NeuroRegulation

ISNR INTERNATIONAL SOCIETY FOR NEUROREGULATION & RESEARCH

The Effectiveness of Neurofeedback Training on Cognitive Function Improvement and Quantitative Electroencephalography Features in Poststroke Cognitive Impairment

Rini Nindela[*], *Yohanes Febrianto, Yusril Yusril, Muhammad H. Haddani, Sri Handayani, Dya Anggraeni, and Mgs. Irsan Saleh*

Sriwijaya University, Mohammad Hoesin Hospital, Palembang, Indonesia

Abstract

Background. Poststroke cognitive impairment (PSCI) involves cognitive deficits emerging within 3 months after stroke. Quantitative EEG (qEEG) in PSCI typically shows changes in relative power, delta-alpha ratio, and peak alpha frequency. Neurofeedback training (NFT) is a promising intervention to improve cognitive function and qEEG patterns, though findings remain inconsistent. Nonetheless, even brief NFT interventions may yield meaningful benefits. **Methods.** This study assessed the effectiveness of five individualized qEEG-guided NFT sessions (30 min each) in 24 PSCI patients, focusing on changes in MoCA-INA scores and qEEG parameters. **Results.** NFT significantly improved MoCA-INA scores ($Z = -4.106$, $p < .001$, effect size = 0.839), particularly in visuospatial/executive and delayed recall domains, with sustained effects 1 month later. QEEG analysis revealed increased temporal alpha ($t = -1.875$, $p = .037$, effect size = 0.23) and parietal beta relative power ($t = -1.827$, $p = .040$, effect size = 0.11). Greater cognitive gains were observed in patients aged ≤60 years. **Conclusion.** These findings support the clinical utility of short-term, qEEG-guided NFT in improving cognitive outcomes and modulating neural activity in PSCI patients. The sustained benefits observed suggest potential for long-term therapeutic impact.

Keywords: Poststroke cognitive impairment; neurofeedback training; quantitative electroencephalography; MoCA-INA

Citation: Nindela, R., Febrianto, Y., Yusril, Y., Haddani, M. H., Handayani, S., Anggraeni, D., & Saleh, M. I. (2026). The effectiveness of neurofeedback training on cognitive function improvement and quantitative electroencephalography features in poststroke cognitive impairment. *NeuroRegulation, 13*(1), 2–19. https://doi.org/10.15540/nr.13.1.2

***Address correspondence to**: Rini Nindela, Jendral Sudirman St. KM 3.5, Palembang, 30126, Indonesia. Email: rini_nindela@unsri.ac.id

Edited by:
Rex L. Cannon, PhD, Currents, Knoxville, Tennessee, USA

Reviewed by:
Rex L. Cannon, PhD, Currents, Knoxville, Tennessee, USA
Randall Lyle, PhD, Mount Mercy University, Cedar Rapids, Iowa, USA

Introduction

Poststroke cognitive impairment (PSCI) is defined as cognitive deficits occurring within the first 3 months after a stroke, unrelated to other medical conditions such as metabolic, endocrine, vasculitis, or depressive disorders. PSCI can be classified into cognitive impairment no dementia (CIND) and poststroke dementia (PSD; Tugasworo et al., 2023). This condition is often underrecognized and overshadowed by the more prominent motor deficits (McDonald et al., 2019). Indonesia Stroke Registry Data showed that 60.59% of stroke patients experienced cognitive impairment in 2013 (Ong et al., 2015).

Quantitative electroencephalography (qEEG) is a low-cost, noninvasive tool with high temporal resolution for assessing brain function, particularly in dementia. It directly measures functional brain status (Hadiyoso et al., 2022; Petrovic et al., 2017). Spectral power analysis has demonstrated that PSCI patients exhibit increased delta relative power, decreased alpha and beta power, globally elevated theta activity, increased frontal delta/alpha ratio (DAR), and delta+theta/alpha+beta ratio (DTABR),

as well as a reduction in peak alpha frequency (PAF), a known indicator of cognitive function (Babiloni et al., 2021; Hadiyoso et al., 2022).

Currently, no traditional cognitive rehabilitation method is recommended as the mainstay therapy with proven effectiveness in improving cognitive function poststroke (Merriman et al., 2019). Limitations of conventional rehabilitation include repetitive tasks and evaluations, reliance on clear patient responses, dependence on complex verbal instructions, and the considerable cognitive effort required. An alternative approach involves adaptive use of brain-computer interface (BCI) technologies. A prominent BCI modality for poststroke cognitive rehabilitation is electroencephalography-based neurofeedback training (EEG-NFT; Kober et al., 2015).

NFT aims to enhance cognitive function through mechanisms such as implicit learning, operant conditioning, self-regulation, and neuroplasticity. It trains individuals to modulate their brain's electrical activity, either by enhancing or inhibiting specific patterns. This process can induce long-term neural changes that support the recovery or enhancement of neurocognitive, emotional, and overall brain function. NFT is also believed to help prevent progression from mild cognitive impairment (MCI) to dementia and may accelerate or enable functional recovery previously thought unattainable (Ali et al., 2020; Tosti et al., 2024).

EEG-NFT is considered a novel and off-label therapeutic approach for cognitive disorders, particularly in stroke patients, and remains understudied. Most studies have reported cognitive improvements following NFT, but these findings are not always consistent or statistically significant. Interestingly, the number and frequency of sessions do not appear to significantly influence EEG-NFT effectiveness (Tosti et al., 2024; Vilou et al., 2023).

Anggraeni et al. (2024) reported a 2.63-point improvement in the Montreal Cognitive Assessment-Indonesian Version (MoCA-INA) scores (p = .019, effect size = −0.828) after 10 sessions of NFT in eight PSCI-ND patients using individualized qEEG protocols, though without significant domain-specific changes. Hohenfeld et al. (2017) found that three MRI-based NFT sessions in healthy individuals led to a 1.187-point increase in MoCA scores (p = .002), whereas Alzheimer's disease patients in the same study exhibited a decline. Jang et al. (2017) conducted an NFT study on MCI patients and observed significant improvements in the Montreal Cognitive Assessment -Korean Version (MoCA-K) scores after both 8 and 16 sessions (p = .042). Marlats et al. (2020) demonstrated improvements in MoCA scores following 3 to 20 sessions of NFT, especially in executive and memory domains. Lavy et al. (2018) reported sustained memory function improvements 1-month postintervention, although Marlats et al. (2020) noted that MoCA scores returned to baseline after 1 month. QEEG improvements following NFT have also been documented, including increased power in targeted frequency bands, enhanced peak alpha frequency, and shifts from slower (theta and delta) to faster (alpha and beta) brain waves, which correlate with cognitive gains (Andrade et al., 2022; Hohenfeld et al., 2017; Wigton & Krigbaum, 2015).

Given the inconsistent findings regarding EEG-NFT impact on cognitive function, the limited evidence on its effectiveness in PSCI patients, particularly over the long term, and the limitations of conventional rehabilitation, further research is warranted to explore NFT as a rehabilitative option for PSCI. Considering the high prevalence and significant burden of PSCI on patients and their families, this study represents the first in Indonesia to assess the efficacy of NFT in improving cognitive function and modifying qEEG parameters both posttreatment and over a longer follow-up period.

Methods

Study Design and Setting

This study employed an analytical quasi-experimental design with a one-group pretest-posttest approach. The research was conducted at the Memory and Neurofeedback Clinic of Mohammad Hoesin Hospital (RSMH), Palembang, between July and December 2024.

Participants

The study involved patients diagnosed with PSCI, encompassing both individuals with PSCI without dementia (PSCI-ND) and those with PSD. Participants were recruited through consecutive sampling at the memory outpatient clinic, where diagnoses were established using comprehensive neuropsychological assessments.

The inclusion criteria were patients aged 18 years or older, with poststroke duration of more than 3 months, a confirmed diagnosis of PSCI, residing in Palembang, and willing to participate in the study. Exclusion criteria included individuals with visual and auditory impairments, moderate to severe depression, aphasia, a history of epilepsy or

seizures, or other neurological brain disorders such as Parkinson's disease, brain tumors, multiple sclerosis, neuromyelitis optica spectrum disorder (NMOSD), and congenital abnormalities. Patients who had previously or were currently undergoing other neurorestorative therapies, such as transcranial magnetic stimulation (TMS) or transcranial direct current stimulation (tDCS), were also excluded. Dropout criteria included patients who withdrew before completing the study or passed away before study completion.

All participants received explanations about the potential benefits and adverse effects of the intervention and provided informed consent before enrollment. This study was approved by the Ethics Committee of RSMH Palembang (Approval No: DP.04.03/D.XVIII.06.08/ETIKRSMH/14/2024).

Procedure and Intervention

Diagnosed PSCI patients underwent baseline assessment of cognitive function using the MoCA-INA (T0), followed by baseline qEEG recordings. The qEEG assessment included relative power measurements in the frontal (F3, F4, F7–F8), central (C3, C4), parietal (P3, P4), temporal (T3, T4, T5, T6), occipital (O1, O2), and global regions, along with frontal DAR and PAF in frontal, central, parietal, temporal, occipital, and global areas.

Each patient then underwent five consecutive daily neurofeedback training (NFT) sessions using the Neurosoft-Neuron-Spectrum-61 system, with each session lasting approximately 30 min. The room setup, preparation, and execution of these sessions are illustrated in Figure 1. The NFT protocol was tailored to each patient's baseline qEEG profile and incorporated audiovisual feedback.

