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Effect of Dual-Task Training on the Number of EEG Bands in Stroke Patients

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ABSTRACT

Background/Objective: Dual-task training (DTT) positively impacts stroke recovery, but its effects on electroencephalography (EEG) using Fourier series analysis are under-researched. This study aimed to evaluate the effects of DTT on EEG in stroke patients by analyzing different EEG bands with fast Fourier transform (FFT).

Methods: Five participants with unilateral ischemic stroke completed 12 sessions of 15-min DTT, three times a week for 4 weeks. EEG data were recorded before and after the intervention, and FFT analysis was conducted. Assessments of upper limb function, elbow flexor muscle tone, and daily living activities were also performed.

Results: FFT analysis showed a reduction in delta, theta, alpha, and beta bands post-DTT, while their correlation between measurement times remained consistent. These changes were somewhat reflected in the participants' improved clinical outcomes.

Conclusion: The results suggest that DTT positively affects EEG band frequencies, with a consistent correlation between pre- and post-intervention measurements. This indicates that FFT analysis could be a useful tool for assessing DTT's impact on stroke recovery.

1 | Introduction

Stroke is among the most prevalent diseases and leading causes of disability worldwide (Ma et al. 2014). This medical condition arises when there is an interruption in the blood flow to the brain tissue, resulting in ischemia and subsequent functional impairments across various bodily systems (Feigin et al. 2021). A particularly common and disabling consequence for stroke patients is upper limb dysfunction, with over 80% of patients experiencing this issue acutely (Coscia et al. 2019; Rodgers et al. 2019) and approximately 60% of stroke survivors continue to be affected by it permanently despite undergoing rehabilitation (Hejazi-Shirmard et al. 2020). Post-stroke alterations in upper limb functionality—including muscle weakness, sensory disturbances, heightened muscle tone, and deficits in neuromuscular control and coordination—hinder individuals from performing routine activities of daily living (ADLs), thereby compromising their autonomy and independence (Verheyden et al. 2006). This need for external help for many of the demands of everyday life has a significant impact both psychologically, with a greater likelihood of depression and a decrease in self-confidence, and on the quality of life, not only for the person who suffers from this condition but also for everyone around them (Persson et al. 2012).

Many ADLs typically necessitate the simultaneous executions of cognitive and motor functions. This dual-task requirement poses a significant challenge for individuals who have experienced a stroke, as their cognitive and physical abilities are compromised, making it difficult to perform multiple tasks concurrently (Pellecchia 2005; Regnaux et al. 2005; Yang et al. 2018). A dual-task paradigm is often used to analyze whether the execution of a motor action requires the use of attentional resources, comparing whether greater error and slower performance occur than in the single-task condition (Olivier et al. 2007). Since stroke is a common occurrence in people with stroke, it is important to establish an effective rehabilitation strategy. Conversely, dual-task training (DTT), defined as a therapeutic method that incorporates exercises requiring the simultaneous performance of two or more tasks related to an individual's ADLs, may present a promising strategy for improving the aforementioned upper limb disorders (Olivier et al. 2007; Pellecchia 2005; Wang et al. 2015). Although the evidence is still sparse, a recent meta-analysis has found statistically significant improvements in upper limb ability (Zhou et al. 2021) and there are also studies that have shown some potential for improving cognitive function and quality of life in stroke patients (An and Kim 2021).

Electroencephalography (EEG) is among the recommended tools for assessing the impact of a treatment or intervention on the central nervous system in individuals who have experienced a stroke. This technique delivers continuous, real-time, non-invasive measurements of brain activity, thereby offering novel insights into the brain's pathophysiological processes (Asadi, Fard, et al. 2023; B. Cohen et al. 1977; B. A. Cohen et al. 1976; Juhasz et al. 1997; Luu et al. 2001). Its low cost, availability and simplicity, as well as sensitivity and specificity, make it a suitable way to assess the effect of different therapeutic interventions (Guggisberg et al. 2019).

Different techniques have been used for EEG data analysis and processing (Das et al. 2023). These approaches include convolutional and graph neural networks (Ahmed et al. 2022; Graña and Morais-Quilez 2023), network analysis and connectivity assessment (Asadi, Cuenca-Zaldivar, et al. 2023; Miljevic et al. 2023), independent component analysis and machine learning-based methods (Dhiman 2023; Ponciano et al. 2020), and assessment of band frequency changes (Arjmandi-Rad et al. 2024), among others. However, these methods require large data sets and complex computational models, which are not always feasible when data availability is limited. To address these challenges, the potential use of the fast Fourier transform (FFT), a well-established technique with wide applications in the processing and analysis of biomedical signals, is raised (Liu 2024). This robust method is utilized for signal frequency analysis since applying of the FFT function transforms a signal from its time domain representation to the frequency domain (Das et al. 2023). Moreover, this EEG analysis technique remains untested in the stroke population after DTT intervention, ensuring a balance between computational efficiency and accurate extraction of EEG bands.

Despite existing evidence examining the efficacy of DTT on various clinical variables in stroke patients, there remains a significant gap in understanding the underlying mechanisms of these observed changes. Consequently, the main objective of this study was to determine whether there are differences in EEG band frequencies (delta, theta, alpha, and beta) after DTT intervention that may elucidate the neurophysiological changes responsible for the clinical improvements observed in stroke patients. A secondary objective was to investigate the analysis of brain signals using a series of FFT to evaluate the representational outcome of this analysis. Understanding this could be crucial for suggesting the analysis of EEG band frequencies as an objective indicator of a stroke patient's recovery and the success of the rehabilitation being applied. This approach may facilitate the implementation of more effective and tailored rehabilitation programs, ultimately enhancing patient care and contributing to advancement in the field of neurorehabilitation.

2 | Materials and Methods

2.1 | Study Design

A case series of five participants with stroke who received a DTT intervention was conducted.

This study was approved by the Ethics Committee of Shahid Beheshti University of Medical Sciences (IR.SBMU.RETECH.REC.1401.842) and has been registered at clinicaltrials.gov (NCT06286436). All the procedures were applied following the Declaration of Helsinki. All participants received information about the conditions of the intervention and how it was going to be carried out, and they signed an informed consent to participate in the study.

2.2 | Participants

The study was carried out in the Mahia Physiotherapy Clinic (Qom, Iran) between February and April 2024. The inclusion criteria were as follows: (1) unilateral ischemic stroke proven by imaging evidence; (2) women between 35 and 75 years old; and (3) at least 6 months since the onset of the stroke. The exclusion criteria were: (1) suffering from another neurological or orthopedic disease; (2) a score greater than three on the Modified Modified Ashworth Scale (MMAS) in the upper limb; (3) having received a botulinum toxin injection before or during the study; (4) history of brain surgery; and (5) be using medication that may alter the cortical activity or brain plasticity or aimed at reducing the level of spasticity.

