

# The Longitudinal BCI-Based Evaluation of Thinking Patterns: Neuro-Cognitive Generative AI Implications in Higher Education

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**Abstract:** Gaining acceptance of Generative AI (GenAI) in higher education has revolutionized how students access information, solve problems, gain knowledge, and engage in learning activities. Although previous research has extensively studied the pedagogical advantages and challenges of using GenAI, there is a lack of focus on the long-term implications of GenAI for learners' thinking processes. With the advent of Brain-Computer Interface (BCI) technologies and low cost electroencephalography (EEG) systems, there is an unprecedented opportunity to explore the effects of prolonged interactions with GenAI on attention, cognitive engagement, creativity, decision-making, and metacognitive behavior. In this paper, a framework for the longitudinal evaluation of changes in students' thinking processes due to regular use of GenAI in higher education settings is proposed. The study aims to bridge the gap between educational technology research and neurocognitive assessment. The paper provides a theoretical context for the importance of GenAI in learning, summarizes recent research on using EEG in education, and proposes a longitudinal study design that can capture neural markers linked to the development of different cognitive behaviors. The proposed framework will address SDG 4 & SDG 9 and will provide evidence based learning about the impact of technology on human cognition and learning in higher education.

**Keywords:** Generative AI; Brain-Computer Interface; EEG; Higher Education; Neuro-Cognition

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## Introduction

Generative AI (GenAI) is revolutionizing the education industry with its rapid progress. GenAI can create human-like text, images, code, simulations, and multimodal education content, not just automate pre-defined tasks. The capabilities have had a profound impact on the nature of teaching and learning in Higher Education institutions. AI tools are now used by students more and more across the fields of ideation, content creation, academic writing, programming, research, and personalized learning guidance. The educational potential of GenAI is recognized, but there are concerns about the impact of GenAI on human cognition in the long term. The proponents state that AI systems augment the intellectual capacity of the human brain by alleviating cognitive pressure when handling repetitive tasks and enabling learners to target higher-order thinking abilities like analysis, synthesis, and evaluation. On the other hand, relying too heavily on AI-generated answers could lead to a decline in critical thinking, deep learning, and mental agility. To fully get an understanding of these contrasting outcomes, research beyond traditional surveys and self-reported measures is needed. The advances in neuroscience offer new potential solutions to this challenge. Brain-Computer Interfaces (BCIs) and specifically systems based on electroencephalography (EEG) allow real-time monitoring of neural activity related to attention, memory, cognitive workload, emotion, and creative thinking. It is especially important that longitudinal studies

be conducted. In the current literature, most work on GenAI in education is done using short-term interventions or cross-sectional surveys. Such methods do not adequately account for a gradual evolution in mental activities that can occur over time as a result of repeated interactions with the AI systems. In the present study, we will focus on this new research gap by introducing a longitudinal framework for the evaluation of BCI based on GenAI usage. The study aims to leverage its integration of educational neuroscience practices and modern AI-driven learning spaces to understand how long-term learning is affected by GenAI in terms of attention, cognitive engagement, creativity, and thinking.

### **Related Work**

As the use of GenAI becomes more popular in higher education, there has been a significant amount of scholarly interest in its pedagogical, cognitive and ethical implications. In recent years, longitudinal studies clearly have pointed to the transformative role of AI technologies in teaching and learning. However, it has been found that the behaviours of learners are substantially changed when using AI in learning environments, which requires ongoing assessment of the cognitive adaptation process [1]. A systematic review was carried out, which highlighted a wide range of pedagogical uses of GenAI in higher education and the need for empirical studies investigating the cognitive impact of prolonged interactions with AI [2]. Likewise, the impact of GenAI in fifth-generation education systems was reviewed and found that future education systems will rely more and more on intelligent technologies that can complement humans' learning capacity. The review also pointed to cognitive dependency and ethical decision-making issues for students [3]. This has garnered a lot of attention about the correlation between GenAI and student engagement. A thorough meta-analysis is conducted to establish a link between GenAI use and learners' engagement, motivation, and participation. The authors nonetheless pointed out that engagement indicators are not enough to identify the deeper cognitive changes [4]. There are also proposals for moving from an automation focus to cognitive augmentation. The results indicated the potential of GenAI to support critical thinking, ethical considerations, and reflective learning when used effectively in learning environments [5]. Another research theme that has come to light is how students feel about GenAI. Analysis of undergraduate attitudes showed that there were significant differences, likely due to subject matter, technological experience, and learning goals [6].

