-based real-time detection pipeline. The classifier operated using a 1.0-s sliding analysis window with a 0.1-s update interval (90% overlap), allowing rapid and stable decision-making throughout therapy.

Across all participants and training sessions, the mean attentional engagement score—defined as the proportion of time during which the classifier identified sufficient attentional focus to sustain video playback—was 71.51 ± 7.98%. Because the goal of the closed-loop system was to maintain reliable engagement-driven control during therapy, this engagement proportion served as the primary online performance metric.

To enhance robustness against artifacts, the online pipeline employed band-specific CSP projection together with temporal decision smoothing, which reduced the influence of ocular and muscle-related activity. ICA was not applied online to avoid computational delays and instability. No adaptive classifier retraining was required during the intervention, and no session was interrupted or aborted due to signal degradation or classifier drift, demonstrating operational stability in a clinical environment.

Together, these results indicate that the proposed BCI-AOT framework can accurately track attentional engagement in real time, maintain stable closed-loop control, and operate reliably over multi-day training in stroke rehabilitation settings.

C. Behavioral Outcomes

The two standardized clinical assessments, BBT and ARAT, were used to evaluate improvements in upper limb motor function (Figure 5). Each assessment was administered before and after both the BCI-AOT and conventional AOT intervention phases.

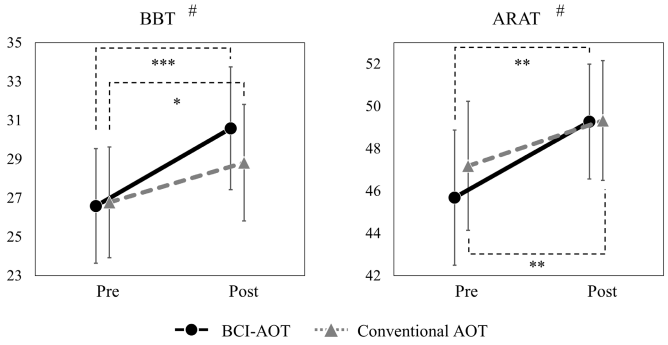

Fig. 5. Changes in BBT and ARAT scores from Pre to Post under two conditions: BCI-AOT (black circles and solid lines) and Conventional AOT (gray triangle markers and dashed lines). Error bars represent standard errors of the mean (SEM). Significant Day (Pre/Post) × Condition interactions (RM-ANOVA) are indicated by #. Asterisks denote significant within-condition Pre-Post differences: *p ‘! 0.05, **p < 0.01, ***$p < 0.001$.

1) BBT: In the BCI-AOT condition, mean BBT performance increased from 26.59 ± 2.95 blocks at pre-test to 30.59 ± 3.16 blocks at post-test, representing an improvement of approximately 15.04%. In the conventional AOT condition, scores improved from 26.77 ± 2.85 to 28.82 ± 3.00 blocks, corresponding to an increase of 7.64%.

RM-ANOVA revealed no significant main effect of condition, $F(1, 21) = 1.03$, $p = 0.323$, but a significant main effect of Day (pre vs. post), $F(1, 21) = 25.32$, $p < 0.001$, and a significant Condition × Day interaction, $F(1, 21) = 17.84$, $p < 0.001$. Post-hoc tests showed that both conditions improved significantly from pre- to post-test (BCI-AOT: $t(21) = 6.48$, $p < 0.001$, $d = 0.28$; conventional AOT: $t(21) = 3.06$, $p < 0.05$, $d = 0.15$), with a larger gain observed in the BCI-AOT condition.

2) ARAT: In the BCI-AOT condition, the mean ARAT score increased from 45.68 ± 3.19 at pre-test to 49.27 ± 2.71 at post-test, reflecting an improvement of 7.86%. In the conventional AOT condition, scores rose from 47.18 ± 3.04 to 49.32 ± 2.83, corresponding to a 4.53% increase. RM-ANOVA revealed no significant main effect of Condition, $F(1, 21) = 2.20$, $p = 0.153$, but a significant main effect of Day, $F(1, 21) = 13.24$, $p < 0.01$, and a significant Condition × Day interaction, $F(1, 21) = 7.22$, $p < 0.05$. Post-hoc comparisons confirmed significant pre-to-post improvements in both conditions (BCI-AOT: $t(21) = 3.69$, $p < 0.01$, $d = 0.26$; conventional AOT: $t(21) = 3.23$, $p < 0.01$, $d = 0.16$), with a larger gain observed in the BCI-AOT condition.