2.3 | Intervention

The intervention consisted of three different tasks that participants had to carry out while performing mental calculations (counting backward from 100 by ones, twos, and threes). The three tasks were as follows: (1) grouping blocks of different colors into groups according to their color; (2) picking up beans with a spoon and carrying them to a specific place; and (3) opening and closing a bottle cap with the affected hand. The total duration of the intervention was 12 sessions, each lasting 15 min, divided into 3 days per week for 4 weeks.

2.4 | Outcomes

First, sociodemographic data (age, height, and weight) were collected. The participants wore comfortable clothing and a quiet environment was used to collect the rest of the variables. Figure 1 clearly represents the data collection and analysis process carried out in this study.

The main outcome was EEG data, collected both pre- and post-intervention, under the supervision of a neurologist, with the participant in a resting state and eyes closed, in a completely dark windowless room, with only the brightness of the computer screen. EEG recording was carried out for 3 min with a 10–20 system, 19 electrodes (Fp1, Fp2, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, T10, P3, Pz, P4, P8, T9, P7) and a sampling rate of 256 Hz. Frequencies below 1 Hz and above 40 Hz were filtered and only one of the 3 min of EEG collection was randomly selected, and analysis was carried out for that minute only. Before data analysis, abnormal waves such as blinking and electromyographic signals were removed. All these operations were carried out in MATLAB and by EEGLab toolbox v14.1.2 (Delorme and Makeig 2004).

Other secondary variables were collected. Upper limb function was evaluated using the Box and Block test, a functional assessment designed to measure unilateral manual dexterity, which includes grasping, carrying, and releasing objects. This test involves transferring 150 colored wooden cubes, each one inch in size, from one box to another as quickly as possible within 60-s period using only the affected hand (Mathiowetz et al. 1985). The tone of the elbow flexor muscles was evaluated using the MMAS, which is scored on an ordinal scale from 0 to 4: 0 = indicating no increase in muscle tone; 1 = indicating slight increase in muscle tone, characterized by a catch and release or minimal resistance at the end of the range of motion during flexion or extension; 2 = indicating a marked increase in muscle tone, with a catch in the middle range and resistance throughout the remainder of the range of motion, though the affected part can be easily moved; 3 = indicating a considerable increase in muscle tone, making passive movement difficult; and 4 = indicating the affected part is rigid in flexion or extension (Gómez-Soriano et al. 2012). The participant's functional ability in ADLs was assessed using the Barthel Index, a scale that scores 10 basic activities related to self-care and mobility (bowels, bladder, grooming, toilet use, feeding, transfer, mobility, dressing, stairs, and bathing) from 0 to 100, with lower scores indicating greater dependency (Mahoney and Barthel 1965).

These variables were also collected before and immediately after the completion of the intervention by a physical therapist.

2.5 | Data Analysis

To address issues pertaining to heat transfer and vibrations, Fourier (Baron Fourier 2003) developed the Fourier series, demonstrating that certain functions can be expressed as infinite sums of harmonic or sinusoidal components. The Fourier transform essentially converts a time series into the frequency domain by employing sinusoidal basis functions. Following the introduction of the Fourier transform, researchers have proposed numerous methods based on Fourier techniques for diverse applications, including time series analysis. One of the methods of the Fourier transform is the Discrete Fourier Transform (formula shown below), which is used to calculate the frequency content of the sampled signal (Liang and Lauterbur 2000).

$$X_k = \sum_{n=0}^{N-1} x_n e^{-2\pi ikn/N}$$

$$\text{For } 0 \le k \le N-1$$

The components of this equation are:

- x_n, the input signal in the time domain.
- N, the total number of samples in the signal.
- X_k, the Fourier coefficients represent the signal in the frequency domain, encoding amplitude and phase.
- k, the frequency index, with frequency $f_k = \frac{k}{N} f_s$ where f_s is the sampling rate.
- $e^{-2\pi ikn/N}$, the basis functions, which are sinusoidal waveforms used to decompose the signal.

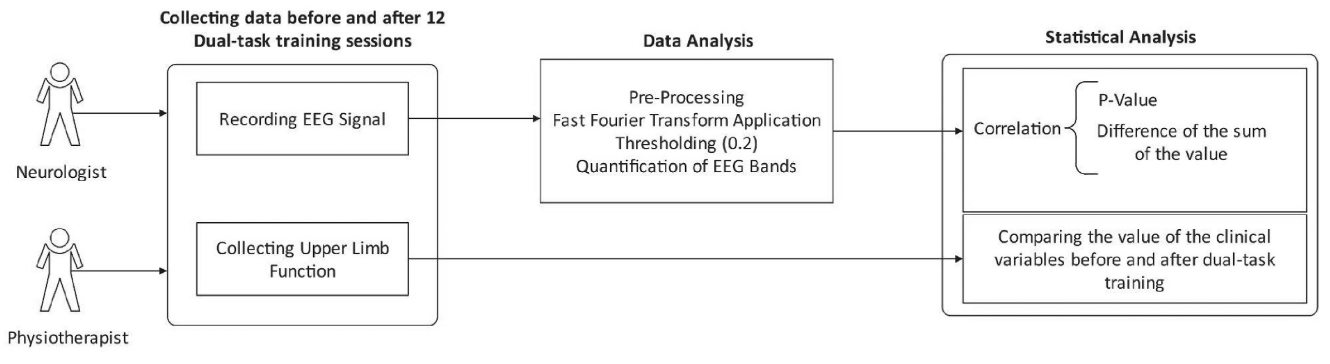

FIGURE 1 | Overview of the study methodology. This flowchart includes the steps of EEG signal and upper limb function data collection before and after dual-task training, as well as EEG signal analysis and statistical analysis of the collected data.

Specifically, the FFT, an optimal method for Discrete Fourier Transform, was used for the data analysis. FFT was selected for its computational efficiency, straightforward implementation, less order complexity, and wide availability. FFT can be performed without specialized hardware and is extensively validated in brain signal analysis, providing reliable and comparable results consistent with existing research (Akin 2002; Duhamel and Vetterli 1990).