Thirteen patients followed the alpha protocol, receiving visual feedback in the form of a mushroom graphic that enlarged upon achieving the alpha threshold. Seven patients followed the beta protocol, with feedback delivered via a car racing animation in which the car accelerated when the beta target was reached. Four patients followed the alpha-theta protocol, receiving feedback through a Millennium Falcon spaceship animation that increased speed when the training target was met. The visual feedback used in each protocol is illustrated in Figure 2.

Following the completion of the five NFT sessions, a postintervention assessment (T1) was conducted using MoCA-INA and qEEG. One month after the intervention, MoCA-INA was reassessed (T2) to evaluate long-term effectiveness. All MoCA-INA assessments were performed by individuals not directly involved in the study to minimize potential assessment bias.

Figure 1. *Room Setup, Preparation, and Execution of NFT Sessions.*

Figure 2A. *Visual Feedback Used in Each Protocol: Mushroom Video for Alpha Protocol.*

Figure 2B. *Visual Feedback Used in Each Protocol: Car Racing Video for Beta Protocol.*

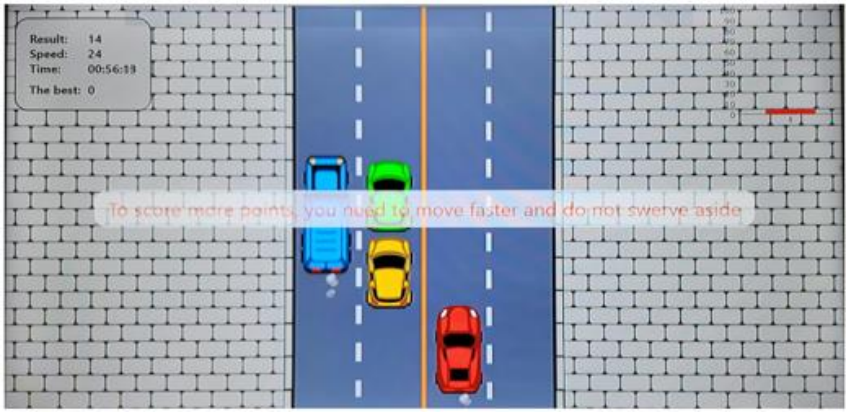
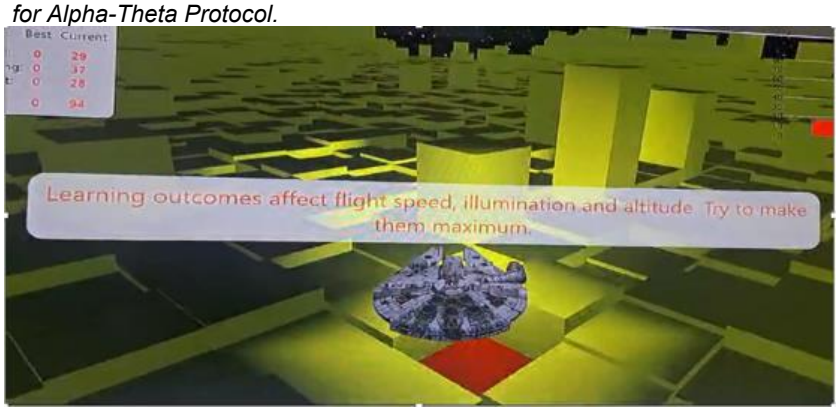


Figure 2C. *Visual Feedback Used in Each Protocol: Millennium Falcon Video for Alpha-Theta Protocol.*



Data Analysis

Data analysis was performed using SPSS version 30. Comparisons of MoCA-INA scores at T0–T1, T1–T2, and T0–T2 were conducted using paired sample *t*-tests for normally distributed data or Wilcoxon tests for non-normally distributed data. Changes in qEEG components—including increased fast-wave relative power, decreased slow-wave relative power, reduced frontal DAR, and increased PAF—were also analyzed using paired sample *t*-tests or Wilcoxon tests, as appropriate. Differences between PSCI-ND and PSD groups were assessed

using independent *t*-tests or Mann-Whitney U tests. Multivariate analysis was conducted using logistic regression to identify factors influencing improvements in MoCA-INA scores.

Results

As shown in Figure 3, a total of 56 PSCI patients were identified through comprehensive neuropsychological testing. However, 26 patients were excluded: 11 declined to participate, 6 presented with depressive symptoms, 4 had aphasia, 2 had seizure disorders, 2 were diagnosed with Parkinson's disease, and 1 had previously received TMS therapy. An additional 6 patients dropped out: 3 did not complete NFT, 1 failed to undergo qEEG evaluation, and 2 missed the 1-month post-NFT follow-up. Ultimately, 24 patients met the inclusion criteria and completed all stages of the study. No adverse effects were reported during the intervention. The clinical and sociodemographic characteristics of the patients are presented in Table 1.

Among the participants, 54.17% were over 60 years old, 62.50% were male, 91.67% had ischemic strokes, 83.34% had subcortical lesions, 62.50% had a stroke onset longer than 6 months, and 66.67% were classified as PSCI-ND. The cognitive domains most commonly impaired based on MoCA-INA results were visuospatial/executive function and delayed memory. The five most affected domains identified through comprehensive neuropsychological testing were delayed memory (83.34%), executive function (75.00%), recognition (75.00%), working memory (70.83%), and language (62.50%).

The average interval between the baseline (T0) and immediate postintervention (T1) assessments was 81.83 days. This relatively long interval was due to several factors, including patient scheduling after initial memory testing, delays in receiving official qEEG reports, and the initiation of NFT sessions. The mean interval between T1 and the 1-month follow-up (T2) was 33.42 days, and the mean total duration from T0 to T2 was 115.25 days.

Figure 3. *Flow Chart of the Study.*

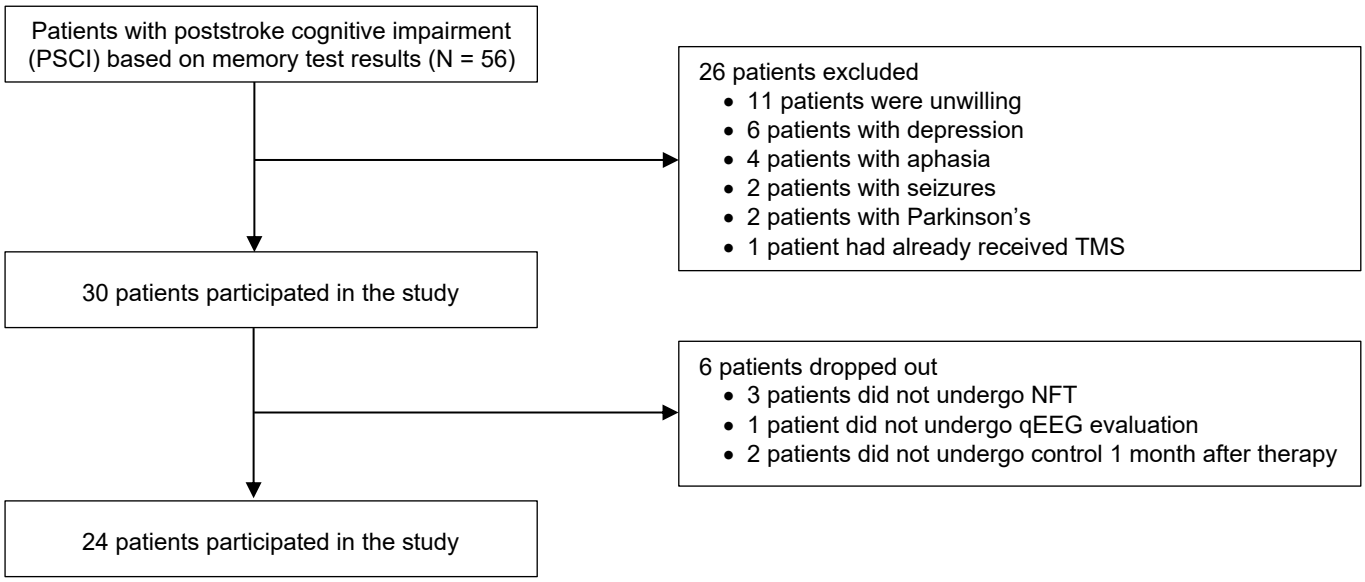


Table 1
Sociodemographic and Clinical Characteristics, and Categorical Analysis of MoCA-INA Score Improvements

Variable	Frequency (*n*)/(%)	*P* T0–T1	*P* T1–T2	*P* T0–T2
Age		0.033[a]	1.000[a]	0.014[c]
≤60 years old	11 (45.83%)			
>60 years old	13 (54.17%)			

Table 1
Sociodemographic and Clinical Characteristics, and Categorical Analysis of MoCA-INA Score Improvements

Variable	Frequency (*n*)/(%)	*P* T0–T1	*P* T1–T2	*P* T0–T2
Sex		1.000[a]	0.533[a]	0.089[a]
Male	15 (62.50%)			
Female	9 (37.50%)			
Education		0.412[a]	1.000[a]	1.000[a]
Higher education (>12 years)	15 (62.50%)			
Lower education (≤12 years)	9 (37.50%)			
Stroke Type		1.000[a]	0.239[a]	1.000[a]
Ischemic	22 (91.67%)			
Hemorrhagic	2 (8.33%)			
Lesion Location		0.390[b]	0.555[b]	1.000[b]
Cortical	2 (8.33%)			
Subcortical	20 (83.34%)			
Corticosubcortical	2 (8.33%)			
Stroke Onset		0.099[a]	0.533[a]	0.400[a]
≤6 months	9 (37.50%)			
>6 months	15 (62.50%)			
Stroke Frequency		1.000[a]	0.437[a]	1.000[a]
1x	20 (83.34%)			
>1x	4 (16.66%)			
Hypertension		1.000[a]	0.343[a]	1.000[a]
No	3 (12.50%)			
Yes	21 (87.50%)			
Diabetes		1.000[a]	1.000[a]	1.000[a]
No	3 (12.50%)			
Yes	21 (87.50%)			
NIHSS at Memory Test		0.631[a]	0.521[a]	0.317[a]
Minor stroke (0–4)	19 (79.17%)			
Moderate stroke (5–15)	5 (20.83%)			
Acethylcholinesterase Inhibitor Treatment		1.000[a]	0.530[a]	1.000[a]
Yes	7 (29.17%)			
No	17 (70.83%)			
PSCI Subtype		1.000[a]	0.526[a]	1.000[a]
PSCI-ND	16 (66.67%)			
PSD	8 (33.33%)			
NFT Protocol		0.160[b]	0.554[b]	0.041[b]
Alpha	13 (54.17%)			
Alpha-theta	4 (16.67%)			
Beta	7 (29.16%)			

[a] = Fisher's exact test; [b] = Likelihood ratio; [c] = Pearson chi-square with continuity correction.