D. EEG Spectral Power Dynamics: Mu Rhythm and Theta

Figure 6 illustrates spectral power variations in the mu and theta frequency bands recorded from ipsilesional sensorimotor (C3/C4) and parietal (P3/P4) regions under the different intervention conditions. In the mu band at C3/C4 (Figure 6, top left), the BCI-AOT condition showed progressive mu

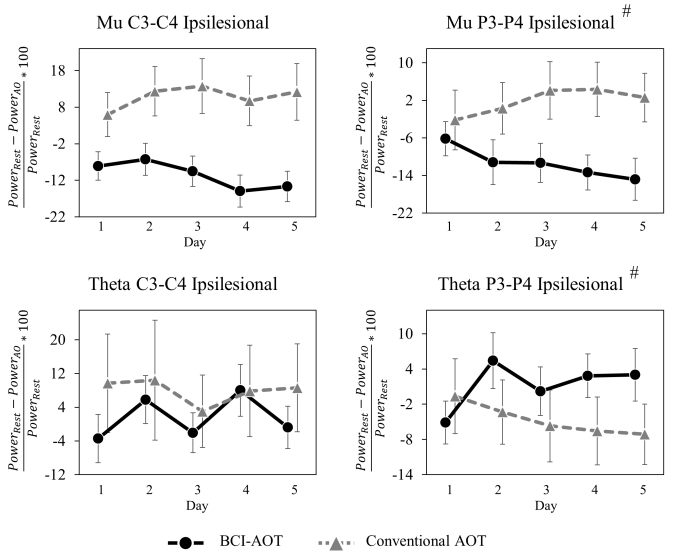

Fig. 6. Time course of Mu and Theta power changes measured at ipsilesional C3/C4 and P3/P4 electrode sites over five days of AOTs. Black solid lines represent the BCI-AOT condition, and gray dashed lines represent the Conventional AOT condition. Mu band activity is shown in the top row and Theta band activity in the bottom row. The y -axis represents the percentage change in EEG power during AOT, relative to pre-rest baseline levels. # indicates a significant Condition × Day interaction ($p < 0.05$). Error bars represent standard error of the mean (SEM).

