IOSR Journal Of Humanities And Social Science (IOSR-JHSS)
Volume 30, Issue 3, Series 2 (March, 2025) 31-36
e-ISSN: 2279-0837, p-ISSN: 2279-0845.
www.iosrjournals.org

Philosophical Mind And Creativity: A Neurophysiological Approach Using EEG And Deep Learning

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Abstract
Background: *Philosophical thinking promotes deep reflection, abstract reasoning, and critical analysis, which are believed to enhance creativity. This study designed a three-month workshop to train high school students (n = 15) in three dimensions of philosophical thinking (comprehensive, penetration, and flexibility). The Torrance Test of Creative Thinking (TTCT) was administered before and after the training. Results, analyzed with SPSS, revealed a statistically significant improvement in creativity. To validate TTCT as a measure of creativity, EEG data (23+ hours at 250 Hz) were recorded. Students were classified into two groups based on TTCT scores, and EEG characteristics related to cognition (remote association, common association, combination, recall, and retrieval) were compared. The EEG data underwent preprocessing using EEGLAB, and were transformed into 1,975 images (224x224x3) for deep learning analysis. MobileNet and ResNet50 models were used to predict creativity based on brain activity. Data augmentation (horizontal flipping, brightness, contrast) and regularization techniques (L2 regularization, dropout, learning rate adjustments, and fine-tuning) were applied to improve model performance. The models achieved high training accuracy (99.66% for MobileNet and 100% for ResNet50), with testing accuracy of 82.2% and 91.85%, respectively. The high testing accuracy for ResNet50 (91.85%) suggests that deep learning approaches can offer a novel approach to assess creativity based on brainwave patterns beyond traditional assessments.*
Keywords: *creativity, training philosophical mind, deep learning, transfer learning, ResNet50.*

Date of Submission: 27-02-2025 Date of Acceptance: 07-03-2025

I. Introduction

Creativity is a crucial cognitive ability essential for problem-solving and innovation across various fields. Guilford [1] identified four core components of creativity: fluency, originality, flexibility, and elaboration. In parallel, philosophical thinking is characterized by three dimensions—comprehensiveness, penetration, and flexibility [2]. Previous research has indicated a relationship between creativity and a philosophical mindset, as demonstrated in a study on managers at Ferdowsi University of Mashhad [3]. Building on this foundation, we designed a workshop aimed at training students in these three philosophical dimensions over a three-month period, with weekly sessions.

The Torrance Test of Creative Thinking (TTCT) is a widely recognized tool for assessing creativity, evaluating an individual's ability to think divergently and generate novel ideas. In this study, TTCT was administered both before and after the training. While TTCT provides valuable insights into creative thinking, the underlying neural mechanisms of creativity remain an area of ongoing research. Electroencephalography (EEG) has emerged as a promising tool for identifying the brain activity associated with creativity, offering insights into the cognitive processes involved in idea generation and problem-solving.

Several studies have explored EEG-based analyses of creativity. Yin et al. [4] examined the role of cognitive processes such as retrieval, recall, association, and combination in creative thinking, using an EEG-based decoding method to identify key factors contributing to creative output. Their findings highlighted association as the dominant cognitive factor in high-quality creative production. Similarly, Camarda et al. [5] found that individuals with higher remote association scores exhibited alpha synchronization in the temporo-parietal regions during creative idea generation, while those with lower remote association scores demonstrated alpha desynchronization. These findings suggest that greater reliance on internal semantic association correlates with more creative ideation.

Philosophy has also been proposed as a means to enhance creativity. Holub and Duchlinski [6] argued that philosophical concepts facilitate the formulation of novel ideas, particularly in challenging situations, and that the cognitive flexibility developed through philosophical education fosters creativity. However, limited research has examined the neurological basis of philosophical thinking training using EEG. In one study, Naderan et al. [7] investigated the effects of mindfulness training—a practice closely related to philosophical reflection—on creativity, finding that it led to an increase in gamma band activity in the central and parietal regions, which correlated with enhanced creativity.