Cognitive Profile

Table 2 and Figure 4 illustrate the comparison of overall and domain-specific MoCA-INA scores before (T0), immediately after NFT (T1), and 1-month postintervention (T2). At baseline, the mean MoCA-INA score was 19.04 ± 6.13, with a median of 20.00 (range: 7.00–25.00). At T1, there was a mean increase of 2.63 points (T1 = 21.67) and a median increase of 3 points (T1 = 23). At T2, the mean decreased slightly by 0.46 points (T2 = 21.21), while the median remained unchanged. The results demonstrated significant improvements in total MoCA-INA scores following the five NFT sessions. Between T0 and T1, the improvement was statistically significant ($Z = -4.106$, $p < 0.001$, effect size = 0.839), as was the change from T0 to T2 ($Z = -3.471$, $p < 0.001$, effect size = 0.709). The comparison between T1 and T2 (long-term effect) showed sustained cognitive improvement, with no significant difference ($Z = -1.331$, $p = 0.183$).

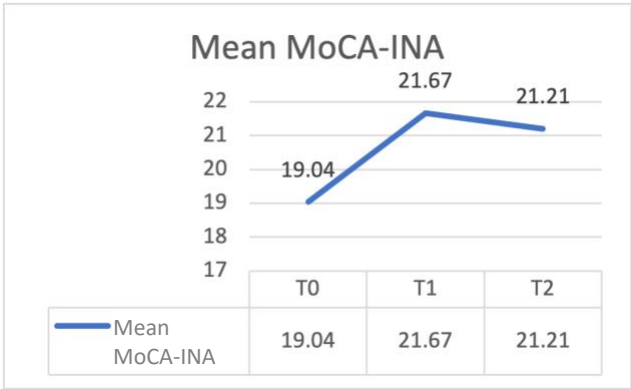
Table 2

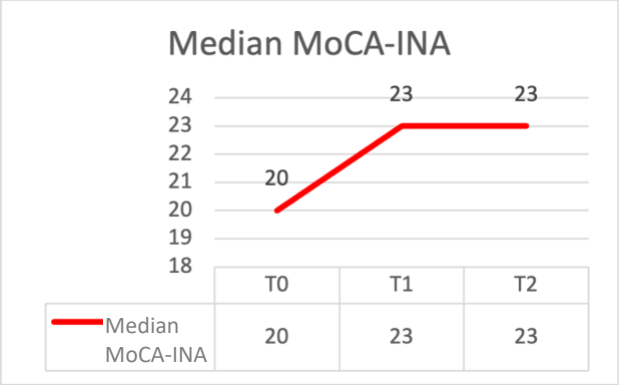
Bivariate Analysis of MoCA-INA Median Scores at T0, T1, and T2

	T0	T1	T2	*p* (T0–T1)	*p* (T1–T2)	*p* (T0–T2)
MoCA-INA Total				**<0.001[a]**	0.183[a]	**<0.001[a]**
Mean ± *SD*	19.04 ± 6.13	21.67 ± 6.24	21.21 ± 6.92			
Median (Min–Max)	20.00 (7–25)	23.00 (9–30)	23.00 (7–29)			
Visuospatial/executive				**0.025[a]**	0.763[a]	**0.032[a]**
Mean ± *SD*	3.21 ± 1.72	3.79 ±1.35	3.83 ± 1.52			
Median (Min–Max)	4.00 (0–5)	4.00 (0–5)	4.50 (0–5)			
Naming				0.052[a]	1.000[a]	0.070[a]
Mean ± *SD*	2.50 ± 0.72	2.79 + 0.51	2.79 + 0.51			
Median (Min–Max)	3.00 (1–3)	3.00 (1–3)	3.00 (1–3)			
Attention				0.232[a]	**0.022[a]**	0.294[a]
Mean ± *SD*	4.46 ± 1.50	4.75 ± 1.45	4.17 ± 1.37			
Median (Min–Max)	5.00 (1–6)	5.00 (1–6)	5.00 (1–6)			
Language				0.593[a]	0.593[a]	1.000[a]
Mean ± *SD*	1.88 ± 0.95	1.79 ± 0.98	1.88 ± 1.11			
Median (Min–Max)	2.00 (0–3)	2.00 (0–3)	2.00 (0–3)			
Abstraction				**0.029[a]**	0.480[a]	0.052[a]
Mean ± *SD*	1.08 ± 0.65	1.46 ± 0.78	1.38 ± 0.82			
Median (Min–Max)	1.00 (0–2)	2.00 (0–3)	2.00 (0–3)			
Delayed Recall				**0.015[a]**	0.917[a]	**0.025[a]**
Mean ± *SD*	1.04 ± 1.30	1.96 ± 1.85	2.00 ± 2.15			
Median (Min–Max)	0.00 (0–4)	2.00 (0–5)	1.00 (0–5)			
Orientation				0.327[a]	0.557[a]	0.144[a]
Mean ± *SD*	4.83 ± 1.71	5.04 ± 1.33	5.13 ± 1.39			
Median (Min–Max)	6.00 (1–6)	6.00 (2–6)	6.00 (2–6)			

[a] = Wilcoxon test.

Figure 4. *Comparison of Mean and Median MoCA-INA Scores at T0 (Baseline), T1 (Post-NFT), and T2 (1-Month Post-NFT).*





Domain-specific analysis showed statistically significant improvements in the visuospatial/executive domain between T0–T1 ($Z = -2.236$, $p = .025$, effect size: 0.457) and T0–T2 ($Z = -2.142$, $p = .032$, effect size: 0.438); abstraction domain at T0–T1 ($Z = -2.183$, $p = .029$, effect size: 0.446); and delayed recall domain at both T0–T1 ($Z = -2.341$, $p = .015$, effect size: 0.497) and T0–T2 ($Z = -2.242$, $p = .025$, effect size: 0.458). The attention domain showed a minor increase at T1, though not statistically significant, followed by a significant decrease at T2 ($p = .022$), but without a significant difference compared to baseline (T0–T2, $p = .294$).

Quantitative Electroencephalography Components

Table 3 and Figure 5 illustrate the comparison of relative power values (both regionally and globally) before and after NFT. At baseline, alpha and beta waves were found to be more dominant than delta and theta waves. This pattern may be attributed to several factors, including a stroke onset of more than 6 months in most participants (mean = 14.75 ± 11.97 months), a majority of subjects classified as PSCI-ND, and the predominance of subcortical lesions. These factors are believed to influence qEEG patterns, where fast waves (alpha and beta) remain more dominant than slow waves (delta and theta).

Following NFT (post-NFT), reductions were observed in the median relative power of occipital delta (13.92% → 11.96%), central delta (15.23% → 14.29%), global theta (13.97% → 13.33%), frontal theta (14.11% → 13.49%), central theta (14.62% → 13.57%), parietal theta (12.98% → 12.48%), and temporal theta (15.16% → 14.99%). In contrast, improvements were seen in fast-wave components, including increased mean frontal alpha (22.50% → 22.61%), median central alpha (19.79% → 22.68%), mean temporal alpha (30.24% → 32.96%), and mean occipital alpha (39.13% → 40.04%). For beta waves, increases were observed in mean central beta (25.49% → 26.52%), mean parietal beta (26.58% → 28.00%), and mean occipital beta (21.15% → 22.56%).

Statistically significant improvements were identified in temporal alpha relative power ($t = -1.875$, $p = .037$, effect size = 0.23) and parietal beta relative power ($t = -1.827$, $p = .040$, effect size = 0.11). Other spectral components did not show statistically significant differences between pre- and postintervention measurements ($p > .05$).

Table 4 presents the comparisons of frontal DAR and PAF before and after therapy. No statistically significant difference was found in the median frontal DAR values ($p = .577$). Similarly, no significant differences were observed in PAF across all brain regions or in global median values ($p > .05$), indicating that these components remained relatively stable following NFT.