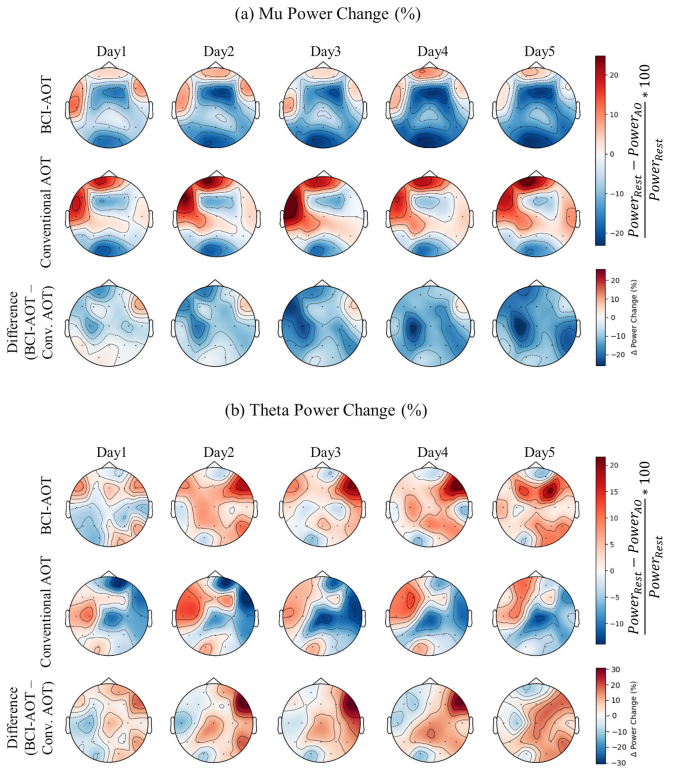

Fig. 7. Topographical distribution of Mu and Theta power changes during AOTs across five days. (a) Mu band; (b) Theta band. In each panel, the top row shows the BCI-AOT condition, the middle row shows the Conventional AOT condition, and the bottom row shows the difference between conditions (BCI-AOT minus Conventional AOT). Each column represents Day 1 through Day 5. The values indicate percentage changes in EEG power during AOT relative to the pre-rest baseline. The colormaps are centered at 0%, with red indicating increased power and blue indicating decreased power for the condition-specific maps. For the difference maps, blue indicates greater suppression (or less increase) in BCI-AOT relative to Conventional AOT, while red indicates the opposite pattern. Consistent scales were applied within each frequency band for comparison.

suppression across sessions, in contrast to the Conventional AOT condition, which exhibited an increase in mu power over time. A significant main effect of Condition was found ($F(1, 21) = 8.47$, $p < 0.01$, partial $\eta^2 = 0.29$). Neither the main effect of Day ($F(4, 84) = 2.07$, $p = 0.09$) nor the Day × Condition interaction ($F(4, 84) = 1.75$, $p = 0.15$) was significant.

At P3/P4 in the mu band (Figure 6, top right), the BCI-AOT condition showed increasing mu suppression across sessions, whereas the Conventional AOT condition exhibited a pattern of increased mu power. RM-ANOVA revealed significant main effects of Condition ($F(1,21) = 4.97$, $p < 0.05$, partial $\eta^2 = 0.19$) and a significant Day × Condition interaction ($F(4, 84) = 3.00$, $p < 0.05$, partial $\eta^2 = 0.13$). The main effect of Day was not significant ($F(4, 84) = 0.54$, $p = 0.71$).

At C3/C4 in the theta band (Figure 6, bottom left), the BCI-AOT condition showed fluctuations across sessions, while the Conventional AOT condition maintained relatively higher theta power overall. RM-ANOVA revealed no significant main effect of Day ($F(4, 84) = 1.21$, $p = 0.31$), Condition ($F(1, 21) = 0.08$, $p = 0.78$), or Day × Condition interaction ($F(4, 84) = 0.67$, $p = 0.62$).

At P3/P4 in the theta band (Figure 6, bottom right), the BCI-AOT condition exhibited increasing theta activity across sessions, whereas the Conventional AOT condition displayed a decreasing trend. RM-ANOVA revealed a significant Day × Condition interaction ($F(4, 84) = 2.56$, $p < 0.05$, partial $\eta^2 = 0.11$). Neither the main effect of Day ($F(4, 84) = 0.73$, $p = 0.57$) nor Condition ($F(1, 21) = 1.24$, $p = 0.28$) was significant.

Figure 7 presents scalp topographic maps depicting the spatial distribution of power changes in the mu (Figure 7.a) and theta (Figure 7.b) frequency bands across the five intervention days for both the BCI-AOT and Conventional AOT conditions.

The mu band maps show that the BCI-AOT condition exhibited progressive mu suppression primarily over the bilateral central and parietal regions over time, while the Conventional AOT condition displayed persistent or increasing mu power in the same regions. The theta band maps indicate that the BCI-AOT condition was associated with widespread increases in theta power across sessions, particularly over bilateral parietal and frontal areas. In contrast, the Conventional AOT condition demonstrated either decreased or stable theta activity over time, with notable reductions in the ipsilesional parietal regions as the intervention progressed.