Despite extensive research on creativity, there is limited empirical evidence on the impact of philosophical thinking training on creative performance. Given that philosophical thinking encourages deep reflection, abstract reasoning, and critical analysis, it is hypothesized to enhance creativity. This study addresses two key research questions:

1. Can philosophical thinking training enhance students' creativity?
2. To what extent does the TTCT align with neuroscience-based measures of creativity? Specifically, is there a relationship between TTCT results and neural markers of creativity?

Prior studies have explored EEG-based classifications of creativity. Stevens Jr. & Zabelina [8] found that alpha power was significantly greater for more creative versus less creative individuals, achieving a classification accuracy of 82.3% using spectral weighted common spatial patterns and quadratic discriminant analysis. Building on this, the present study collected EEG data to explore the neural correlates of creativity, and using Deep learning models, assess whether brain activity can predict TTCT creativity scores. By integrating philosophical thinking training, TTCT assessment, and EEG analysis, this research aims to provide novel insights into the cognitive and neural mechanisms of creativity and the potential role of philosophical training in fostering creative thinking.

II. Related Works

Creativity involves discovering, understanding, developing, and expressing meaningful and structured relationships. It unfolds in three key stages: preparation, which entails acquiring essential knowledge and skills through both innate ability and learning; innovation, where creative solutions emerge; and creative production. Effective preparation depends on general intelligence, expertise in a specific field, and, in highly creative individuals, potential anatomical differences in certain neocortical areas. The innovation stage requires disengagement and divergent thinking, primarily governed by frontal brain networks. Creative individuals tend to be risk-takers and seekers of novelty, behaviors linked to the activation of the ventral striatal reward system. Additionally, innovation relies on associative and convergent thinking, which depend on the coordination of widely distributed neural networks. People often reach peak creativity in mental states characterized by lower brain norepinephrine levels, which may facilitate better communication across these networks [9].

Dietrich et al. [10] analyzed 72 experiments categorized into three domains: divergent thinking, artistic creativity, and insight. Their findings indicate that creative thinking does not critically depend on a single mental process or brain region, nor is it exclusively associated with right-brain dominance, defocused attention, low arousal, or alpha synchronization. Contrary to some hypotheses, creative cognition appears to be more complex and distributed across multiple neural mechanisms.

Numerous studies have established a relationship between alpha power and creativity. For instance, Fink and Benedek [11] reported that an increase in alpha activity during creative ideation might reflect internally oriented attention and top-down cognitive control. Schwab et al. [12] further observed a specific pattern of alpha power modulation: an initial increase at the beginning of the idea generation phase, followed by a decrease, and then another increase at parietal and temporal regions of the right hemisphere. Additionally, producing more original ideas was associated with higher alpha power in the right hemisphere, particularly during prolonged ideation periods. Other research also highlights the importance of theta and gamma bands in creative cognition [13]. Power spectrum analysis has revealed significant increases in delta, beta, theta, and gamma bands during creative processes [14].

Rominger et al. [15] examined EEG activity in the upper alpha band during the Picture Completion Task of the Torrance Test of Creative Thinking (TTCT). Their findings suggest that during the idea generation phase, upper alpha desynchronization occurs in parietal and occipital regions, reflecting high visual and figural processing demands. Conversely, during the idea elaboration phase, upper alpha power increases in these regions, indicating heightened top-down cognitive control. These results emphasize the importance of inhibitory control over stimulus-driven information processing in achieving creative outputs. Similarly, Cruz-Garza et al. [16] found that information transfer from anterior-frontal to temporal-parietal regions occurs during the preparation stage, whereas, in the generation stage, information flows from temporal-parietal toward frontal locations, possibly reflecting decision-making processes involved in creativity.