Table 3
Comparison of Relative Power Values Pre- and Post-NFT

	Pre-NFT (%)		Post-NFT (%)		
	Mean ± SD	**Median (Min–Max)**	**Mean ± *SD***	**Median (Min–Max)**	***p***
Relative power					
Delta					
Global	17.62 ± 8.00	16.13 (4.64–39.55)*	17.85 ± 7.30	17.11 (5.21–40.54)*	.558[a]
Frontal	23.11 ± 6.92*	21.23 (10.34–35.15)	24.77 ± 8.08*	23.75 (12.96–40.54)	.065[b]
Central	16.91 ± 7.98	15.23 (5.97–34.10)*	16.81 ± 5.81	14.29 (8.37–28.08)*	.689[a]
Parietal	15.02 ± 7.56	12.09 (5.73–33.47)*	15.26 ± 5.97	12.93 (7.17–24.69)*	.689[a]
Temporal	17.15 ± 5.80*	16.52 (8.36–31.37)	17.80 ± 6.14*	16.85 (5.21–29.40)	.250[b]
Occipital	15.89 ± 9.28	13.92 (4.63–39.55)*	14.60 ± 6.79	11.96 (6.98–26.53)*	.241[a]
Theta					
Global	16.69 ± 9.66	13.97 (5.58–47.83)*	16.39 ± 9.45	13.33 (5.97–58.36)*	.401[a]
Frontal	17.16 ± 9.83	14.11 (6.35–46.37)*	16.59 ± 8.93	13.49 (7.81–50.84)*	.732[a]
Central	15.94 ± 7.41	14.62 (5.58–34.78)*	15.63 ± 7.59	13.57 (6.42–38.34)*	.648[a]
Parietal	15.14 ± 8.45	12.98 (5.91–29.28)*	15.11 ± 9.06	12.48 (5.97–43.35)*	.549[a]
Temporal	18.23 ± 10.95	15.16 (7.34–46.69)*	18.16 ± 10.59	14.99 (8.63–58.36)*	.841[a]
Occipital	17.00 ± 11.56	12.83 (6.80–47.83)*	16.45 ± 11.65	13.31 (6.26–53.72)*	.466[a]
Alpha					
Global	30.15 ± 14.46	28.29 (7.45–63.06)*	30.69 ± 13.93	28.12 (6.94–67.29)*	.570[a]
Frontal	22.50 ± 10.00*	20.80 (7.45–42.49)	22.61 ± 9.97*	21.84 (6.94–49.41)	.451[b]
Central	24.46 ± 11.47	19.79 (8.63–43.97)*	24.53 ± 10.16	22.68 (7.47–47.12)*	.797[a]
Parietal	34.40 ± 14.55	36.92 (7.89–56.26)	33.28 ± 14.06	32.70 (9.59–58.59)	.259[b]
Temporal	30.24 ± 11.81*	29.79 (11.46–51.88)	32.96 ± 11.52*	36.25 (12.40–49.89)	**.037[b]**
Occipital	39.13 ± 17.37*	42.16 (9.56–63.06)	40.04 ± 16.10*	45.09 (10.64–67.28)	.314[b]
Beta					
Global	22.71 ± 9.41	23.29 (4.22–54.35)*	23.37 ± 10.86	22.50 (4.07–62.31)*	.539[a]
Frontal	20. 61 ± 6.65*	21.63 (7.34–33.67)	20.53 ± 8.15*	21.92 (6.09–40.69)	.451[b]
Central	25.49 ± 8.83*	26.07 (10.12–42.48)	26.52 ± 10.24*	27.68 (9.25–52.77)	.169[b]
Parietal	26.58 ± 11.77*	26.92 (7.41–54.35)	28.00 ± 13.36*	31.13 (5.96–62.31)	**.040[b]**
Temporal	19.73 ± 7.13*	19.43 (6.39–31.60)	19.28 ± 7.58*	20.41 (5.39–39.71)	.238[b]
Occipital	21.15 ± 10.31*	20.98 (4.22–54.35)	22.56 ± 11.96*	22.60 (4.07–53.03)	.090[b]

[a] = Wilcoxon test; [b] = Paired sample *T*-Test; * = Data analyzed.

Figure 5. *Comparison of Relative Power Values Pre- and Post-NFT.*

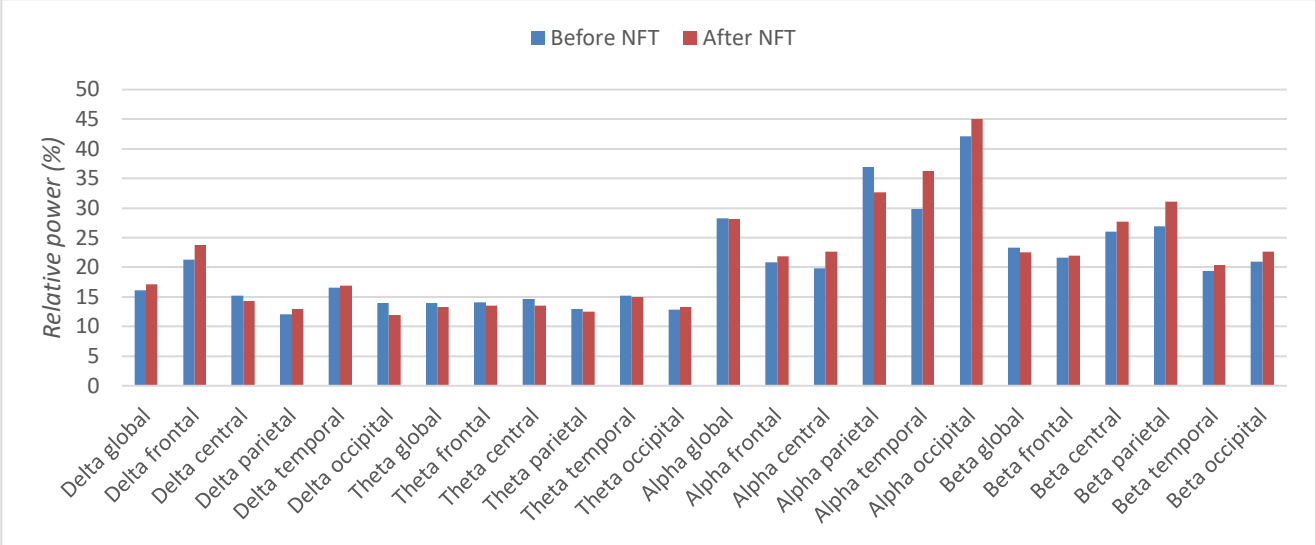


Table 4
Differences in Frontal DAR and PAF Before and After NFT

	Pre-NFT	Post-NFT	*p*
Frontal delta/alpha ratio (DAR)			0.577[a]
Mean ± *SD*	1.41 ± 1.04	1.50 ± 1.07	
Median (Min–Max)	1.06 (0.37–4.74)*	1.15 (0.27–4.72)*	
Peak alpha frequency (PAF)			
Frontal			0.345[b]
Mean ± *SD*	9.54 ± 0.36*	9.55 ± 0.37*	
Median (Min–Max)	9.63 (8.85–10.09)	9.66 (8.89–10.28)	
Central			0.254[b]
Mean ± *SD*	9.61 ± 0.33*	9.59 ± 0.30*	
Median (Min–Max)	9.66 (9.03–10.08)	9.67 (8.96–10.10)	
Parietal			0.488[b]
Mean ± *SD*	9.75 ± 0.40*	9.75 ± 0.45*	
Median (Min–Max)	9.73 (9.12–10.53)	9.79 (9.04–10.77)	
Temporal			0.480[b]
Mean ± *SD*	9.44 ± 0.38*	9.44 ± 0.37*	
Median (Min–Max)	9.40 (8.82–10.13)	9.46 (8.81–9.99)	
Occipital			0.237[b]
Mean ± *SD*	9.67 ± 0.54*	9.64 ± 0.47*	
Median (Min–Max)	9.69 (8.86–10.61)	9.73 (8.84–10.42)	
Global			0.076[a]
Mean ± *SD*	9.60 ± 0.41	9.59 ± 0.40	
Median (Min–Max)	9.63 (8.82–10.62)*	9.63(8.82–10.42)*	

[a] = Wilcoxon test; [b] = Paired sample *T*-Test; * = Data analyzed.

Factors Influencing MoCA-INA Score Improvement

A categorical analysis was conducted to evaluate cognitive improvement by grouping variables based on defined categories. In this analysis, the criterion for improvement was based on previous literature, which defines a clinically meaningful change in MoCA-INA scores as an increase of more than 2 points (Zuo et al., 2022). The analysis compared score changes across three time points: T0–T1, T1–T2, and T0–T2. The distribution of MoCA-INA improvement is illustrated in Figure 6. At T0–T1 (baseline to postintervention), 16 patients (66.67%) demonstrated improvement, while 8 patients (33.33%) showed no improvement.

Cross-tabulation analysis of potential sociodemographic and clinical predictors of MoCA-INA score improvement is presented in Table 1, covering comparisons at T0–T1, T1–T2, and T0–T2. In the T0–T1 analysis, among all the variables assessed, only age was significantly associated with cognitive improvement. Patients under 60 years of age showed statistically significant improvement in MoCA-INA scores (p = .033).

In the T1–T2 analysis, no sociodemographic or clinical variables were found to significantly influence MoCA-INA score changes (p > .05). However, in the T0–T2 comparison (baseline to 1-month postintervention), two variables were significantly associated with improvement in mean MoCA-INA scores: age (p = .014) and the type of NFT protocol applied (p = .041).

PSCI Subtypes Analysis

A subgroup analysis was conducted by stratifying patients based on the severity of cognitive impairment into PSCI-ND and PSD groups. The analysis assessed changes in average MoCA-INA scores and qEEG wave patterns in both groups.