Before performing FFT on the electrode signals, frequency segmentation of the brain signals into delta (between 1 and 4 Hz), theta (between 4 and 8 Hz), alpha (between 8 and 13 Hz), and beta (between 13 and 20 Hz) was performed. Then, FFT was applied to each of these sections. After applying FFT on the EEG bands, only numbers that exceeded a threshold of 0.2 were considered valid so that if the FFT intensity of a specific EEG band for each numerical sample was > 0.2 it was counted, but if it was less it was omitted. Finally, for each of the electrodes, the number of delta, theta, alpha, and beta bands pre- and post-intervention was obtained.

The threshold value of 0.2 was determined based on an initial assessment of the signal's power. During preliminary evaluations, it was found that this threshold effectively differentiated significant components within the frequency bands. By selecting a threshold of 0.2, the inclusion of signals with adequate power to be considered significant while excluding noise is ensured. This threshold aligns with established EEG analysis methodologies, where similar values are frequently utilized to balance sensitivity and specificity in signal detection. As outlined in standard EEG preprocessing practices, such thresholds enhance the reliability of detected signals and represent a common strategy in the field (Kim 2018).

The EEG toolbox (EEGLab) was exclusively utilized for preprocessing activities, including artifact elimination and signal normalization. The FFT analysis was conducted independently using custom MATLAB code rather than relying on any particular FFT toolbox. This analysis encompassed the entire EEG signal, thereby eliminating the necessity to choose a window size or type. This approach was adopted to maintain the integrity of the frequency analysis by preserving the raw signal data without introducing any additional modifications through windowing techniques.

Statistical analysis was carried out with Python version 3.11.5; also pandas, numpy, scipy and pyplot libraries were used. Data for quantitative variables are represented as median (range), and for qualitative variables as percentages. First, correlation analysis was used to evaluate the acquired data. Specifically, the relationship between the number of bands recorded at each electrode pre- and post-intervention was analyzed to assess the degree of correlation. To determine the validity of the correlations, the associated p-values were examined. A p-value of < 0.05 was considered indicative of a statistically significant correlation. Pearson's correlation coefficient was used to calculate the correlation between two columns of a data frame. The strength of the identified correlations was classified according to established criteria: correlations above 0.8 were considered very strong, those between 0.6 and 0.8 were classified as relatively strong, correlations between 0.3 and 0.5 were considered balanced, while correlations below 0.3 were classified as weak (Chan 2003). On the other hand, to check the changes in the clinical variables (Box and Block test, MMAS, and Barthel Index), the number of changes in these indexes was analyzed, comparing the value of these indicators before and after DTT and calculating their difference to analyze the degree of improvement of each participant after the intervention.

After checking the correlation between the number of bands for each electrode, the difference of these values was obtained for each electrode and the sum of these differences was obtained for each band and each participant. This difference shows how the number of bands changes pre- and post-intervention for each participant.

3 | Results

A total of five women with a median age of 63 (53–69) years, of which 60% were affected on the left side, with a mean of 15 (14–156) months since the onset of the stroke were selected based on the inclusion and exclusion criteria (Table 1).

The EEG analysis results, focusing on the number of extracted bands using FFT transformation, are shown in Figures 2–5. Notably, following DTT intervention, distinct patterns emerged across various frequency bands.

Figure 2 illustrates the changes in the number of delta bands. Overall, a consistent reduction in delta band activity was observed post-intervention across most electrodes and participants. However, there were variances noted among electrodes,

TABLE 1 | Demographic and clinical characteristics at baseline of the five participants with stroke.

Participant	Age (years)	Duration of disease (months)	Affected side	Upper limb function (Box and Block test)	Elbow flexor muscle tone (MMAS)	ADLs (Barthel index)
1	66	14	Left	14	2	14
2	60	18	Left	2	3	15
3	53	156	Left	12	2	16
4	63	15	Right	16	3	15
5	69	15	Right	18	1	17

Abbreviations: ADLs, activities of daily living; MMAS, Modified Modified Ashworth Scale.