E. Corticospinal Excitability: MEP Amplitude and Latency

For MEP amplitude, RM-ANOVA revealed a significant main effect of Day (F (5, 100) = 12.34, $p < 0.001$), indicating a progressive increase over time (Figure 8). In the BCI-AOT condition, the mean amplitude across all participants increased from 783.96 ± 181.70 μV at baseline to 1247.84 ± 224.29 μV

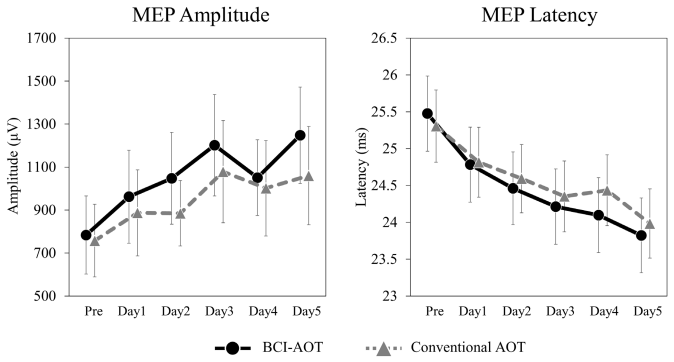

Fig. 8. Changes in MEP amplitude (left) and latency (right) at baseline and across training days 1 – 5 for the BCI-AOT (black solid line) and conventional AOT (gray dashed line) conditions. Error bars represent standard error of the mean.

on day 5, representing an improvement of 59.17%. In the conventional AOT condition, the amplitude increased from 757.94 ± 169.28 μV at baseline to 1060.46 ± 228.82 μV on day 5, corresponding to an increase of 39.91%. Neither the main effect of Condition ($p = 0.43$) nor the Condition × Day interaction ($p = 0.86$) reached significance.

Similarly, for MEP latency, there was a significant main effect of Day ($F(5, 100) = 48.46$, $p < 0.001$), reflecting a gradual reduction in latency across sessions. In the BCI-AOT condition, latency decreased from 25.48 ± 0.51 ms at baseline to 23.82 ± 0.51 ms on day 5, representing a 6.49% decrease. In the conventional AOT condition, it decreased from 25.31 ± 0.49 ms at baseline to 23.99 ± 0.47 ms on day 5, corresponding to a 5.22% decrease. Neither a significant main effect of Condition ($p = 0.51$) nor a Condition × Day interaction ($p = 0.33$) was observed.

F. Subjective Feedback: Motivation, Focus, and Experience

Figure 9 presents a radar plot summarizing the average scores for the 13-item User Experience Questionnaire. Analysis revealed statistically significant differences between conditions on several questionnaire items assessing user experience. Compared to the Conventional AOT condition, the BCI-AOT condition showed significantly higher ratings for Item 3 ("The training was helpful for rehabilitation therapy"; BCI-AOT: 4.18 ± 0.18 vs. Conventional AOT: 3.73 ± 0.19, $p < 0.01$), Item 6 ("I felt bored during the training"; reverse scored; BCI-AOT: 3.41 ± 0.28 vs. Conventional AOT: 2.91 ± 0.27, $p < 0.05$), Item 7 ("The training was interesting"; BCI-AOT: 4.00 ± 0.21 vs. Conventional AOT: 3.55 ± 0.27, $p < 0.05$), Item 9 ("I had distracting thoughts during the training"; reverse scored; BCI-AOT: 3.77 ± 0.21 vs. Conventional AOT: 2.77 ± 0.30, $p < 0.05$), and Item 13 ("I want to continue using this method for future therapy sessions"; BCI-AOT: 4.27 ± 0.15 vs. Conventional AOT: 3.64 ± 0.28, $p < 0.01$). These items reflect greater perceived therapeutic value, engagement, sustained attention, and willingness to continue therapy in the BCI-AOT condition. In contrast, Item 12 ("I was satisfied with the rehabilitation experience using this method") was rated significantly higher in the Conventional AOT condition (BCI-AOT: 3.86 ± 0.19 vs. Conventional AOT: 4.18 ± 0.17, $p < 0.01$). No other items showed significant differences between the two intervention conditions.

IV. Discussion

This study evaluated the effectiveness of a closed-loop SSVEP-based BCI-AOT for upper limb rehabilitation in patients with stroke. While both BCI-AOT and conventional AOT led to improvements in motor function, significant Condition × Day interactions for the BBT and ARAT scores indicated that BCI-AOT resulted in greater functional gains over time. These behavioral findings were complemented by EEG and subjective feedback data, suggesting that the closed-loop feedback mechanism in BCI-AOT may promote greater engagement and neuroplastic adaptation than conventional AOT.