Table 5 shows that the PSCI-ND group had higher median MoCA-INA scores than the PSD group at all three time points (T0, T1, and T2). However, no statistically significant differences were observed in the change scores (Δ MoCA-INA) across the time intervals T0–T1, T1–T2, and T0–T2, indicating that the effectiveness of NFT did not differ significantly between the PSCI-ND and PSD groups at any measurement point.

Figure 6. *Categories of Mean MoCa-INA Score Improvement.*

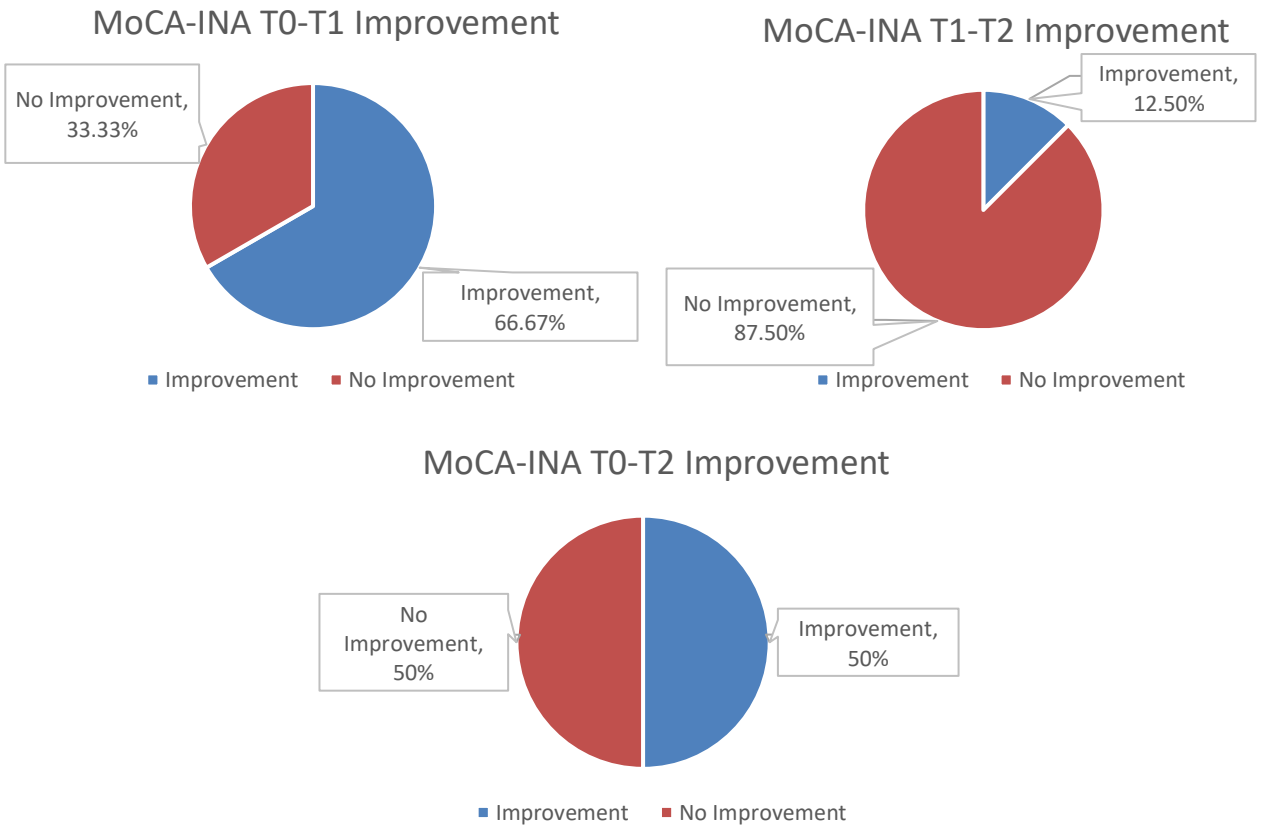


Table 5
Bivariate Analysis of Differences Between PSCI-ND and PSD Groups

Variable	PSCI-ND		PSD		p
	Mean ± *SD*	Median (Min–Max)	Mean ± *SD*	Median (Min–Max)	
MoCA-INA					
MoCA-INA T0	20.75 ± 5.67	23.50 (7–25)*	15.63 + 5.88	15.50 (8–25)*	.063[a]
MoCA-INA T1	23.56 ± 5.93	26.00 (9–30)*	17.88 + 5.28	17.00 (12–25)*	**.034[a]**
MoCA-INA T2	23.25 + 6.37	25.00 (7–29)*	17.13 + 6.44	17.50 (8–25)*	**.027[a]**
∆ MoCA-INA T0–T1	2.81 ± 2.26*	2.50 (−1–(8))	2.25 ± 1.58*	2.50 (0–5)	.536[b]
∆ MoCA-INA T1–T2	−0.31 ± 1.53	0.00 (−3–(2))*	-0.75 ± 0.88	0.00 (−4–(1))*	.445[a]
∆ MoCA-INA T0–T2	2.50 ± 2.16	3.00 (0–6)*	1.50 ± 2.26*	2.00 (−3–(4))*	.508[a]

[a] = Mann-Whitney test; [b] = Independent *T*-Test; * = Data analyzed.

Subgroup analysis revealed that both groups showed significant improvement from T0 to T1 (PSCI-ND: p < .001, effect size = 0.845; PSD: p = .003, effect size = 0.40). From T0 to T2, only the PSCI-ND group showed a statistically significant improvement (p = .002, effect size = 0.7725). At the domain level, significant improvements were observed primarily in the visuospatial/executive and delayed recall domains, especially among the PSCI-ND group.

Regarding qEEG, the PSCI-ND group exhibited increases in nearly all fast-wave spectra (alpha and beta), with significant changes in median global alpha (26.04% → 27.90%, *p* = .032), mean temporal alpha (29.18% → 32.97%, *p* = .037), and mean occipital beta (23.08% → 25.66%, *p* = .039). No significant changes were observed in DAR or PAF. In contrast, the PSD group displayed inconsistent delta wave patterns with no statistical significance (*p* > .05), a significant decrease in global theta (20.51% → 19.33%, *p* = .043), and reductions in global alpha (30.84% → 29.97%, *p* = .027) and central alpha (18.37% → 26.13%, *p* = .019). Although beta power increased, the changes were not statistically significant (*p* > .05).

Kendall's Tau correlation analysis (Table 6) showed no significant associations between the timing of MoCA-INA assessments and the magnitude of score changes. Additionally, no significant correlations were found between post-NFT qEEG components and MoCA-INA scores at T1.

Table 6
Kendall's Tau Correlation Analysis

Variable	Correlation Coefficients	p
Time Interval T0–T1*Mean MoCA-INA T1	0.315	.018
Time Interval T1–T2*Mean MoCA-INA T2	0.004	.490
Time Interval T0–T2*Mean MoCA-INA T2	0.296	.024
Time Interval T0–T1* ∆ MoCA- INA T0–T1	0.172	.136
Time Interval T1–T2* ∆ MoCA- INA T1–T2	−0.025	.438
Time Interval T0–T2* ∆ MoCA- INA T0–T2	0.251	.054
Absolute Power Global Delta*Mean MoCA-INA T1	−0.082	.292
Absolute Power Global Teta*Mean MoCA-INA T1	−0.112	.227
Absolute Power Global Alpha*Mean MoCA-INA T1	−0.015	.460
Absolute Power Global Beta*Mean MoCA-INA T1	−0.097	.258
Relative Power Global Delta*Mean MoCA-INA T1	0.067	.327

Table 6
Kendall's Tau Correlation Analysis

Variable	Correlation Coefficients	p
Relative Power Global Teta*Mean MoCA-INA T1	−0.126	.198
Relative Power Global Alpha *Mean MoCA-INA T1	0.082	.292
Relative Power Global Beta*Mean MoCA-INA T1	−0.022	.441
Frontal DAR*Mean MoCA-INA T1	−0.108	.235
Global PAF*Mean MoCA-INA T1	0.037	.402

Multivariate Analysis

In the multivariate analysis for T0–T1, age <60 years was identified as the most influential factor associated with improvement in MoCA-INA scores at T1, with an Exp(B) value of 20.045, p = .035, and a 95% confidence interval (CI) of 1.241–323.771. Similarly, in the T0–T2 analysis, age <60 years remained the most significant factor, with an Exp(B) of 22.778, p = .014, and a 95% CI of 1.876–276.572.

Discussion

The findings of this study demonstrate that after five sessions of NFT using individualized qEEG-based protocols, cognitive function improved significantly, and the effect persisted for up to 1-month postintervention. A statistically significant increase in MoCA-INA scores was observed at T1 (p = .001) with a large effect size (0.839). No decline in MoCA-INA scores was noted 1 month after NFT, and comparison between T0 and T2 also revealed significant improvement (p < .001; effect size = 0.709). At the domain level, significant improvements were found, particularly in visuospatial/executive function and delayed recall.

Improvements were also observed in fast-wave EEG spectra, alongside reductions in slow-wave activity. These findings indicate that NFT may serve as a beneficial adjunctive therapy for patients with PSCI, including both PSCI-ND and PSD, showing both immediate and sustained effects 1-month posttreatment. Based on these results, NFT appears to be an effective cognitive rehabilitation modality, potentially superior to conventional approaches, even with only five sessions.