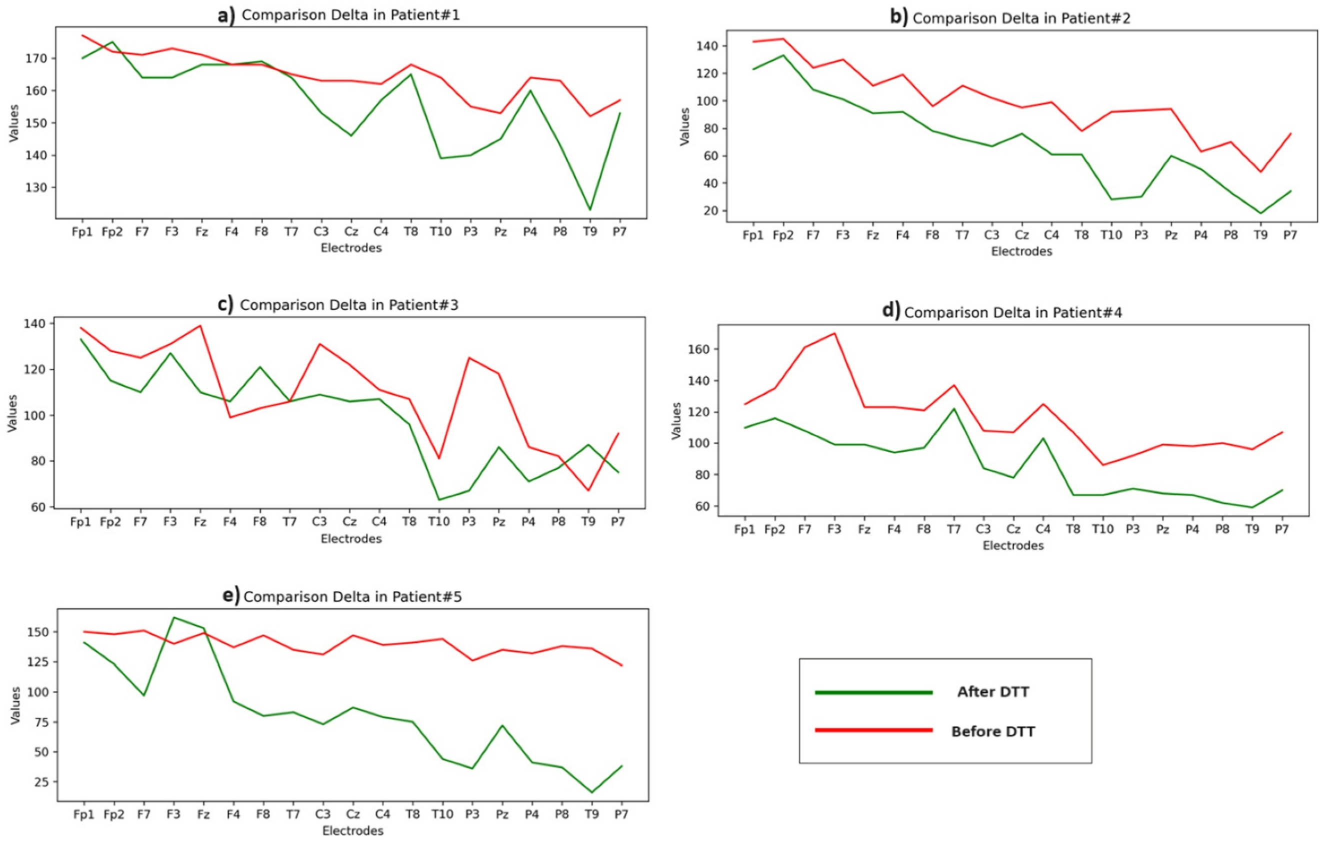

FIGURE 2 | Changes in delta band activity before and after dual-task training (DTT). The figure represents the delta band across 19 EEG electrode sites in five stroke patients before (red line) and after (green line) 12 sessions of DTT. Each subplot (a–e) corresponds to an individual patient. Following the intervention, a general reduction in delta band activity is observed across most electrode sites. However, Patient 3 (subplot c), who had a longer post-stroke duration than the others, exhibited a less pronounced reduction.

with one participant (participant P3) displaying less pronounced changes compared to others. Similarly, Figure 3 demonstrates the changes in theta band activity post-DTT intervention. In line with delta band findings, important reductions in theta band activity were observed across most participants and electrodes. However, participant P3 exhibited heterogeneous results with varying changes in the number of theta bands depending on the electrode analyzed. In Figure 4, the changes in alpha band activity are depicted. Following intervention, a notable decrease in the number of alpha bands was observed across all participants, indicating a consistent response to DTT. Interestingly, simultaneous changes in alpha band activity were noted both pre- and post-intervention, suggesting concurrent increases and decreases across different electrodes. Finally, Figure 5 illustrates the changes in beta band activity post-DTT intervention. Consistent with findings in delta and theta bands, noteworthy reductions in beta band activity were observed across most participants. Again, participant P3 exhibited divergent responses similar to observations in theta band activity. Within Table 2, the final column presents the cumulative disparity in-band values for each participant. This metric was computed by aggregating the pre- and post-intervention values, illustrating a positive deviation across all subjects except for participant P3 within the theta band.

The results of the correlations for the analysis of the relationship between the number of EEG bands pre- and post-intervention are summarized in Table 2. The table presents correlations between the number of bands recorded from each electrode (delta, theta, alpha, and beta) pre- and post-intervention for each participant, along with corresponding *p*-values. The results indicate significant correlations ($p < 0.05$) between the number of delta, theta, alpha, and beta bands pre- and post-intervention for most participants, with notable exceptions in the theta band for participant P1 and the beta band for participant P5. In the delta band, strong correlations were evident across all participants with coefficients ranging from 0.618 to 0.896. Notably, the alpha band consistently exhibited very strong correlations for all participants (coefficients between 0.847 and 0.919, $p < 0.001$). Theta and beta bands analyses displayed varying strengths, from weak to very strong correlations, emphasizing the diverse relationships within these frequency ranges.

In addition to the observed modifications in EEG bands and values, changes were also observed for the other variables after DTT intervention. Firstly, enhancements were observed in upper limb function, as evidenced by the Box and Block test, wherein all participants demonstrated improvements (Figure 6). Conversely, in the MMAS, only participants P2 and P4 exhibited improvement in elbow flexor muscle tone, while the remaining participants maintained pre-intervention levels (Figure 6). Furthermore, analysis of the Barthel Index indicated a slight trend toward improvement in ADLs functionality for all participants post-intervention (Figure 6).