Distinct neurophysiological modulations in the BCI-AOT condition paralleled behavioral improvements. EEG findings showed greater mu suppression at ipsilesional central sites (C3/C4), suggesting sustained activation of the MNS, potentially reflecting cumulative neural priming that supports motor recovery [41]. Additionally, a significant Day × Condition interaction in theta power at ipsilesional parietal sites (P3/P4) was observed, indicating consistent attentional engagement throughout training [42]. Beyond attentional modulation, the observed increase in parietal theta power during the BCI-AOT condition may also reflect higher-order cognitive processes supporting visuomotor integration and action understanding. Theta oscillations in posterior parietal regions have been consistently linked to cognitive control, sensorimotor transformation, and the coordination of perception and action during motor observation and imitation learning [43], [44]. Within this framework, enhanced parietal theta activity is thought to facilitate the mapping of observed actions onto internal motor representations—a fundamental mechanism of the mirror neuron system (MNS)—thereby contributing to motor learning and adaptation [45]. The progressive enhancement of theta power observed across training days in the BCI-AOT condition may therefore represent not only sustained attentional engagement but also the dynamic engagement of neural circuits responsible for integrating perceptual input with motor planning. This interpretation aligns with concurrent findings of mu suppression over central sensorimotor areas, which signifies increased cortical activation associated with motor resonance. Together, these oscillatory dynamics suggest that the closed-loop feedback provided by the BCI enhanced neuroplastic processes by synchronizing periods of optimal attention with motor-relevant visual input. Accordingly, increased parietal theta may serve as a neurophysiological marker of cognitive–motor coupling that bridges attentional control, mirror-neuron activation, and sensorimotor learning.

The topographic maps in Figure 7 illustrate relative changes in oscillatory activity across the entire scalp and reflect contributions from both sensorimotor and parietal networks. Decreases in mu-band (8–13 Hz) power over central electrodes (i.e., mu suppression) correspond to increased activation of