In another study, Bieth et al. [17] investigated EEG activity during the Remote Associates Test (RAT), an insight-based creativity task requiring participants to identify a word linking three unrelated words. Their analysis revealed that semantic remoteness was associated with distinct EEG patterns:

- Alpha band (8–12 Hz) increases in left parieto-temporal clusters
- Beta band (13–30 Hz) increases in right fronto-temporal clusters during the early phase of the task
- Theta band (3–7 Hz) increases in bilateral frontal regions just before participants responded

Additionally, gamma-band activity (31–60 Hz) in left temporal regions was linked to insight problem-solving.

Recent research by Wang et al. [18] investigated how abstract and concrete stimuli affect neural activity. They discovered that abstract stimuli evoked higher upper alpha power across 13 Brodmann areas in the frontal, temporal, and occipital lobes, correlating positively with novelty and surprise scores. Similarly, Rosen et al. [19] reported that higher-quality creative improvisations were associated with greater posterior left-hemisphere activity, while lower-quality improvisations corresponded with right temporo-parietal and fronto-polar activity.

Jia and Zeng [20] examined whole-brain network interactions during three distinct thinking modes: idea generation, idea evolution, and evaluation. Their study found a significant reduction in alpha power when transitioning from resting states to active creative thinking. Notably, in the lower alpha band, there was a broad decrease in alpha power across the entire scalp during the idea evolution phase, suggesting that this stage requires less general attentional demand. In the upper alpha band, a more substantial decrease in alpha power was observed over central brain regions during the evaluation phase, indicating higher task-specific cognitive demands.

Their results also revealed that the default mode network (DMN) was more active during idea evolution, while the cognitive control network exhibited greater engagement during evaluation, reflecting increased goal-directed cognitive processing.

These studies highlight the crucial role of neural oscillations and brain network dynamics in creativity, emphasizing the interplay between bottom-up sensory processing, top-down cognitive control, and associative thinking. Given these findings, different brain pattern for high vs. low creativity was expected. Also, investigating the impact of philosophical thinking training on creativity and its neural basis presents an important avenue for further research.

III. Research Methodology & Findings

Philosophical mindfulness training

Participants

The study involved 15 high school students in their final year (aged 17-18). The students participated in a philosophical mindfulness training program aimed at enhancing creativity. The training focused on three key dimensions of creativity: comprehensiveness, penetration, and flexibility. Each dimension was further divided into four sub-dimensions, resulting in a total of 12 distinct aspects of creativity, covered over the course of 12 sessions.

Intervention: Philosophical Mindfulness Training

To boost creativity, the participants underwent philosophical mindfulness training, which was designed to target the following creative dimensions:

- **Comprehensiveness:** Broadening thought processes to incorporate diverse perspectives.
- **Penetration:** Deepening understanding and challenging assumptions.
- **Flexibility:** Enhancing the ability to adapt and generate novel ideas.

The effectiveness of the training was assessed using the Torrance Test of Creative Thinking (TTCT), administered both pre- and post-training. The TTCT measures creativity across four scales: fluidity, flexibility, originality, and elaboration. Cronbach's alpha reliability for the TTCT was as follows: 87% for overall creativity, 87% for fluidity, 81% for flexibility, 37% for originality, and 70% for elaboration.

Statistical Analysis of TTCT Results

To evaluate the effectiveness of the philosophical mindfulness training, the TTCT results were analyzed using **SPSS** software. **Paired sample t-tests** were conducted to compare pre- and post-training creativity scores. The table 1 illustrating the students' scores before and after the philosophical mindfulness training provide the improvement in creativity scores.