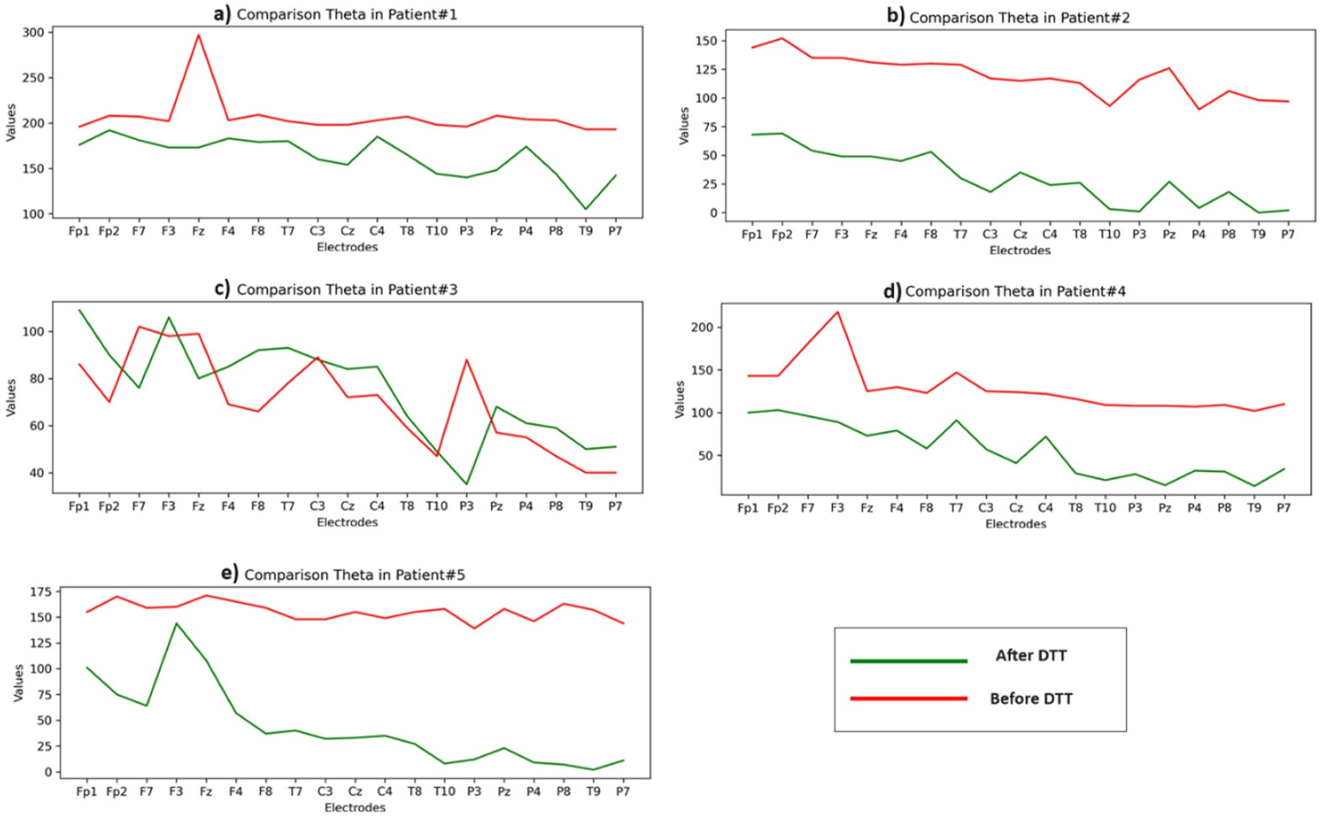

FIGURE 3 | Changes in theta band activity before and after dual-task training (DTT). The figure represents the theta band across 19 EEG electrode sites in five stroke patients before (red line) and after (green line) 12 sessions of DTT. Each subplot (a–e) corresponds to an individual patient. Following the intervention, a general reduction in theta band activity is observed across most electrode sites. However, Patient 3 (subplot c), who had a longer post-stroke duration than the others, exhibited a less pronounced reduction.

4 | Discussion

The main objective of this study was to investigate the impact of DTT on EEG band frequencies in stroke patients. This case series demonstrates changes in EEG patterns post-intervention, particularly in the delta, theta, alpha, and beta bands across multiple electrodes. We used FFT analysis in this research, which is widely used for filtering EEG data and has significant applications in this field. In our research, FFT analysis of the EEG data indicates relative improvements in participants, corroborated mainly by the improvements in the Box and Block tests together with the slight tendency to improve in the rest of the clinical outcomes. The cumulative disparity in the band values for each participant showed that clinical improvements were associated with a decrease in the number of bands on the electrodes, indicating consistent changes in brain activity patterns across specific frequency bands post-intervention. This suggests a possible association between the change in clinical status and the number of bands on the 19 electrodes.

FFT can preprocess EEG signals to extract relevant information in the frequency domain for further analysis. In this context, a study investigated the effects of action observation training and mirror therapy on EEG activity in stroke patients (Lee et al. 2021). The researchers employed FFT to filter the EEG signals and then performed statistical analyses, ultimately observing a positive impact of the intervention on the alpha band. These findings align with our results, reinforcing that FFT-based EEG signal processing effectively captures potential relevant neurophysiological changes induced by therapeutic interventions in stroke patients.

Previous studies have examined changes in EEG coherence across various frequency bands following DTT (Zhavoronkova et al. 2020). In contrast, the current study provides novel insights by specifically observing an important decrease in the number of delta, theta, alpha, and beta bands after 12 sessions of DTT. The observed reduction in band numbers after DTT represents an important contribution to the existing literature. By analyzing band-specific changes, this study offers a more granular understanding of the neurophysiological adaptations associated with DTT in stroke patients. Focusing on the number of bands, rather than just coherence measures, this study offers a novel perspective on how the brain's oscillatory dynamics may be modulated through intensive DTT. These findings may guide future investigations focused on uncovering the neural mechanisms responsible for the positive effects of DTT on cognitive and motor rehabilitation after a stroke.

The reduced delta band activity after DTT suggests potential neurophysiological changes associated with stroke recovery. Delta waves, typically linked to deep sleep and unconsciousness, may indicate brain injury or dysfunction when present in awake states (Gloor et al. 1977; Steriade et al. 1993). This band is mainly activated during fundamental brain processes, such as sensorimotor information processing and movement initiation

