PERCOLATION THRESHOLD AND FUNCTIONAL ORGANIZATION OF NEURONAL NETWORKS. ANALYSIS OF COGNITIVE STATES USING EEG WAVES

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ABSTRACT:

This paper investigates how neuronal networks modify their functional organization according to cognitive demands, using the percolation threshold as an indicator of the distance from the critical state. Based on EEG recordings collected during rest and two cognitive tasks (working memory and inhibitory control), functional networks were constructed, and variations in the giant cluster were analyzed in relation to the connectivity threshold.
Results show that under high cognitive load, the neuronal network approaches a near-critical zone, characterized by efficient integration and functional dynamism. Moreover, lower percolation threshold values correlate with better cognitive performance, suggesting that optimal information processing occurs near criticality. The study confirms the relevance of the critical brain theory and highlights the potential of ***p_c*** *as a functional biomarker for assessing cognitive flexibility.*
Keywords: *percolation, EEG, neuronal networks, criticality, giant cluster, connectivity, working memory, synchronization, cognitive performance*

1. INTRODUCTION

The present study is situated within the framework of contemporary research on the human brain as a complex, dynamic, and adaptive system. Brain activity is not static but reflects continuous reorganizations of neuronal connectivity, depending on cognitive demands and contextual factors. Modern neuroscience describes the brain as a complex network of distributed interactions capable of both integrating and segregating information to maintain functional flexibility (Bullmore & Sporns, 2009).

Electroencephalography (EEG) provides a privileged tool for studying these processes due to its high temporal resolution and its capacity to capture rapid variations in neuronal activity (Nunez & Srinivasan, 2006).

The central problem of this research arises from the need to identify critical indicators signaling major reorganizations of brain networks. Percolation theory, originating from the physics of complex systems, describes transitions from fragmented states to globally connected structures (Stauffer & Aharony, 1994). Its application to EEG analysis can reveal how the brain oscillates between integration and functional segregation—an approach still insufficiently explored (Paraschiv, R.V., & Zamfirescu, V., 2025).

The motivation behind the study lies in the hypothesis that the brain operates near critical states—intermediate zones between order and chaos—that optimize sensitivity to stimuli and the efficiency of information processing (Beggs & Plenz, 2003; Chialvo, 2010). Estimating the percolation threshold in EEG-

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derived networks could provide a marker of this critical state, offering insights into how the brain adapts its functional structure in real time according to cognitive task demands.

The general objective of the research is to estimate and compare the percolation threshold in neuronal networks derived from EEG signals recorded under two conditions: rest and tasks with cognitive load (Breakspear, 2017). The study aims to determine whether the percolation threshold differs between these states and whether proximity to the critical state predicts cognitive performance.

The paper is structured into six sections: conceptual introduction, theoretical foundations, methodology (including EEG procedures and percolation estimation technique), results analysis, critical interpretation, and general conclusions integrating theoretical implications and future research directions.

2. THEORETICAL FOUNDATIONS

Percolation theory provides a fundamental conceptual and mathematical framework for understanding how connectivity develops within a complex system composed of numerous interdependent elements. Originating in the physics of disordered systems, it describes the transition from a fragmented state to a globally connected configuration, marked by the emergence of a “giant cluster” (Stauffer & Aharony, 1994). In neuroscience, this explanatory model enables the identification of moments when neuronal networks reach an optimal level of integration, essential for efficient information processing (Chialvo, 2010).

A central concept is that of the cluster, referring to groups of interconnected nodes forming functional sub-networks. In the brain, these correspond to cortical–subcortical regions co-activated in performing specific cognitive functions (Bunde & Havlin, 1996). Through EEG analysis, clusters can be detected based on neuronal oscillation synchronization, offering information about the cohesion and integration of the network (Sporns, 2011). The percolation threshold (p_c), the point at which the giant cluster emerges, marks the system’s transition from a disorganized to an integrated state. In neural terms, reaching this threshold indicates an optimal balance between integration and flexibility, associated with efficient information processing (Beggs & Plenz, 2003). The phenomenon is considered a self-organized phase transition, characteristic of complex systems that spontaneously reach critical states without external control (Bak, 1996).

Large-scale neuronal networks operate through the interplay between structural connectivity—the anatomical infrastructure of connections (Hagmann et al., 2008)—and functional connectivity, defined by the temporal correlation of activity between regions (Friston, 2011). The near-critical brain hypothesis posits that neuronal systems operate constantly near a critical state situated between order and chaos (Chialvo, 2010), a zone that maximizes both integration and cognitive flexibility. In this context, estimating the EEG percolation threshold offers an objective measure of the brain’s organizational efficiency.