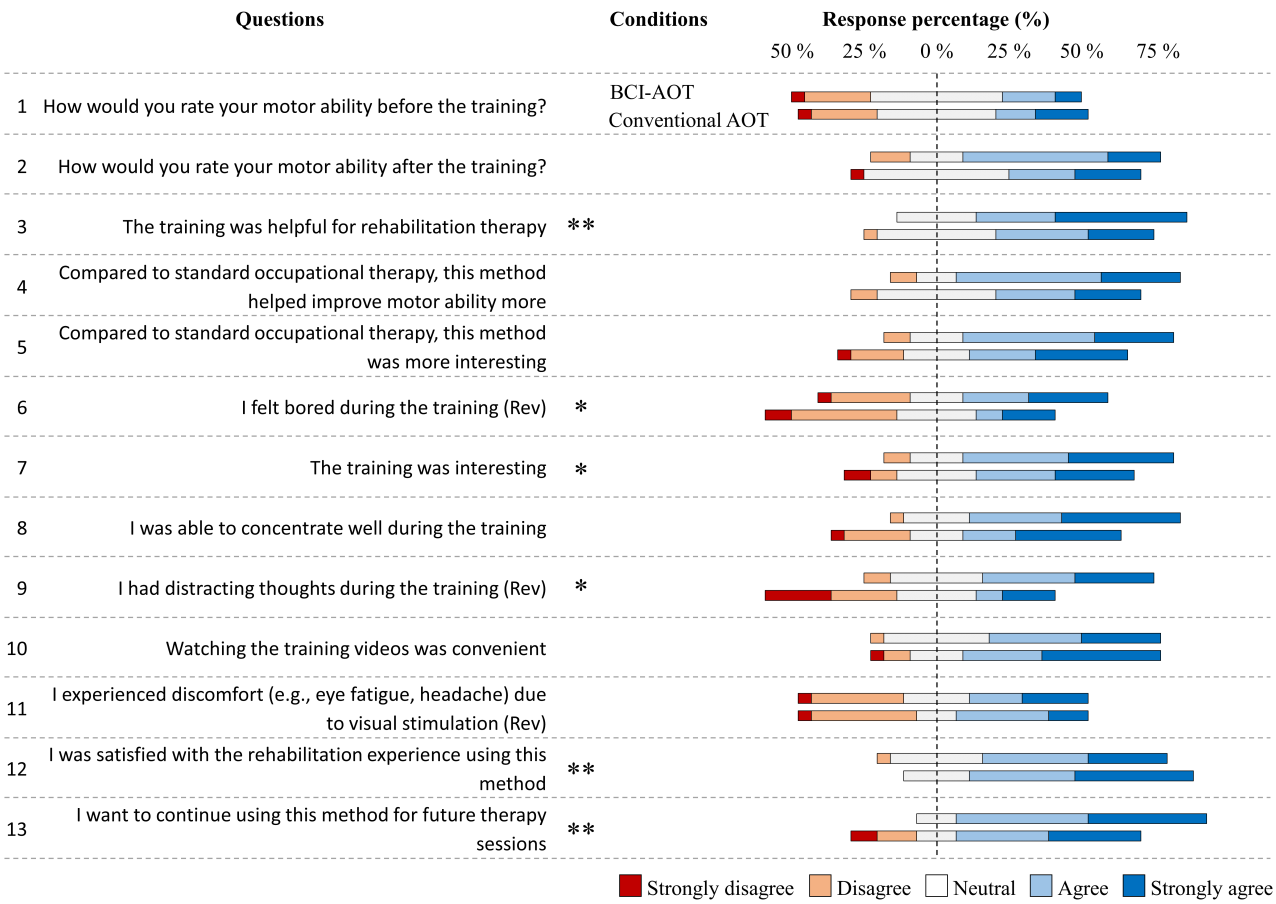

Fig. 9. Participant responses to 13 questionnaire items regarding the AOT. The figure shows the distribution of Likert-scale responses comparing BCI-AOT and Conventional AOT conditions. Reverse-coded items are indicated by "(Rev)". Items marked with * or ** indicate statistically significant differences between conditions (* $p < 0.05$, ** $p < 0.01$).

the sensorimotor cortex, consistent with mirror-neuron–driven motor resonance. In contrast, increases in theta-band (4–7 Hz) power at ipsilesional parietal sites (P3/P4) reflect heightened attentional control, cognitive integration, and visuomotor mapping processes that are commonly engaged during action observation and attentional tasks. These parietal theta effects therefore represent genuine cognitive-motor engagement rather than stimulus-driven artifacts. Importantly, all motor-specific interpretations were based on ROI-based statistical analyses (C3/C4 and P3/P4; Fig. 6), rather than on global topographic gradients alone. Furthermore, to verify that these ROI effects were not influenced by prefrontal signals through the re-referencing process, we conducted a supplementary analysis using a common average reference that excluded prefrontal channels. The main effect of Condition for mu power at C3/C4 and the Day $\times$ Condition interactions at P3/P4 for both mu and theta bands all retained statistical significance, supporting the regional specificity of the observed effects.

In contrast, MEP results showed no significant condition effects, although both amplitude and latency changed significantly over time, indicating experience-dependent plasticity in the corticospinal system. The absence of between-condition differences may reflect shared elements in both interventions, such as repeated action observation and matched motor execution, which are known to enhance corticospinal excitability. [46], [47]. It is also plausible that both interventions were potent enough to induce near-maximal changes in corticospinal excitability at rest, potentially creating a ceiling effect that masked subtle differences between the conditions. Alternatively, because MEPs were measured at rest rather than during task engagement, they may have lacked sensitivity to detect subtle, task-specific neural dynamics or top-down modulation associated with BCI-enhanced feedback [48], [49]. This methodological limitation may partly explain the discrepancy between the absence of condition-specific MEP effects and the significantly greater functional gains and distinct EEG modulations observed in the BCI-AOT condition.