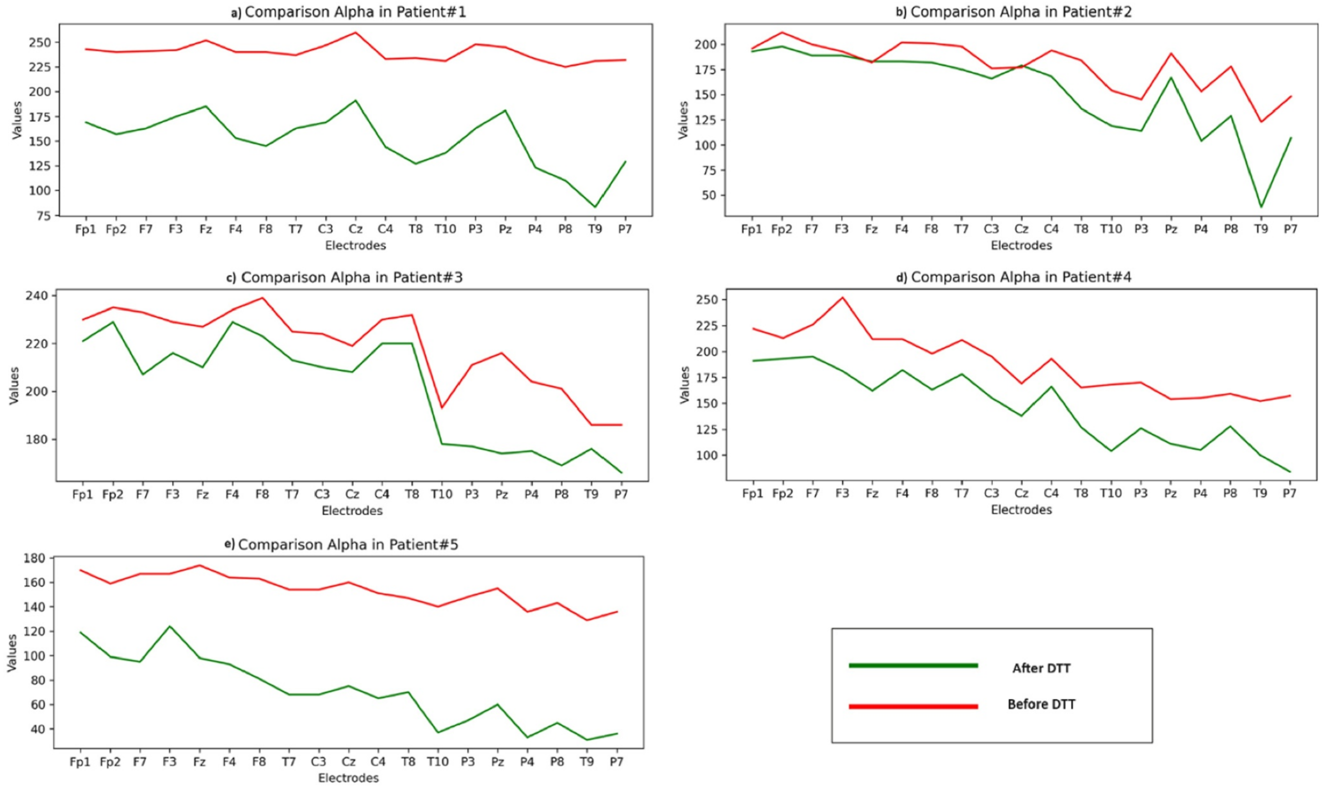

FIGURE 4 | Changes in alpha band activity before and after dual-task training (DTT). The figure represents the alpha band across 19 EEG electrode sites in five stroke patients before (red line) and after (green line) 12 sessions of DTT. Each subplot (a–e) corresponds to an individual patient. Following the intervention, a consistent reduction in theta band activity is observed across most electrode sites.

(Kobler et al. 2020). Thus, the consistent reduction in delta band activity across most participants and electrodes likely reflects improved neural efficiency and reduced pathological activity following DTT.

Similarly, the decrease in theta band activity post-intervention is noteworthy. Theta waves are associated with drowsiness, relaxation, and memory processes (Klimesch 1999). Excessive theta activity is often seen in conditions such as stress, anxiety, or cognitive impairment (Gruzelier et al. 1999; Knyazev 2007; Smit et al. 2005). Furthermore, previous studies have shown that theta band activity increases during movements requiring simultaneous execution of multiple actions, indicating parallel processing (Mueller et al. 2025). However, in our study, theta band activity was reduced after completing all DTT sessions and not during the DTT tasks themselves. Therefore, the significant reduction in theta band activity following DTT suggests the possible modulation of cognitive processes and neural network reorganization, potentially contributing to improved functional outcomes.

Furthermore, the decrease in alpha band activity observed post-DTT is intriguing. Alpha waves dominate during relaxed wakefulness and decrease with attention or cognitive effort (Knyazev 2007). Excessive alpha power can indicate cortical inhibition or impaired cognitive function (Klimesch 2012). Additionally, several studies have shown that alpha wave activity decreases during voluntary concentration on sensorimotor processes (Cannon et al. 2014; Foxe and Snyder 2011). This phenomenon aligns with the consistent decrease in alpha band activity observed in all participants in our study, implying increased cortical engagement and possibly improved attentional control and cognitive function after DTT.

Additionally, reductions in beta band activity post-intervention align with previous findings indicating excessive beta activity in neurological disorders, including stroke (Gola et al. 2012). Beta waves are associated with active thinking, problem-solving, and muscle activity (Engel and Fries 2010). In the study by Zhang et al. (Zhang et al. 2020), a decrease in beta oscillations was observed during movement execution in both slow self-regulated and ballistic movements, followed by a rebound increase in beta oscillations after movement cessation. In contrast, our study observed that, after 12 sessions of DTT, there was a reduction in the total number of beta bands, which suggests improved neural regulation and potentially enhanced motor function and control.

Correlations between pre- and post-intervention EEG band frequencies highlight the relationship induced by DTT. Particularly, strong correlations in the delta and alpha bands suggest robust and consistent neural responses to the intervention across participants. Variability in theta and beta band correlations underscores individual differences in neural plasticity and responsiveness to DTT, emphasizing the need for personalized rehabilitation approaches.

In addition to EEG findings, some changes in upper limb function, elbow flexor muscle tone, and functionality during