Electroencephalography (EEG) is a reference method for studying real-time brain activity, due to its high temporal resolution, which allows the rapid detection of network reorganizations (Paraschiv, R.V., & Zamfirescu, V., 2025; Nunez & Srinivasan, 2006). The EEG signal arises from the synchronized activity of cortical pyramidal neurons (Buzsáki, 2006) and reflects the dynamics of neuronal populations—crucial for the analysis of complex networks. EEG oscillations, grouped into delta, theta, alpha, beta, and gamma bands, correspond to different cognitive and affective functions (Steriade, 2006; Klimesch, 1999; Palva & Palva, 2007; Engel & Fries, 2010). Interactions between these bands, through phase–amplitude coupling mechanisms, describe hierarchical levels of neuronal coordination (Canolty & Knight, 2010).

Neuronal synchronization, meaning the temporal alignment of activity between brain regions, represents the fundamental mechanism of information integration (Fries, 2005). It can be quantified using indicators such as spectral coherence, PLV, or wPLI (Vinck et al., 2011). In percolation theory terms, synchronization reflects the consolidation of connections facilitating the formation of the giant cluster—the neuronal expression of the critical state (Breakspear, 2017).

EEG network analysis involves calculating connectivity measures, constructing the relational matrix, and representing it as a graph. By varying the connectivity threshold, one can identify the moment when the network becomes globally integrated (Stauffer & Aharony, 1994). Graph representation enables adaptive evaluation of the balance between integration and segregation (Sporns, 2011).

Applying percolation theory to brain dynamics provides a unified explanation of how the brain integrates and segregates information during cognitive processing. Optimal functioning depends on maintaining a balance between integration, which ensures global coordination (Tononi, 2004), and segregation, which supports regional specialization (Bullmore & Sporns, 2009). At rest, segregation predominates, while complex cognitive tasks increase network integration by activating fronto-parietal circuits involved in executive control (Deco, Tononi, Boly & Kringelbach, 2015).

The near-criticality hypothesis states that neuronal networks operate near a critical point between order and chaos (Beggs & Plenz, 2003; Chialvo, 2010). In this state, the system maximizes information transfer and

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cognitive flexibility—conditions essential for attention, memory, and consciousness (Shew & Plenz, 2013). From a neurocognitive perspective, the percolation threshold becomes a marker of mental state: during rest, the default mode network predominates (Raichle, 2015); during cognitive tasks, integration increases (Cocchi et al., 2017); and in altered states—such as fatigue or affective disorders—the system drifts away from criticality (Deco et al., 2021).

Thus, EEG percolation analysis provides a dynamic perspective on how the brain transitions between distinct cognitive and affective states.

3. METHODOLOGY

3.1. Participants

The study included 30 participants, university students and young adults aged 18 to 35, selected to minimize neurophysiological variability associated with aging (Pfefferbaum et al., 2011). All participants had normal or corrected vision and reported no neurological or psychiatric disorders, nor the use of substances that could affect brain activity. Recruitment was voluntary, conducted through university announcements, and all participants were fully informed about the purpose and procedures of the study in accordance with APA ethical guidelines (2020).

Inclusion criteria included age (18–35 years), absence of neurological or psychiatric diagnoses, no psychotropic medication, and avoidance of alcohol or excessive caffeine consumption (Barry et al., 2020).

The research complied with international ethical standards and the Declaration of Helsinki (World Medical Association, 2013). Informed consent was obtained, and data were anonymized and processed according to GDPR regulations.

3.2. Experimental Design

The experimental design aimed to compare brain connectivity dynamics between the resting state and two distinct cognitive tasks, to observe how the neuronal network reorganizes according to cognitive demands (Raichle, 2015; Cocchi et al., 2017).

EEG activity was recorded in standardized intervals, with control of ocular and muscular movements (Luck, 2014). The order of conditions was counterbalanced to eliminate fatigue effects.

In the resting state, participants sat relaxed with eyes closed for 5 minutes, engaging the default mode network (Raichle, 2015).

The first cognitive task, a 2-back test, targeted working memory and executive processes (Owen et al., 2005; Fuster, 2009), consisting of three blocks of 2 minutes each.