In this crossover design, a one-week washout period was employed to minimize any potential carryover between intervention phases. This duration aligns with previous motor learning and stroke rehabilitation studies, which have demonstrated that a one-week interval is sufficient to dissipate short-term intervention effects while remaining short enough to avoid spontaneous recovery influences in chronic stroke populations. To confirm the adequacy of this washout period in our dataset, we conducted additional analyses evaluating potential period and sequence effects. Across behavioral outcomes (BBT, ARAT), mixed-effects models revealed no significant

main effects of period or sequence and no interactions involving sequence (all $p \geq 0.10$). Similarly, for neurophysiological measures—including MEP amplitude/latency and EEG mu/theta power—no significant Condition × Day × Order or other sequence-related interactions were observed (all $p \geq 0.10$). These findings confirm that neither period nor sequence influenced behavioral or neural outcomes, supporting the validity of the crossover design and the sufficiency of the one-week washout interval.

The BCI-AOT intervention, delivered prior to motor execution, appeared to exert a more robust priming effect by concurrently engaging attentional and sensorimotor systems, thereby facilitating subsequent goal-directed movement. This finding aligns with previous evidence that real-time feedback enhances motor learning and promotes cortical reorganization during neurorehabilitation [33], [50]. The simultaneous activation of visual-attentional networks via SSVEP-based monitoring and sensorimotor networks through AOT likely established a bidirectional reinforcement loop, where top-down cognitive engagement and bottom-up motor priming interacted synergistically. This multimodal neural engagement may underlie the superior functional and cortical outcomes observed in the BCI-AOT condition.

One novel aspect of this study is the implementation of an SSVEP-based system that modulates video playback in real-time based on users' attentional states. To our knowledge, this is the first study to use attention-contingent video suspension within an AOT framework for stroke rehabilitation. While recent studies in personalized learning and virtual reality have used EEG signals to adjust sensory feedback (e.g., visual, auditory, or haptic) [51], [52]. there remains a distinct lack of research specifically targeting real-time control of video playback itself. By pausing and resuming video playback according to attentional focus, the system aligns therapeutic input with periods of heightened readiness, potentially enhancing neuroplastic priming. Additionally, the low cognitive load and elimination of complex calibration of the SSVEP approach offer practical advantages over conventional ERD-based BCIs, making it more accessible for individuals with cognitive or motor impairments [53]. However, the exclusive use of video pauses may not represent the most effective feedback modality for sustaining attention or promoting neuroplasticity. Future developments should systematically compare alternative or multimodal feedback strategies—such as haptic cues, auditory reinforcement, adaptive pacing, or reward-based mechanisms—to identify the optimal configuration for maximizing engagement and neural adaptation during training.

The feedback mechanism also conceptually aligns with the Challenge Point Framework, which posits that motor learning is maximized when task demands are matched to the learner's skill level and cognitive capacity [54]. Adaptive feedback ensured that training remained wistroke in each patient's optimal challenge zone, likely facilitating neuroplastic priming. Ensuring that training occurs during periods of heightened cognitive readiness may be key to sustaining engagement and enhancing motor learning outcomes.

Subjective feedback from participants further supports the system's effectiveness. The BCI-AOT condition yielded significantly higher ratings in domains reflecting reduced boredom, sustained attention, and increased motivation. These findings align with prior research suggesting that greater cognitive and emotional engagement enhances treatment adherence and rehabilitation outcomes [55], [56]. Notably, despite its higher cognitive demands, the BCI-AOT intervention was perceived as more interesting and beneficial, reinforcing evidence that interactive, adaptive systems promote intrinsic motivation [57], [58]. Moreover, specific gamified elements—such as goal-directed actions like "placing a cake" or "feeding a parrot"—may have contributed to higher motivation and engagement by introducing clear, rewarding objectives and a sense of accomplishment during training. The higher satisfaction scores for conventional AOT may reflect the comfort of a familiar and less cognitively taxing format, underscoring the importance of balancing innovation with user comfort in intervention design.