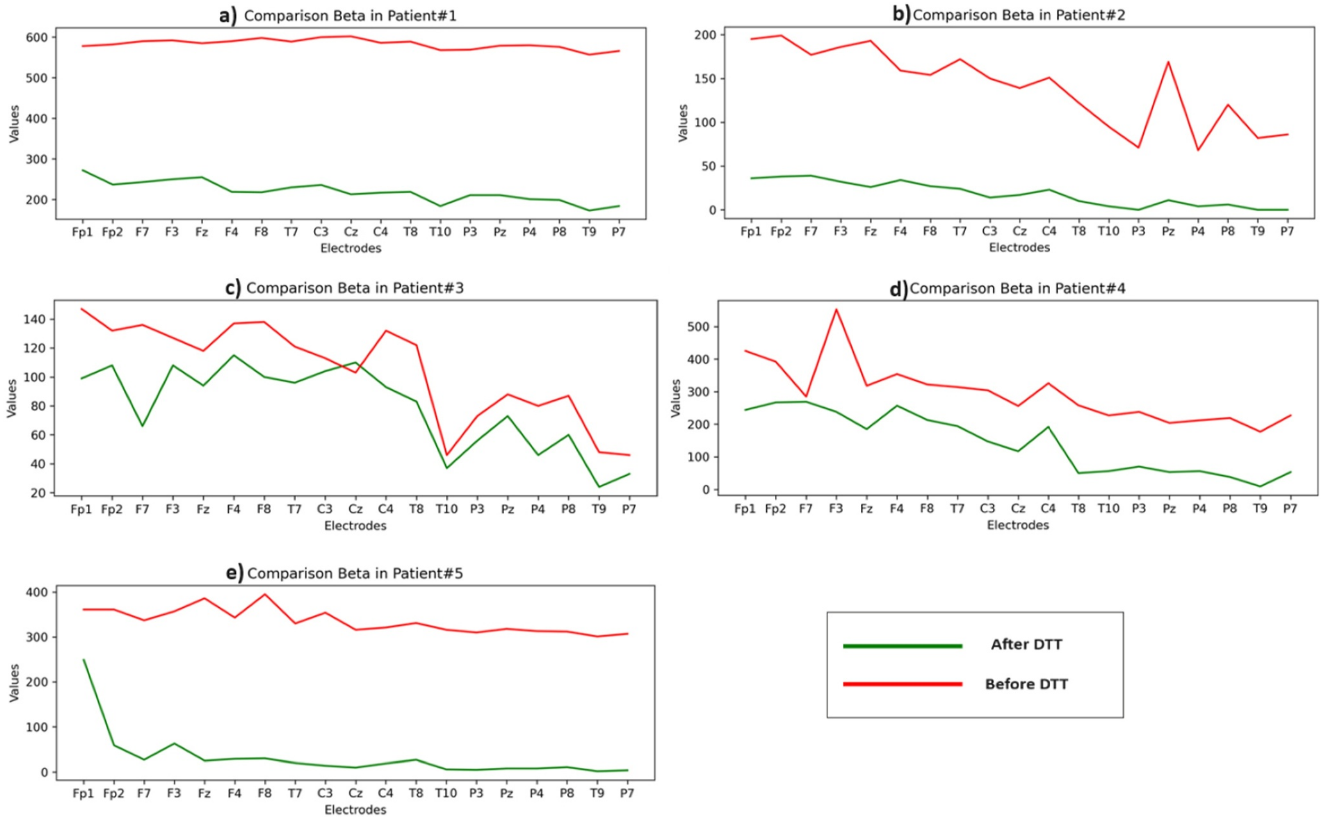

FIGURE 5 | Changes in beta band activity before and after dual-task training (DTT). The figure represents the beta band across 19 EEG electrode sites in five stroke patients before (red line) and after (green line) 12 sessions of DTT. Each subplot (a–e) corresponds to an individual patient. Following the intervention, a general reduction in beta band activity is observed across most electrode sites. However, Patient 3 (subplot c), who had a longer post-stroke duration than the others, exhibited a less pronounced reduction.

ADLs were observed post-DTT; however, it cannot be concluded that these are clinically relevant changes. These functional improvements could align with previous studies demonstrating the efficacy of DTT in enhancing motor and cognitive outcomes in stroke patients (Ali et al. 2022). The integrated approach of combining motor tasks with cognitive demands during DTT likely promotes neuroplasticity, sensorimotor integration, and task-specific learning (Plummer and Eskes 2015).

Notably, patient-specific variations in EEG responses were observed, particularly in participant P3, whose chronic stroke history may have influenced treatment outcomes. Chronic stroke survivors often exhibit distinct neural adaptations and limited recovery potential compared with acute stroke patients (Zeiler and Krakauer 2013). From these results, it can be suggested that this type of analysis has greater potential and reliability in cases in which the stroke is relatively acute, in which some brain areas are still functional, and a certain level of activity is preserved; however, the variability shown in the case of chronic stroke makes the analysis less consistent, since in this case the changes observed in the analysis of the difference in the sum of EEG bands values are contradicted by the improvements in clinical variables, and therefore cannot be directly attributed to ineffectiveness of the treatment.

In essence, this study underscores the potential of DTT as an effective rehabilitation strategy for stroke patients, facilitating a possible reorganization or normalization of brain activity patterns. This is evidenced by the changes observed in EEG band frequencies and relative improvements in certain clinical variables, measured through established and clinically relevant metrics for assessing functional recovery. These findings suggest a possible association between neurophysiological changes and functional recovery in stroke patients.

To our knowledge, this is the first study to investigate alterations in the number of EEG bands in response to DTT. The results provide a comprehensive overview of how DTT influences both brain function and patient outcomes, emphasizing the importance of understanding the neural mechanisms behind functional improvements in stroke rehabilitation. This Fourier-based method for examining EEG band characteristics can enhance the analysis and interpretation of brain activity signals. Consequently, EEG is proposed as a possible valuable biomarker of rehabilitation efficacy based on the following points: (1) Identifying specific neural changes associated with recovery enables clinicians to design individualized rehabilitation programs. By targeting the most affected brain regions or functions, personalized treatment plans can improve the effectiveness of rehabilitation efforts; (2) EEG metrics offer objective indicators of patient progress, complementing traditional clinical assessments and providing a more detailed understanding of recovery. This facilitates more precise monitoring and adjustment of rehabilitation strategies; and (3) Subtle changes in brain activity may precede

TABLE 2 | Correlation analysis results.

Bands	Participants	Correlation	*p*-value	Difference of the sum of the values
Delta	P1	0.825	< 0.001*	163
	P2	0.896	< 0.001*	573
	P3	0.641	0.003*	219
	P4	0.796	< 0.001*	579
	P5	0.618	0.005*	1119
Theta	P1	0.248	0.304	827
	P2	0.917	< 0.001*	1698
	P3	0.560	0.012*	−90
	P4	0.742	< 0.001*	1387
	P5	0.495	0.031*	2134
Alpha	P1	0.847	< 0.001*	1686
	P2	0.925	< 0.001*	488
	P3	0.902	< 0.001*	333
	P4	0.911	< 0.001*	794
	P5	0.919	< 0.001*	1573
Beta	P1	0.558	0.013*	6904
	P2	0.891	< 0.001*	2343
	P3	0.863	< 0.001*	489
	P4	0.803	< 0.001*	2903
	P5	0.417	0.076	5753

Note: The "Correlation" column presents the results of the correlation analysis between the number of EEG bands before and after the intervention. The "*p*-value" column shows the statistical comparison results, indicating the significance of the observed changes. The "Difference of the sum of the values" column represents the difference between the pre- and post-intervention values for each participant and each EEG band. The values in this table are derived from Figures 1–4.
*Statistically significant correlation ($p < 0.05$).

detectable functional improvements, as demonstrated for example in preclinical Alzheimer's disease (Herold et al. 2019). Recognizing these early neural indicators allows clinicians to adjust interventions early, which could accelerate rehabilitation and improve patient outcomes.

However, due to the inherent limitations of this study, mainly due to its design as a case series, the results presented should be interpreted as a preliminary hypothesis. Primarily, this case series features a limited sample size, exclusively composed of women, with variability in the duration of the disease among participants. Another limitation is the inability to conduct extended follow-ups to determine if the observed changes persist in the medium to long term, particularly in relation to the Barthel Index, which is more accurately assessed over at least 1 week of typical daily activities rather than immediately post-intervention. Additionally, while the findings have significant technical relevance, their application to clinical practice requires further research and additional statistical analyses. Given the exploratory nature of this study and the challenges posed by the data types, there is insufficient statistical evidence to confirm the clinical relevance of the observed changes in clinical scale scores. Lastly, a potential limitation not considered in this study is the possible influence of transient fatigue on reductions in EEG power. Despite these limitations, this study is of significant relevance as it paves the way for a new line of research in the field of rehabilitation. It highlights the potential of EEG as an objective measure, suggesting promising directions for future studies to explore and validate.