Table 1: Distribution of Pre- and Post- Training Creativity Scores

One-Sample Statistics				
	N	Mean	Std. Deviation	Std. Error Mean
pretest	15	67.27	14.626	3.776
posttest	15	75.40	11.255	2.906

T-test Results

The results of the paired sample t-test showed a statistically significant improvement in the overall creativity scores and in the individual scales (fluidity, flexibility, and elaboration). The **T-test** results table is presented below:

Table 2: Paired Sample T-Test Results for TTCT Scores

One-Sample Test	
	Test Value = 0

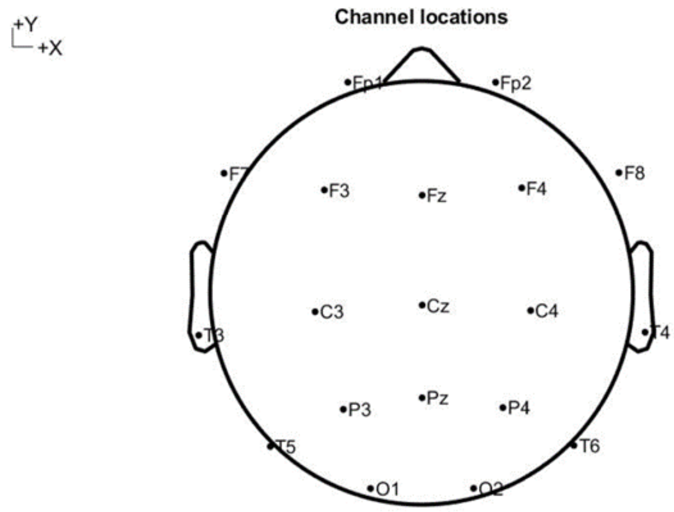
	t	df	Sig. (2-tailed)	Mean Difference	99% Confidence Interval of the Difference	
					Lower	Upper
pretest	17.812	14	.000	67.267	56.02	78.51
posttest	25.945	14	.000	75.400	66.75	84.05

These results showed that after philosophical mindfulness training, creativity increased by 99% confidence interval of the difference in these students (sig.<0.01).

EEG Validation of Torrance Test for Creativity Prediction

To validate the TTCT as an accurate measure of creativity, the EEG data was collected to assess brain activity linked to creative thinking. More than 23 hours of EEG recordings were captured at 250 Hz from 19 channels, with their locations shown in Figure 1. The students were divided into two groups based on their TTCT scores: group 1 (high scorers, n=6) and group 2 (low scorers, n=4), using a score of 75 as the threshold for classification.

Figure1- Channel locations



The task I applied for was based on the paper "Understanding the Creativity Process Through Electroencephalograph Measurement of Creativity-Related Cognitive Factors." In this study, Yin and colleagues [21] aimed to identify and compare EEG characteristics associated with specific cognitive factors, including remote association, common association, combination, recall, and retrieval. The test questions were translated and adapted for Persian students.

The EEG data were preprocessed using EEGLAB, where steps such as noise removal, data cleaning, and artifact rejection (ASR and ICA) were applied to ensure that the signals accurately reflected meaningful brain activity.

For EEG data analysis, deep learning models were implemented using TensorFlow and Keras in Python. The models were developed and trained in Google Colab, an online platform that provides the necessary computational resources for executing deep learning tasks. Google Colab enabled the use of GPU acceleration, improving the efficiency of model training.

After preprocessing, the cleaned EEG data were transformed into 1,975 images (each with a resolution of 224×224×3). These images were analyzed using deep learning models, including MobileNet and ResNet50, to determine whether EEG-recorded brain activity could reliably predict creativity scores. To enhance model performance, various optimization techniques were applied, including data augmentation (horizontal flipping, brightness, and contrast adjustments), L2 regularization, dropout (0.5), learning rate adjustments, and fine-tuning. Despite these optimizations, the models achieved high training accuracy—99.66% for MobileNet and 100% for ResNet50—while the testing accuracy remained at 82.2% and 91.85%, respectively.