There have been parallel developments in the field of educational neuroscience research. A thorough survey of applications of EEG in education identified a range of increasing research on using brain-computer interfaces to understand attention, cognitive engagement, and learning effectiveness [7]. EEG methodologies have been employed to study attention in college students in blended learning settings. They showed that the use of neurophysiological markers could be effective in detecting attention fluctuations that were not observable in traditional ways [8]. In recent years, when examining the effect of AI-generated content on student creativity and neural states in the context of product design using a setup for EEG measurements, there were measurable changes in neural activity related to creative performance during interaction with AI-generated learning resources [9]. While these advances have been made, there are still many areas of research that are still lacking. The existing literature either focuses on the adoption of GenAI or on the assessment

of learning with EEG without considering the two together. Few studies have combined both areas to assess the effects of long-term use of GenAI on neurocognitive processes. To fill this void, the proposed study aims to develop a BCI-based framework that can capture cognitive changes observed during long-term interaction with GenAI, as outlined in Table 1 below.

*Table 1. Comparative analysis of Existing Literature and the Proposed Work*

| Reference                 | Longitudinal Assessment of GenAI Usage | Pedagogical Engagement of GenAI | EEG / BCI-Based Cognitive Assessment | Cognitive Analysis | Integration of GenAI and EEG for Cognitive Assessment |
|---------------------------|----------------------------------------|---------------------------------|--------------------------------------|--------------------|-------------------------------------------------------|
| [1] Leite (2025)          | Yes                                    | Yes                             | No                                   | No                 | No                                                    |
| [2] Qian (2025)           | No                                     | Yes                             | No                                   | Yes                | No                                                    |
| [3] Chakraborty (2026)    | No                                     | Yes                             | No                                   | Yes                | No                                                    |
| [4] Wang & Guo (2025)     | No                                     | Yes                             | No                                   | No                 | No                                                    |
| [5] Perdana et al. (2026) | No                                     | Yes                             | No                                   | Yes                | No                                                    |
| [6] Sun & Zhou (2025)     | No                                     | No                              | No                                   | Yes                | No                                                    |
| [7] Orovas et al. (2025)  | No                                     | No                              | Yes                                  | No                 | No                                                    |
| [8] Tang et al. (2024)    | No                                     | No                              | Yes                                  | No                 | No                                                    |
| [9] Wang et al. (2025)    | No                                     | Yes                             | Yes                                  | No                 | Partial                                               |
| Proposed Work             | Yes                                    | Yes                             | Yes                                  | Yes                | Yes                                                   |

The study is guided by the following objectives:

- To measure the impact of long-term use of Generative AI tools on students' attention and cognitive engagement in higher education.
- To explore the impact of Generative AI on patterns of creativity, critical thinking and problem-solving using EEG-based neuro-cognitive metrics.
- To identify neural markers of cognitive enhancement and cognitive reliance over extended periods of engagement with GenAI systems.
- To create a framework that combines educational performance metrics and BCI analytics for a neuro-cognitive assessment of the long-term impacts of GenAI-assisted learning.

### **Key Contribution**

This paper presents one of the first conceptual models to assess the neuro-cognitive impact of Generative AI on higher education students across the entire lifespan of the learning experience, thus allowing for an objective and accurate evaluation of changing thinking patterns, cognitive engagement, and AI-enhanced cognition.