Although the findings may possess a certain degree of validity and consistency, they require substantial further research to be confirmed. This pilot study aims to serve for future sample size and statistical power calculations in future larger-scale investigations, with the primary goal of elucidating the underlying neurophysiological mechanisms driving DTT-induced EEG changes and optimizing treatment protocols to enhance stroke recovery. These investigations should include both men and women, control groups, and acute and chronic stroke cohorts to determine the utility of this EEG data analysis and to identify differences in treatment responses among these subgroups. Studies should also examine longitudinal EEG changes and their associations with functional outcomes to clarify the long-term effect of DTT on stroke recovery. Given the importance of statistical validation of the results presented in this study, rigorous statistical analyses are essential to ensure the reliability and generalizability of the findings, providing a more comprehensive understanding of the effects of DTT in stroke rehabilitation. Regarding the concern about the influence of transient fatigue, future studies should incorporate measures to mitigate

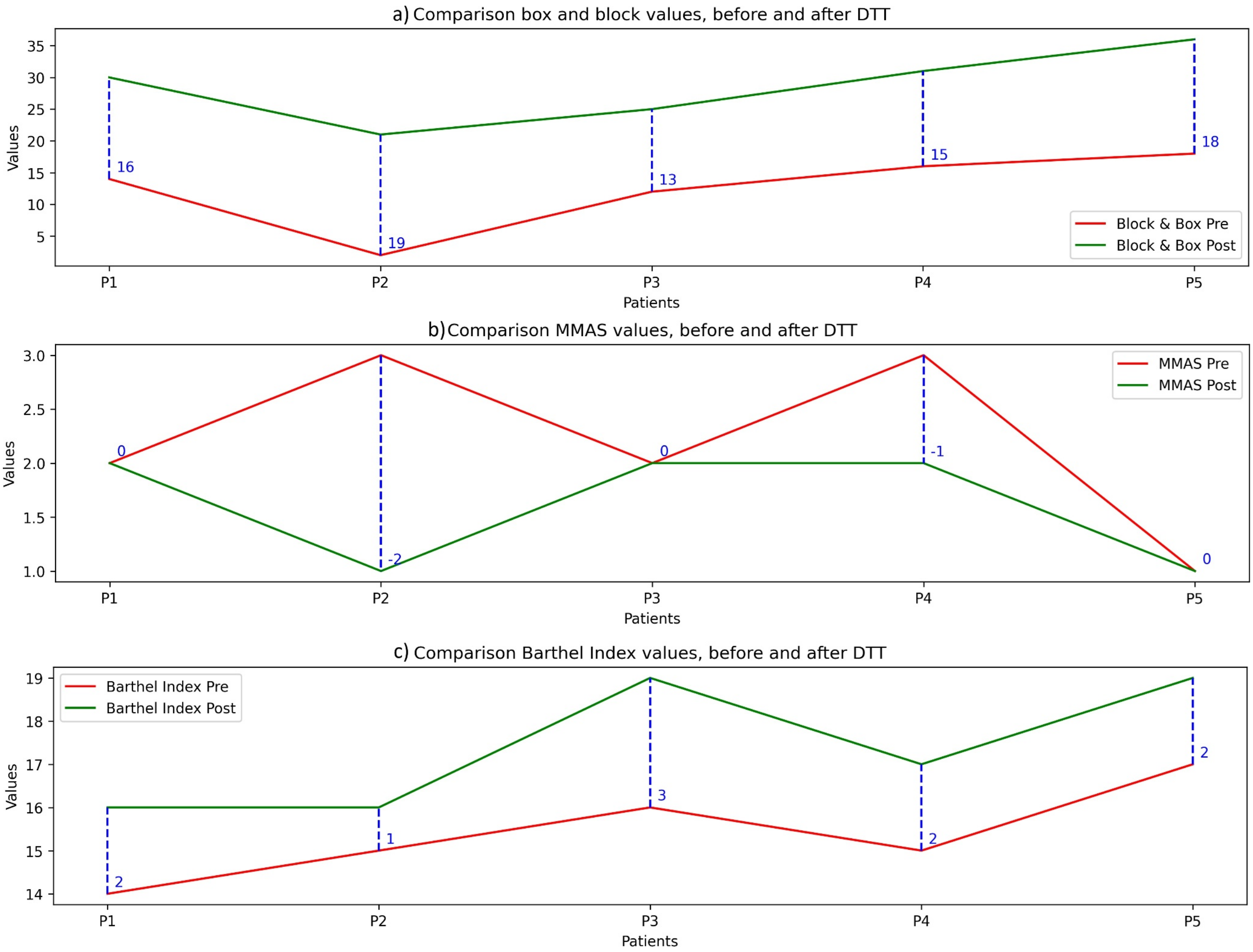

FIGURE 6 | Functional assessment changes before and after dual-task training (DTT). This figure represents the changes observed in three functional outcome measures following the DTT intervention: (a) Box and Block test; (b) Modified Modified Ashworth Scale (MMAS); and (c) Barthel Index. The red line represents pre-intervention values, while the green line indicates post-intervention values. The blue dashed line illustrates the difference between pre- and post-intervention values for each participant.

this possibility and distinguish between genuine neuroplastic changes and transient states such as fatigue. This can be achieved through repeated assessments over prolonged periods, the inclusion of control groups to better isolate the effects of the intervention, and the implementation of specific assessments to account for and control fatigue-related factors.

5 | Conclusions

The present study investigated the impact of DTT in stroke patients, focusing on objective measures such as EEG band frequencies and different clinical outcomes. The results revealed consistent changes in the number of bands in the EEG electrodes, with a significant correlation between measurements made before and after the intervention, also showing a possible association with the changes produced in clinical outcomes post- DTT. Moreover, the graphical representation of EEG changes for the first time using the FFT seems to be able to become a valuable tool to assess the effects before and after the intervention if it is validated by studies of higher methodological quality. Thus, the findings of this study, although preliminary and still in need of much research, highlight the possible potential of EEG analysis as an objective measure of both patient progress and rehabilitation program efficacy.

Author Contributions

B.A., Z.K., S.S.N., P.H., N.N.A., and D.L.-H. contributed substantially to the work's concept and design. B.A. performed data analysis and B.A., P.H., and D.L.-H. interpreted the data. Z.K. and S.S.N. collected data. B.A., Z.K., S.S.N., P.H., N.N.A, and D.L.-H. drafted the article and critically revised it for important intellectual content. All authors approved the publication of the version and contributed to the final version of the manuscript. All authors have read and agreed to the published version of the manuscript.

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The authors have nothing to report.

Ethics Statement

The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of Shahid Beheshti University of Medical Sciences (IR.SBMU.RETECH.REC.1401.842).

Consent

Informed consent was obtained from all subjects involved in the study.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data generated during and/or analyzed during the current study are available from the first author on reasonable request.

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