The second task, a Stroop test variant, assessed inhibitory control and cognitive conflict (Stroop, 1935; MacLeod, 1991), with a total duration of 6 minutes.

3.3. EEG Data Acquisition

Brain electrical activity was recorded using electroencephalography (EEG), a high–temporal-resolution method that enables real-time observation of neuronal dynamics. The acquisition protocol was standardized to minimize physiological and technical artifacts, following methodological recommendations (Luck, 2014).

Recordings were performed using an 8-channel EEG system, with electrodes placed according to the international 10–20 system (Jasper, 1958), maintaining impedance below 5 kΩ (Teplan, 2002). The experimental environment was controlled for light and noise (Niedermeyer & da Silva, 2005). Signals were sampled at 500–1,000 Hz, filtered between 0.1 and 100 Hz, and notch-filtered at 50/60 Hz (Nunez & Srinivasan, 2006).

Preprocessing included digital filtering (1–45 Hz), artifact correction (ocular and muscular) via Independent Component Analysis (ICA) (Delorme & Makeig, 2004), re-referencing to the average of all channels (Yao, 2001), and removal of contaminated segments. These steps ensured the quality and authenticity of the EEG signal for percolation analysis.

3.4. Construction of Neuronal Networks

After EEG preprocessing, the neuronal signal was transformed into a functional network, where connections between nodes reflected the degree of synchronization between cortical regions (Friston, 2011; Sporns, 2011). The process included two stages: extraction of connectivity measures and construction of weighted graphs.

For each pair of electrodes, measures of neuronal synchronization were computed, such as spectral coherence (Nunez & Srinivasan, 2006), Phase-Locking Value (PLV) (Lachaux et al., 1999), and Weighted Phase Lag Index (wPLI) (Vinck et al., 2011). These measures were obtained over standardized time windows (2–5 seconds) using Fourier or wavelet transforms.

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Connectivity values were organized into an N×N matrix, interpreted as a weighted graph, where nodes represent electrodes and edges represent functional connections (Rubinov & Sporns, 2010). By applying variable thresholds to the weights, the transition from local clusters to the giant cluster was identified, indicating the neuronal percolation threshold (Stauffer & Aharony, 1994).

3.5. Estimation of the Percolation Threshold

The estimation of the percolation threshold (p(c)) represents the core stage of the analysis, indicating the critical point where the neuronal network transitions from a fragmented to an integrated structure — corresponding to a phase transition in complex systems (Stauffer & Aharony, 1994; Chialvo, 2010). The process involved three stages: variation of connectivity threshold, identification of the giant cluster, and determination of the p(c) value.

The connectivity matrix was progressively binarized by applying successive thresholds, observing how the network evolved from a dense to a fragmented state (Sporns, 2011). For each threshold, the giant cluster—the subnetwork with the largest number of nodes—was identified, marking the onset of critical organization (Breakspear, 2017).

The p(c) value was determined via the derivative of the G(p) curve, indicating the point of maximum rate of change. Low thresholds suggested hyper-integration, high thresholds indicated fragmentation, and intermediate values reflected near-critical functioning, associated with cognitive flexibility and information processing efficiency (Shew & Plenz, 2013).

3.6. Statistical Analysis

Statistical analysis aimed to compare neuronal network organization between resting and cognitive conditions, as well as to explore the relationship between the critical threshold (p(c)) and cognitive performance, using specialized software such as MATLAB, Python, SPSS, or R (Field, 2017).

To test differences between conditions, a repeated-measures ANOVA was applied, followed by Bonferroni corrections when data met normality assumptions (Maxwell & Delaney, 2004); for nonparametric distributions, Friedman and Wilcoxon tests were used (Gibbons & Chakraborti, 2011). The analysis focused on significant variations in the degree of network integration between cognitive states.

Correlations between p(c) and performance (accuracy, reaction time, n-back score) were analyzed using Pearson or Spearman coefficients (Cohen, 1988) to evaluate the relationship between near-critical states and cognitive efficiency (Shew & Plenz, 2013).

Results were reported according to APA (2020) standards, including test statistics, effect size, and graphical visualizations (violin plots, boxplots, scatter plots).

4. RESULTS

The results revealed significant differences in the percolation threshold (p(c)) between experimental conditions. During rest, moderate p(c) values reflected a balance between integration and fragmentation, characteristic of the default mode network (Raichle, 2015). In the n-back task, p(c) decreased significantly, indicating increased integration and proximity to the critical state (Fuster, 2009), while in the Stroop task, intermediate values suggested flexible cognitive reorganization (MacLeod, 1991).