## Method and Experiments

We propose a non-invasive BCI framework with high fidelity to investigate the neural dynamics of GenAI interaction and validate scaffolding strategies. The current research design involves the use of real-time Electroencephalography (EEG) to record and analyze the electrical activity of the prefrontal cortex during different cognitive tasks. The proposed framework is given as Figure 1.



Figure 1. Signal acquisition and processing pipeline of the proposed BCI-EEG model.

The study suggests a longitudinal mixed-methods research design with undergraduate and postgraduate students (approx. 100) in different areas of academic studies. Selected learning activities will be conducted using wearable EEG device to record neurophysiological signals. The brain wave measurements taken with alpha, beta, theta and gamma frequency bands will be captured. The results will be analysed statistically over the course of time and using machine learning methods to detect patterns and connections between GenAI use and neuro-cognitive results.

## Conclusion

The purpose of this paper is to suggest a longitudinal BCI-based framework for evaluating thinking patterns among higher-education learners using GenAI. The study will combine the neurophysiological evaluation using EEG with educational analytics to offer objective proof of changes in attention, engagement, creativity, and cognitive processing. The proposed framework aims to connect the educational technology research with neuroscience, providing a holistic view of the effects of AI-supported learning environments on human brain functioning. This proposed evaluation structure based on the BCI can help address SDG 4 (Quality Education) and SDG 9 (Industry, Innovation and Infrastructure) by promoting the responsible use of cutting-edge AI tools and the sustainable advancement of learner cognition and educational results.

## References

1. Leite, H. (2025). Artificial intelligence in higher education: Research notes from a longitudinal study. *Technological Forecasting and Social Change*, 215, 124115. <https://doi.org/10.1016/j.techfore.2025.124115>
2. Qian, Y. (2025). Pedagogical Applications of Generative AI in Higher Education: A Systematic Review of the Field. *TechTrends*, 69, 1105–1120. <https://doi.org/10.1007/s11528-025-01100-1>

3. Chakraborty, S. (2026). Generative artificial intelligence in fifth-generation education systems: A systematic review. *Engineering Applications of Artificial Intelligence*, 173, 114463. <https://doi.org/10.1016/j.engappai.2026.114463>.
4. Wang, K., & Guo, Z. (2025). Can Learners' Use of GenAI Enhance Learning Engagement?—A Meta-Analysis. *Education Sciences*, 15, 1578. <https://doi.org/10.3390/educsci15121578>
5. Perdana, A., Bharathi S, V., & Lee, W. E. (2026). From automation to augmentation: GenAI's role in promoting students' cognitive and ethical development. *Thinking Skills and Creativity*, 59, 102035. <https://doi.org/10.1016/j.tsc.2025.102035>
6. Sun, L., & Zhou, L. (2025). Generative artificial intelligence attitude analysis of undergraduate students and their precise improvement strategies: A differential analysis of multifactorial influences. *Education and Information Technologies*, 30(8), 10591–10626. <https://doi.org/10.1007/s10639-024-13236-3>
7. Orovas, C., Sapounidis, T., Volioti, C., & Keramopoulos, E. (2025). EEG in Education: A Scoping Review of Hardware, Software, and Methodological Aspects. *Sensors*, 25, 182. <https://doi.org/10.3390/s25010182>
8. Tang, H., Dai, M., Du, X., Hung, J. L., & Li, H. (2024). An EEG study on college students' attention levels in a blended computer science class. *Innovations in Education and Teaching International*, 61(4), 789–801. <https://doi.org/10.1080/14703297.2023.2166562>
9. Wang, S., Tao, X., Ma, H., Li, F., & Wu, C. (2025). EEG assessment of artificial intelligence-generated content impact on student creative performance and neurophysiological states in product design. *Frontiers in Psychology*, 16, 1508383. <https://doi.org/10.3389/fpsyg.2025.1508383>