In the present system, SSVEP-based attention monitoring was selected because it provides a direct neurophysiological index of attentional engagement. In SSVEP paradigms, both overt (gaze-directed) and covert (internally shifted) attention modulate the amplitude of steady-state responses. Even when gaze remains fixed elsewhere, selectively attending to a flickering region increases SSVEP power through top-down modulation of occipito-parietal networks [18]. This property enables SSVEPs to capture the depth and continuity of attention beyond simple gaze fixation. By contrast, conventional eye-tracking primarily measures overt eye movements and may fail to detect instances where a participant is looking at the correct target but is no longer cognitively engaged. For closed-loop neurorehabilitation, where therapeutic input should be delivered only when the brain is actively attending, such neurophysiological confirmation is advantageous. Nevertheless, prolonged 15-Hz flicker stimulation may induce mild visual fatigue in some users, and the requirement for scalp EEG setup can limit usability in home-based or mobile applications. Eye-tracking, on the other hand, offers strong complementary advantages in terms of non-invasiveness, comfort, and setup efficiency. Future iterations of the system may therefore adopt a hybrid configuration, using eye-tracking to verify overt fixation and EEG/SSVEP to confirm covert cortical engagement. Such an integrated approach would combine the practicality of eye-tracking with the neurophysiological precision of EEG-based monitoring, enhancing the system's clinical scalability and user comfort.

Certain limitations should be acknowledged. First, the relatively small sample size may limit the generalizability of the findings. While the cross-subject design helped reduce inter-individual variability, larger multi-site studies are needed to validate these results in diverse populations. Second, the duration of the intervention was limited to five consecutive sessions per condition, limiting conclusions regarding long-term efficacy. Future research should involve larger patient cohorts and extended follow-up periods to more comprehensively characterize the long-term effects of BCI-AOT interventions. Third, to avoid interference with EEG signals, MEPs were not recorded during the AO, which may have limited the ability to detect condition-specific differences in

corticospinal excitability. Future studies should consider measuring MEPs during AO training to more precisely isolate the effects of feedback-driven neural modulation. Additionally, the present study did not include post-training FMA-UE assessments, as the focus was on short-term, activity-level outcomes (BBT and ARAT). Future studies with longer intervention periods will incorporate FMA-UE evaluations to assess impairment-level recovery in greater detail. Finally, although both conditions were matched in visual content, session duration, and motor execution, the BCI-AOT condition incorporated real-time attention-contingent feedback (e.g., auditory prompts, video pauses, and gamified visual elements) that may have introduced non-specific engagement effects such as increased arousal, novelty, or cognitive load. The auditory tones and pauses were not intended as external motivational cues but were intrinsic components of the closed-loop mechanism designed to ensure that action observation occurred only during verified attentional engagement. These elements dynamically linked the user's cognitive state with the progression of the therapeutic task, representing a core feature of the adaptive neurofeedback framework rather than an auxiliary stimulation. Nonetheless, the potential contribution of these additional sensory or interactive components to overall engagement cannot be fully ruled out. While both interventions provided identical visual content and equivalent exposure to motor actions, the closed-loop feedback in BCI-AOT may have enhanced perceived interactivity or novelty, potentially amplifying user motivation and engagement independently of pure attention modulation. The significant EEG modulations observed—particularly stronger mu suppression and theta power increases over central and parietal sites—are, however, more consistent with genuine attention- and motor-related neural processes than with general arousal or alerting responses. To further disentangle these overlapping factors, future research should include a matched sham or non-contingent feedback control condition in which pauses and prompts are presented independently of the user's attentional state. Such a design would allow for direct isolation of the specific neurophysiological and behavioral benefits attributable to attention-adaptive feedback, as distinct from non-specific influences of gamification, novelty, or increased alertness. Additionally, future work could examine how varying the feedback modality (e.g., auditory vs. visual), frequency, or contingency strength influences engagement, arousal, and cortical activation patterns. These investigations would help optimize the balance between adaptive responsiveness and user comfort, ensuring that attention-based feedback contributes primarily to neuroplastic facilitation rather than to extraneous cognitive load.

In summary, this study revealed that a closed-loop BCI-AOT system integrating SSVEP-based real-time attention monitoring with dynamic feedback can enhance motor recovery, cortical engagement, and user experience in stroke rehabilitation. These findings support the clinical feasibility of BCI-AOT as a scalable, individualized rehabilitation method. Future integration with robotic or virtual environments may further augment its rehabilitative efficacy by reinforcing cognitive-motor coupling and neuroplastic adaptation.

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