Analysis of the G(p) curves showed a rapid transition toward the giant cluster in the n-back task, a gradual one during rest, and a moderate transition in the Stroop condition (Chialvo, 2010; Breakspear, 2017).

A repeated-measures ANOVA ($p < .05$) confirmed significant differences among all conditions ($\eta^2 > 0.25$). Correlations indicated that lower p(c) values were associated with higher n-back performance and faster reaction times in the Stroop task, supporting the near-critical brain hypothesis (Shew & Plenz, 2013).

Results were visually summarized through curves, boxplots, scatter plots, and comparative tables.

5. DISCUSSION

The results of the study confirm the hypothesis that the organization of neuronal networks depends on cognitive demands, approaching the critical threshold under high-load conditions. Lower percolation threshold values (p(c)) during the working memory task indicate an increase in network integration, compatible with an optimal operational regime for information processing (Fuster, 2009). The dynamics of the giant cluster support the existence of a functional phase transition, and the negative correlations between p(c) and performance suggest that proximity to the critical state enhances cognitive efficiency (Shew & Plenz, 2013).

These findings align with critical brain theories (Chialvo, 2010), which propose that neuronal systems function near a balance point between order and chaos, thereby maximizing cognitive flexibility (Deco & Kringelbach, 2020). The percolation threshold can thus serve as a direct index of distance from the near-critical state (Cocchi, Gollo & Zalesky, 2017).

From an applied perspective, p(c) becomes a valuable neurophysiological indicator for assessing cognitive load (neuroergonomics), diagnosing disorders characterized by network imbalances (e.g., epilepsy, schizophrenia), and optimizing performance through neurofeedback training.

The study also highlights that working memory involves maximal inter-regional integration, inhibitory control elicits an intermediate reorganization, while the resting state reflects a neutral balance between integration and segregation (Raichle, 2015). This supports the notion of a dynamic and metastable brain (Tognoli & Kelso, 2014).

Limitations include the relatively small sample size, the limited spatial resolution of EEG, the reliance on functional connectivity measures, and the absence of correlation with structural imaging (Bastos & Schoffelen, 2016). Future research should integrate multimodal methods (EEG–fMRI), larger samples, and computational predictive models to simulate and validate network transitions.

6. CONCLUSIONS

6.1. General Conclusion

The study demonstrated that the percolation threshold (p(c)) is a valid indicator of the functional organization of neuronal networks, varying according to the cognitive state. Under high-demand conditions, such as working memory, the brain network approaches the critical zone, characterized by a dynamic balance between integration and segregation. This shift is expressed through a decrease in p(c) and a rapid transition of the giant cluster, suggesting maximum efficiency in neuronal communication. The negative relationship between p(c) and cognitive performance confirms the hypothesis that optimal processing occurs near the near-critical state, consistent with critical brain theory.

The theoretical contributions of the study include:

1.Defining p(c) as a quantitative indicator of the distance from criticality.

2.Integrating percolation theory into the analysis of large-scale neuronal networks.

3.Providing empirical evidence that brain networks optimize performance by approaching the critical state, thereby offering conceptual support for near-critical brain models as a foundation for cognitive flexibility.

6.2. Methodological Contributions

From a methodological standpoint, the research:

1.Proposed and validated a practical procedure for estimating the percolation threshold from EEG-based networks using functional connectivity measures.

2.Demonstrated the utility of G(p) curve analysis (giant cluster size as a function of threshold) in identifying network transitions.

3.Integrated network analysis with behavioral performance, providing a multimodal approach to evaluating cognitive functioning.

4.Highlighted the potential of p_c as a functional, reproducible, and transferable biomarker applicable to other experimental paradigms.

This approach can be effectively applied in clinical, neuroergonomic, and performance-optimization contexts.

6.3. Development Perspectives

Based on the conclusions obtained, several promising directions for future research emerge:

– Extending the analysis to clinical populations, to investigate whether deviations from criticality serve as indicators of neurocognitive disorders (e.g., depression, schizophrenia, epilepsy).

– Integrating multimodal EEG–fMRI–DTI approaches, to correlate near-critical functional states with the structural substrate of brain connectivity.

– Implementing neurofeedback-based interventions to train the neuronal system to adaptively reach near-critical states for optimizing cognitive performance.

– Developing advanced computational models to simulate phase transitions in dynamic neuronal networks.

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