These findings are consistent with a study by Anggraeni et al. (2024), which reported a 2.63-point improvement in MoCA-INA scores (14.75 → 17.38; p = .019) after 10 NFT sessions over 2 weeks in PSCI-ND patients. A comparable result was observed in the PSCI-ND subgroup of the present study, with a 2.81-point increase in mean MoCA-INA scores (20.75 → 23.56; p < .001). However, unlike the 2024 study by Anggraeni et al., which found no significant domain-level differences, the current study reported significant improvements in the visuospatial/executive, abstraction, and delayed recall domains, possibly due to the larger sample size (Anggraeni et al., 2024).

Similar results were reported by Jang et al. (2019) in Korea, who studied five MCI patients (aged 40–80 years, baseline MoCA <22) receiving 16 NFT sessions. MoCA scores increased by 4.4 points after eight sessions (week 4; 19.4 → 23.8, p = .042), and by 6.2 points after 16 sessions (week 8; 19.4 → 25.6, p = .042). Improvements were also noted in complex memory, cognitive flexibility, attention, reaction time, and executive function. The larger increase in MoCA scores in Jang's study may be due to the higher number of sessions and the differing study population. These findings suggest that greater session frequency may yield greater improvements.

Madijova et al. (2024) similarly, reported significant improvements in MoCA scores among poststroke patients following 30 days of NFT combined with pharmacological therapy. In Group 1 (NFT + Cytoflavin), MoCA scores increased by 3.9 points (20.3 → 24.2); in Group 2 (NFT + Memantine), by 4.6 points (19.9 → 24.5); and in Group 3 (NFT + Cytoflavin + Memantine), by 4.9 points (20.2 → 25.1). Another study supporting these findings is Marlats et al. (2020), which investigated 20 MCI patients undergoing 20 sessions of SMR/theta NFT. The study reported a mean MoCA increase of 1.9 points (23.2 → 25.1; p = .007), which was lower than the improvement observed in the present study. This lower gain may be attributable to the older age of participants (mean age 76.1 years) compared to this study (mean age 61.17 years).

Comparable cognitive improvements were also reported by Kober et al. (2015), who found that among 11 poststroke patients (>1 month) receiving

NFT with SMR protocols and six patients receiving upper alpha protocols, there were enhancements in both short-term and long-term verbal memory. Specifically, SMR training led to improvements in short-term visuospatial memory, while upper alpha protocols were more effective in enhancing working memory compared to no intervention. Similarly, Cho et al. (2016) found improved visual discrimination and visual memory among 13 poststroke patients who underwent six sessions of NFT using the SMR-beta protocol.

Various theories have been proposed to explain how NFT can improve cognitive function in patients. First, the initial phase of learning is dominated by the frontal brain regions, supported by the striatum, which generates distinct representations (e.g., increased SMR activity) and reinforces those that yield positive feedback signals (e.g., visual feedback). Second, the most efficient frontal representations are activated and modulate connections to and within the thalamus. Third, the targeted brain state and the associated subjective experiences act as secondary reinforcers that help close the interoceptive homeostatic loop. The synergistic interaction between brain structure and function lies at the core of NFT. By targeting functional changes, NFT may induce structural modifications in the brain, which in turn support more persistent functional reorganization (Pinter et al., 2021).

The primary goal of NFT is to enable individuals to become aware of specific cortical activity patterns associated with more optimal behavioral or cognitive states. NFT can induce changes in brain electrical activity that synergize with cognitive enhancement through the patient's ability to self-modulate brainwave activity. Increases in alpha waves are associated with improvements in working memory and short-term memory. Alpha activity also plays a role in suppressing irrelevant or distracting processes, thereby enhancing attention and memory by inhibiting disruptive stimuli. Accordingly, NFT may accelerate functional recovery or even achieve improvements that are not possible through other therapies. These insights support the recommendation of NFT as a viable cognitive rehabilitation modality for poststroke patients (Anggraeni et al., 2024). The results of this study suggest that even with fewer sessions than other comparative studies (only five sessions in this study), a statistically significant improvement was observed in both the mean and median MoCA-INA total scores. Although not all cognitive domains showed significant improvement, this domain-specific variation in response may be influenced by factors such as differences in brain structure, individual neuropsychological and psychological profiles, limitations of the MoCA-INA tool, baseline domain scores that were not low enough, cognitive strategies employed, and the NFT protocol used (Anggraeni et al., 2024).

To date, relatively few studies have assessed the long-term effectiveness of NFT on cognitive function. Furthermore, there remains debate regarding the durability of NFT effects after the intervention ends. No clear cut-off criteria have been established, and specific categorizations based on different disease types remain lacking (Weber et al., 2020).

In this study, a slight decrease of 0.46 points was observed in the mean MoCA-INA total score 1-month posttherapy (21.67 → 21.21), with the same median value of 20.00, and this difference was not statistically significant (p = .183). However, the T0−T2 comparison still showed a significant increase in mean score by 2.17 points and in median by 3 points (p < .001). These findings suggest that the cognitive improvement resulting from NFT remains relatively stable over 1 month. This aligns with the study by Lavy et al. (2018), which involved 11 MCI patients who received 10 sessions of NFT using the upper alpha protocol. Improvements in memory scores (both verbal and nonverbal immediate memory) were sustained for up to 30 days postintervention (p = .441; Lavy et al., 2018).

These findings differ from those reported by Marlats et al. (2020), who studied 20 MCI patients receiving 30 sessions of SMR/theta NFT. One month after the intervention, a statistically significant decrease of 1.5 points was found in mean MoCA scores (25.1 → 23.6; p = .015), and there was no significant difference between baseline and 1-month posttherapy scores (23.2 → 23.6; p = .0937). However, performance on other memory tests (e.g., Logical Memory, RAVLT, TMT-A, and TMT-B) remained stable and comparable to posttreatment levels. The decline in MoCA scores in Marlat et al.'s study may be attributed to the older participant age range (65–90 years, mean age 76.1 years), in contrast to the younger mean age of 61.17 years in the present study. Bivariate analysis in our study also showed that younger age (<60 years) was significantly associated with improved MoCA-INA scores.

The persistence of clinical improvements following NFT may be explained by neuronal-level effects. As

NFT is a form of learning, it involves consolidation and reconsolidation processes that continue over time. Gradual improvements observed in the weeks following NFT may reflect slow but ongoing consolidation, regardless of the extent of practice. At the network level, NFT has been shown to affect brain structure postintervention. According to the Hebbian principle of neuroplasticity, "fire together, wire together," neurons' structural changes become more pronounced over time, and the regions engaged during NFT show increased synchronization, strengthening their functional connectivity (Rance et al., 2018).

This study also found statistically significant changes in specific regions of the fast-wave spectrum. In particular, mean temporal alpha relative power increased by 2.72% (p = .037), and parietal beta relative power increased by 1.42% (p = .040). Although no global changes were observed, the relative power results, which provide a more accurate representation of brainwave dynamics, tended to show increases in fast-wave activity (alpha and beta) and decreases in slow-wave activity (theta) post-NFT. Median relative theta power decreased in all regions except occipital theta, while alpha and beta waves generally increased, though not all reached statistical significance.

These results are consistent with the study by Cho et al. (2016), which reported increased relative beta power in the frontal and parietal regions of poststroke patients with cognitive impairment (MMSE scores 18–23) at 3 months post-onset. However, their intervention involved a longer duration of 30 NFT sessions using a beta-SMR protocol over 6 weeks. Cho suggested that NFT might promote the redistribution of brain activity to other regions, facilitating long-term improvements. Similarly, a study by Jang et al. (2019) reported a significant increase in average beta power after 16 NFT sessions over 8 weeks in patients with MCI (p = .001).

Marcos-Martínez et al. (2021) conducted a study on 11 cognitively healthy individuals over the age of 60 who received five sessions of motor imagery-based NFT. They observed increases in relative theta, alpha, and beta power (particularly alpha and beta), with statistically significant changes (p < .01). Specifically, mean relative alpha power increased by 3.7% (11.2% → 14.9%), and beta power by 4.3% (13.2% → 17.5%). Although similar trends were observed in the present study, the magnitude of increase was smaller (global alpha: 0.54%; global beta: 0.56%; p > .05).

A study by Marlats et al. (2020) involving 20 MCI patients who underwent 20 sessions of SMR/theta NFT also reported significant increases in log power of theta (p = .016) and alpha (p = .027) after treatment. The increase in alpha was hypothesized to reflect the effect of NFT in enhancing fast-wave brain activity while suppressing slow-wave spectra. Interestingly, a protocol designed to enhance beta instead led to increased alpha, supporting the hypothesis that the activation of specific frequency bands may influence others. The absence of global statistically significant changes in the present study—whether from overall or alpha/theta-specific protocols—may be attributed to the lower number of sessions.

In this study, no significant differences were found between pre- and postintervention values of frontal DAR and PAF. This contrasts with findings from Andrade et al. (2022) in cognitively impaired older adults undergoing 20 NFT sessions and from Lavy et al. (2018) in 11 MCI patients who received 10 NFT sessions. Both studies reported posttreatment improvements in PAF, although Lavy noted a decline after 30 days. These differences may stem from variations in the number of sessions and patient characteristics. To date, only a few studies have investigated the impact of NFT on DAR and PAF in PSCI patients.

The small and limited number of sessions in the present study (only five, compared to more than 10 in most other studies) may have contributed to the lack of significant changes in qEEG components. This aligns with findings by Zhou et al. (2024), who conducted a study involving five sessions of alpha-protocol NFT in 20 healthy individuals (mean age 23.83 years). No significant changes in alpha amplitude were found posttreatment. Zhou et al. (2024) suggested that unengaging feedback might lead to reduced motivation and diminished learning efficiency during NFT. Additionally, insufficient training sessions may contribute to the failure of long-term neurofeedback (NF) learning, which generally requires more than five sessions.