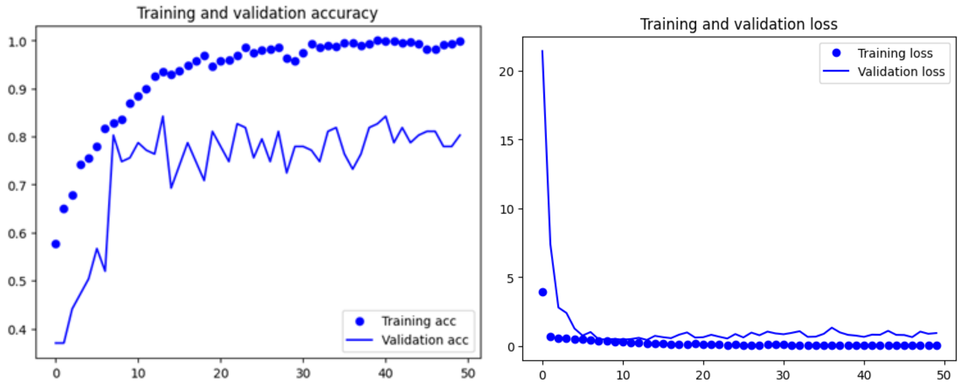
Model Architecture and Training Details

• **Base Model**: Pre-trained ResNet50 with an additional fully connected (FC) layer (1024 nodes, ReLU activation function, L2 regularization, and dropout of 0.5).
• **Fine-Tuning**: The last 20 layers were unfrozen and retrained.

• **Optimizer**: Adam for the first 100 epochs (without fine-tuning), followed by Stochastic Gradient Descent (SGD) with a learning rate of 0.001 for the last 50 epochs (with fine-tuning).
• **Number of Epochs**: 150
• **Data Augmentation**: Applied techniques included horizontal flipping, brightness adjustments, and contrast modifications.
• **Final Test Accuracy**: 91.85%

Below is the ResNet50 model training and validation accuracy and lost in one of 50 epochs:

Figure2- Training & Validation accuracy & lost



Several factors likely contributed to this performance gap. First, the limited sample size could have affected the model ability to generalize effectively. Additionally, all students underwent the same philosophical mindfulness training, which may have led to more similar brain activity patterns across participants. This reduced the distinctiveness between the groups, making classification more challenging.

Despite these challenges, the ResNet50 model structure, which consists of multiple convolutional layers with residual connections to improve deep feature extraction, proved to be the most effective in predicting creativity. However, the model achieved a testing accuracy of 91.85%, suggesting that EEG-based deep learning models can effectively predict creativity levels, even with subtle group differences.

IV. Conclusion

This study aimed to explore the impact of philosophical mindfulness training on high school students' creativity, focusing on the dimensions of comprehensiveness, penetration, and flexibility. The results from the Torrance Test of Creative Thinking (TTCT) showed a statistically significant improvement in creativity scores, demonstrating that philosophical mindfulness training can enhance students' creative abilities.

In addition to the TTCT, EEG data were collected to validate the measurement of creativity. Using deep learning models, we analyzed EEG signals to explore the relationship between brain activity and creativity. The models, including MobileNet and ResNet50, achieved impressive training accuracies of 99.66% and 100%, respectively, with testing accuracies of 82.2% and 91.85%. The high testing accuracy for ResNet50 (91.85%) suggests that deep learning approaches can serve as reliable tools for predicting creativity based on brainwave patterns, offering a novel approach to assess creativity beyond traditional assessments.

The findings from this study not only emphasize the efficacy of philosophical mindfulness training in boosting creativity but also highlight the potential of deep learning models in predicting creative thinking by analyzing EEG data. These results open new possibilities for integrating advanced computational techniques into educational and cognitive psychology research, providing deeper insights into the neural underpinnings of creativity.

Future research could explore the application of deep learning techniques in other cognitive domains and expand the use of EEG to assess long-term effects of philosophical mindfulness training on creativity. Additionally, combining these technological advancements with traditional creativity measures could further enhance our understanding of the complex relationship between brain activity and creative performance.

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