Other factors that may account for the absence of qEEG wave changes include interindividual differences such as variations in brain structure, neurophysiological and psychological characteristics, and cognitive strategies (Kober et al., 2017). Furthermore, the baseline power values in this study's participants were already close to normal topographic patterns—that is, dominance of fast-wave spectra (alpha and beta) over slow-wave spectra—due to several factors discussed earlier. As

a result, the range of posttreatment changes may have been limited, given that the initial patterns already resembled those of a healthy population. This near-normal baseline could be attributed to a longer stroke duration, a greater proportion of PSCI-ND cases, or the effects of pharmacologic treatment in the PSD group. Although the analysis did not reveal any significant effects of medication on MoCA-INA score improvement, such treatment may influence brainwave activity.

When analyzing the differences in NFT effectiveness between the PSCI-ND and PSD groups, both groups demonstrated improvements in total MoCA-INA scores—both mean and median—at T1, followed by a slight decline 1 month later, though scores remained higher than at baseline (T0). Statistically significant improvements at T1 were observed in both groups (PSCI-ND: $p < .001$; PSD: $p = .003$). No significant changes were found between T1 and T2. However, when comparing T0 and T2, the PSCI-ND group maintained a statistically significant improvement ($p = .002$), while the PSD group did not ($p = .052$). At the domain level, more cognitive domains showed improvement in the PSCI-ND group. No statistically significant differences were found in the delta MoCA-INA values between the two groups across T0–T1, T1–T2, or T0–T2, indicating that the magnitude of cognitive improvement was comparable between patients with MCI and those with dementia.

These findings align with the theoretical basis of NFT, which posits that the therapy can be effective in patients with cognitive impairments, including both MCI and dementia. Lujimes et al. (2016) evaluated NFT in 10 patients with Alzheimer's dementia who were already receiving cholinesterase inhibitors. Cognitive function was assessed using the Cambridge Cognitive Examination (CAMCOG), and 30 NFT sessions were conducted twice weekly. A 2% improvement in total CAMCOG scores was observed, with the memory subscale showing the most statistically significant gain. This suggests preserved neuroplasticity even in dementia patients.

Another study by Surmeli et al. (2016) involved nine patients with Alzheimer's dementia and 11 with vascular dementia who underwent 10–96 hours of NFT based on qEEG findings. Posttherapy MMSE scores improved significantly (overall: 18.8 → 24.5; Alzheimer's: 19.22 → 25.22; vascular: 18.45 → 23.0). The most notable improvements occurred in the orientation and recall domains. Cognitive gains were attributed to improved connectivity in the medial prefrontal cortex, medial temporal lobe, posterior cingulate cortex, precuneus, and the medial, lateral, and inferior parietal cortices. Notably, 19 out of 20 patients reportedly discontinued medication due to substantial symptom improvement (Surmeli et al., 2016; Trambaiolli et al., 2021). These findings support the use of NFT across a broad spectrum of patients, including those with dementia.

In terms of relative power, the PSCI-ND group showed significant increases in global and temporal alpha power as well as occipital beta power. In contrast, the PSD group exhibited decreases in theta, global alpha, and central alpha power. These findings support the theory that NFT promotes increased fast-wave (e.g., alpha and beta) activity while reducing slow-wave (e.g., theta) activity, thus enhancing cognitive function. Alpha activity in particular is known to increase significantly following EEG-based NFT (Marlats et al., 2020).

This suggests that, in terms of relative power—a more sensitive EEG measure—the PSCI-ND group demonstrated better self-regulation across qEEG parameters compared to the PSD group. Few studies have directly compared qEEG changes between MCI and dementia groups poststroke. Most available data are from single-group studies or case reports, especially among dementia populations, limiting direct comparisons. The lack of significant qEEG changes in this study compared to other research may be due to the lower number of sessions, as most studies use 10–30 sessions, or to relatively normal baseline values.

Multivariate analysis for both T0–T1 and T0–T2 indicated that age was a significant predictor of MoCA-INA score improvement (defined as a gain >2 points). Participants aged <60 years had a higher likelihood of cognitive improvement after NFT. This supports existing theories that age plays a crucial role in cognitive deficits, recovery, and NFT efficacy.

However, the influence of age on NFT effectiveness in PSCI patients could not be directly analyzed using comparable age-based subgroups, as no prior studies have made this comparison. The study by Anggraeni et al. (2024) used a different age cut-off (65 years) and had a smaller sample size. Another study, a meta-analysis by Lin et al. (2024) concluded that the impact of NFT on memory function differs between older and younger adults. Older age was associated with reduced NFT effectiveness for episodic memory, though working memory appeared unaffected. Nonetheless, NFT can enhance memory in older adults, especially with appropriate protocols and adequate training duration. It was noted that

over 300 min of training—roughly 10 sessions—is typically needed to achieve beneficial outcomes in older adults, which contrasts with the five-session design of the present study.

Neuroplasticity, the mechanism underlying post-NFT improvement, is also influenced by age. It is widely assumed that brain plasticity peaks in youth and gradually declines with age. Although new motor and cognitive skills can be acquired at any age, progress may be slower in older populations. Aging brains undergo characteristic neurodegenerative changes, including progressive loss of structure, function, or neuronal count. Neurodegeneration, to some extent, is a natural process in late life (Arcos-Burgos et al., 2019; Pauwels et al., 2018).

In older adults, no significant activation or modulation of the striatal system occurs during cognitive learning. This suggests that older individuals may require more extensive training to achieve the same neural and cognitive outcomes as younger individuals. Alternatively, it may reflect more limited behavioral and neural adaptability. Cognitive decline in older adults is often linked to diminished brain function, leading to reduced concentration, memory, and mental flexibility (Nguyen et al., 2019).

Limitations

This study has several limitations. First, it lacked a sham control or untreated comparison group, precluding direct conclusions about the effectiveness of NFT in avoiding placebo or learning effects. Second, scheduling difficulties for qEEG assessments and NFT sessions—often due to prolonged examination procedures—led to a relatively high dropout rate. Third, assessments could not be performed on patients with early stroke onset, as most posthospitalization stroke patients returned to type B referral hospitals, and only a few returned to RSMH. Consequently, most participants were chronic stroke patients with comorbidities or recurrent strokes. Finally, the follow-up period was limited to 1 month, which may not sufficiently reflect the long-term effects of NFT.

Conclusion

Five sessions of NFT using individualized qEEG-based protocols were effective in improving cognitive function, as measured by MoCA-INA, both immediately after training and 1-month postintervention. Improvements were also observed in qEEG relative power components. No significant differences in NFT effectiveness were found between the PSCI-ND and PSD groups. Younger age was associated with a greater likelihood of cognitive improvement.

Author Disclosure

The authors have no grants, financial interests, or conflicts to disclose. There was no use of AI in the preparation, creation, and completion of this manuscript. The researcher is responsible for the originality of the manuscript.

References

Ali, J. I., Viczko, J., & Smart, C. M. (2020). Efficacy of neurofeedback interventions for cognitive rehabilitation following brain injury: Systematic review and recommendations for future research. *Journal of the International Neuropsychological Society, 26*(1), 31–46. https://doi.org/10.1017/s1355617719001061

Andrade, K., Guieysse, T., Razafimahatratra, S., Houmani, N., Klarsfeld, A., Dreyfus, G., Dubois, B., Medani, T., & Vialatte, F. (2022). EEG-neurofeedback for promoting neuromodulation in the elderly: Evidence from a double-blind study. *bioRxiv,* Article 509227. https://doi.org/10.1101/2022.09.26.509227

Anggraeni, D., Haddani, M., Handayani, S., Nindela, R., & Febrianto, Y. (2024). Effectiveness of neurofeedback training in poststroke cognitive impairment. *NeuroRegulation, 11*(3), 296–303. https://doi.org/10.15540/nr.11.3.296

Arcos-Burgos, M., Lopera, F., Sepulveda-Falla, D., & Mastronardi, C. (2019). Neural plasticity during aging. *Neural Plasticity, 2019*, Article 6042132. https://doi.org/10.1155/2019/6042132

Babiloni, C., Arakaki, X., Bonanni, L., Bujan, A., Carrillo, M. C., Del Percio, C., Edelmayer, R. M., Egan, G., Elahh, F. M., Evans, A., Ferri, R., Frisoni, G. B., Güntekin, B., Hainsworth, A., Hampel, H., Jelic, V., Jeong, J., Kim, D. K., Kramberger, M., … Yener, G. (2021). EEG measures for clinical research in major vascular cognitive impairment: Recommendations by an expert panel. *Neurobiology of Aging, 103*, 78–97. https://doi.org/10.1016/j.neurobiolaging.2021.03.003

Cho, H.-Y., Kim, K.-T., & Jung, J.-H. (2016). Effects of neurofeedback and computer-assisted cognitive rehabilitation on relative brain wave ratios and activities of daily living of stroke patients: A randomized control trial. *Journal of Physical Therapy Science, 28*(7), 2154–2158. https://doi.org/10.1589/jpts.28.2154

Hadiyoso, S., Zakaria, H., Anam, P. A., & Rajab, T. L. E. (2022). EEG-based spectral dynamic in characterization of poststroke patients with cognitive impairment for early detection of vascular dementia. *Journal of Healthcare Engineering, 2022*(1), Article 5666229. https://doi.org/10.1155/2022/5666229

Hohenfeld, C., Nellessen, N., Dogan, I., Kuhn, H., Müller, C., & Papa, F., Ketteler, S., Goebel, R., Heinecke, A., Shah, N. J., Schulz, J. B., Reske, M., & Reetz, K. (2017). Cognitive improvement and brain changes after real-time functional MRI neurofeedback training in healthy elderly and prodromal Alzheimer's disease. *Frontiers in Neurology, 8*, Article 384. https://doi.org/10.3389/fneur.2017.00384

Jang, J.-H., Kim, J., Park, G., Kim, H., Jung, E.-S., Cha, J.-Y., Kim, C.-Y., Kim, S., Lee, J.-H., & Yoo, H. (2019). Beta wave enhancement neurofeedback improves cognitive functions in patients with mild cognitive impairment. *Medicine (Baltimore), 98*(50), Article e18357. https://doi.org/10.1097/md.0000000000018357

Kober, S. E., Schweiger, D., Witte, M., Grieshofer, P., Neuper, C., & Wood, G. (2017). Upper alpha based neurofeedback training in chronic stroke: Brain plasticity processes and

cognitive effects. *Applied Psychophysiology and Biofeedback, 42*(1), 69–83. https://doi.org/10.1007/s10484-017-9353-5

Kober, S. E., Schweiger, D., Witte, M., Reichert, J. L., Grieshofer, P., Neuper, C., & Wood, G. (2015). Specific effects of EEG based neurofeedback training on memory functions in post-stroke victims. *Journal of NeuroEngineering and Rehabilitation, 12*(1), Article 107. https://doi.org/10.1186/s12984-015-0105-6

Lavy, Y., Dwolatzky, T., Kaplan, Z., Guez, J., & Todder, D. (2018). Neurofeedback improves memory and peak alpha frequency in individuals with mild cognitive impairment. *Applied Psychophysiology and Biofeedback, 44*, 41–49. https://doi.org/10.1007/s10484-018-9418-0

Lin, Y.-R., Hsu, T.-W., Hsu, C.-W., Chen, P.-Y., Tseng, P.-T., & Liang, C.-S. (2024). Effectiveness of electroencephalography neurofeedback for improving working memory and episodic memory in the elderly: A meta-analysis. *Medicina, 60*(3), 369. https://doi.org/10.3390/medicina60030369

Lujimes, R. E., Pouwel, S., & Boonman, J. (2016). The effectiveness of neurofeedback on cognitive functioning in patients with Alzheimer's disease: Preliminary results. *Neurophysiologie Clinique, 46*(3), 179–187. https://doi.org/10.1016/j.neucli.2016.05.069

Madijova, Y. N., Azimoba, N. M., Xusenoa, N. T., & Salikhoa, S. M. (2024). Optimization of cognitive disorders in dementia using the neurofeedback therapy. *International Scientific Journal, 3*(2), 183–193. https://doi.org/10.5281/zenodo.10714723

Marcos-Martínez, D., Martínez-Cagigal, V., Santamaría-Vázquez, E., Pérez-Velasco, S., & Hornero, R. (2021). Neurofeedback training based on motor imagery strategies increases EEG complexity in elderly population. *Entropy, 23*(12), 1574. https://doi.org/10.3390/e23121574

Marlats, F., Bao, G., Chevallier, S., Boubaya, M., Djabelkhir-Jemmi, L., Wu, Y.-H., Lenoir, H., Rigaud, A.-S., & Azabou, E. (2020). SMR/theta neurofeedback training improves cognitive performance and EEG activity in elderly with mild cognitive impairment: A pilot study. *Frontiers in Aging Neuroscience, 12*, Article 147. https://doi.org/10.3389/fnagi.2020.00147

McDonald, M. W., Black, S. E., Copland, D. A., Corbett, D., Dijkhuizen, R. M., Farr, T. D., Jeffers, M. S., Kalaria, R. N., Karayanidis, F., Leff, A. P., Nithianantharajah, J., Pendlebury, S., Quinn, T. J., Clarkson, A. N., & O'Sullivan, M. J. (2019). Cognition in stroke rehabilitation and recovery research: Consensus-based core recommendations from the second stroke recovery and rehabilitation roundtable. *International Journal of Stroke, 14*(8), 774–782. https://doi.org/10.1177/1747493019873600

Merriman, N. A., Sexton, E., McCabe, G., Walsh, M. E., Rohde, D., Gorman, A., Jeffares, I., Donnelly, N.-A., Pender, N., Williams, D. J., Horgan, F., Doyle, F., Wren, M.-A., Bennett, K. E., & Hickey, A. (2019). Addressing cognitive impairment following stroke: Systematic review and meta-analysis of non-randomised controlled studies of psychological interventions. *BMJ Open, 9*(2), Article e024429. https://doi.org/10.1136/bmjopen-2018-024429

Nguyen, L., Murphy, K., & Andrews, G. (2019). Cognitive and neural plasticity in old age: A systematic review of evidence from executive functions cognitive training. *Ageing Research Reviews, 53*, Article 100912. https://doi.org/10.1016/j.arr.2019.100912

Ong, P. A., Muis, A., Rambe, A. S., Widjojo, F. S., Laksmidewi, A. A., & Pramono, A. (2015). *Panduan praktik klinik: Diagnosis dan penatalaksanaan demensia*. Perhimpunan Dokter Spesialis Saraf Indonesia.

Pauwels, L., Chalavi, S., & Swinnen, S. P. (2018). Aging and brain plasticity. *Aging, 10*(8), 1789–1790. https://doi.org/10.18632/aging.101514

Petrovic, J., Milosevic, V., Zivkovic, M., Stojanov, D., Milojkovic, O., Kalauzi, A., & Saponjic, J. (2017). Slower EEG alpha generation, synchronization and "flow"—possible biomarkers of cognitive impairment and neuropathology of minor stroke. *PeerJ*, *5*, Article e3839. https://doi.org/10.7717/peerj.3839

Pinter, D., Kober, S. E., Fruhwirth, V., Berger, L., Damulina, A., Khalil, M., Neuper, C., Wood, G., & Enzinger, C. (2021). MRI correlates of cognitive improvement after home-based EEG neurofeedback training in patients with multiple sclerosis: A pilot study. *Journal of Neurology, 268*(10), 3808–3816. https://doi.org/10.1007/s00415-021-10530-9

Rance, M., Walsh, C., Sukhodolsky, D. G., Pittman, B., Qiu, M., Kichuk, S. A., Wasylink, S., Koller, W. N., Bloch, M., Gruner, P., Scheinost, D., Pittenger, C., & Hampson, M. (2018). Time course of clinical change following neurofeedback. *NeuroImage, 181*, 807–813. https://doi.org/10.1016/j.neuroimage.2018.05.001

Surmeli, T., Eralp, E., Mustafazade, I., Kos, H., Özer, G. E., & Surmeli, O. H. (2016). Quantitative EEG neurometric analysis–Guided neurofeedback treatment in dementia. *Clinical EEG and Neuroscience, 47*(2), 118–133. https://doi.org/10.1177/1550059415590750

Tosti, B., Corrado, S., Mancone, S., Di Libero, T., Rodio, A., Andrade, A., & Diotaiuti, P. (2024). Integrated use of biofeedback and neurofeedback techniques in treating pathological conditions and improving performance: A narrative review. *Frontiers in Neuroscience, 18*, Article 1358481. https://doi.org/10.3389/fnins.2024.1358481

Trambaiolli, L. R., Cassani, R., Mehler, D. M. A., & Falk, T. H. (2021). Neurofeedback and the aging brain: A systematic review of training protocols for dementia and mild cognitive impairment. *Frontiers in Aging Neuroscience, 13*, Article 682683. https://doi.org/10.3389/fnagi.2021.682683

Tugasworo, D., Agung, L., Retnaningsih, R., Husni, A., Bintoro, A. C., & Wati, A. P. (2023). The correlation of glial fibrillary acid protein level to cognitive function outcome in acute lacunar ischemic stroke patient. *Open Access Macedonian Journal of Medical Sciences, 11*(B), 330–334. https://doi.org/10.3889/oamjms.2023.11393

Vilou, I., Varka, A., Parisis, D., Afrantou, T., & Ioannidis, P. (2023). EEG-neurofeedback as a potential therapeutic approach for cognitive deficits in patients with dementia, multiple sclerosis, stroke and traumatic brain injury. *Life, 13*(2), 365. https://doi.org/10.3390/life13020365

Weber, L. A., Ethofer, T., & Ehlis, A.-C. (2020). Predictors of neurofeedback training outcome: A systematic review. *NeuroImage: Clinical, 27*, Article 102301. https://doi.org/10.1016/j.nicl.2020.102301

Wigton, N., & Krigbaum, G. (2015). A review of qEEG-guided neurofeedback. *NeuroRegulation, 2*(3), 149–155. https://doi.org/10.15540/nr.2.3.149

Zhou, W., Nan, W., Xiong, K., & Ku, Y. (2024). Alpha neurofeedback training improves visual working memory in healthy individuals. *Npj Science of Learning, 9*(1), Article 32. https://doi.org/10.1038/s41539-024-00242-w

Zuo, L., Dong, Y., Liao, X., Pan, Y., Xiang, X., Meng, X., Li, H., Zhao, X., Wang, Y., Shi, J., & Wang, Y. (2022). Risk factors for decline in Montreal Cognitive Assessment (MoCA) scores in patients with acute transient ischemic attack and minor stroke. *The Journal of Clinical Hypertension, 24*(7), 851–857. https://doi.org/10.1111/jch.14453

Received: May 30, 2025
Accepted: July 3, 2025
Published: March 31, 2026