

EEG Markers of Cognitive Load and Mental Fatigue in University Students: A Systematic Review [†]

Nikol Petrović 

Biomedical Engineering, Faculty of Technical Sciences, University of Novi Sad, Trg Dositeja Obradovića 6, 21000 Novi Sad, Serbia; nikolpetrovic@uns.ac.rs

[†] Presented at the 5th International Electronic Conference on Brain Sciences & 1st International Electronic Conference on Neurosciences, 9–11 March 2026; Available online: <https://sciforum.net/event/IECBS-IECNS2026>.

Abstract

University students are frequently exposed to high cognitive demands, which can lead to sustained cognitive load and mental fatigue and may negatively affect learning outcomes and well-being. Electroencephalography (EEG) provides a non-invasive, real-time window into neural activity associated with cognitive effort. This systematic review aims to synthesize current evidence on EEG markers of cognitive load and mental fatigue in university students. The review was conducted in accordance with the PRISMA 2020 statement, and electronic databases including PubMed, Scopus, and Web of Science were systematically searched for peer-reviewed studies on EEG-based assessment of cognitive load and mental fatigue in healthy university students. Seven studies met the inclusion criteria, comprising 179 participants. Cognitive load was most often reflected in changes in theta, alpha, and beta power, as well as band ratios such as theta/alpha. Studies manipulating multimedia design principles generally reported lower cognitive load indicators and better learning performance when these principles were applied. EEG-based markers, particularly theta and posterior alpha activity, show promising potential for monitoring cognitive strain in educational settings; however, methodological variability and small sample sizes limit generalizability.

Keywords: EEG; cognitive load; mental fatigue; university students; learning performance; systematic review

1. Introduction

University students are frequently exposed to high cognitive demands due to continuous academic obligations, including lectures, assignments, deadlines, examinations, and prolonged study periods. Recent studies have also shown that EEG-based machine learning models can successfully classify cognitive performance during arithmetic tasks, further supporting the use of EEG as an objective biomarker of cognitive effort and task efficiency [1]. These demands often result in sustained cognitive load and increased levels of mental fatigue, which may negatively affect attention, memory, learning efficiency, and overall well-being. Academic stress is particularly pronounced during examination periods, where prolonged cognitive effort and reduced recovery may significantly impair performance [2].

Cognitive load refers to the amount of mental effort required for information processing within working memory. According to cognitive load theory, when the cognitive demands of a task exceed the learner's processing capacity, learning efficiency decreases



Academic Editor: Carla Masala

Published: 24 July 2026

Copyright: © 2026 by the author.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

and mental fatigue develops. Mental fatigue is commonly characterized by reduced concentration, slower information processing, impaired decision-making, and decreased task performance. Therefore, objective assessment of cognitive load and fatigue is essential for understanding learning processes and improving educational outcomes. Although cognitive load and mental fatigue are closely related, they represent distinct neurocognitive constructs. Cognitive load refers to the mental effort required to perform a specific task, whereas mental fatigue develops after prolonged cognitive activity and is characterized by reduced alertness, slower information processing, and decreased cognitive performance. Therefore, these concepts should not be used interchangeably, although they often coexist during demanding learning activities.

Electroencephalography (EEG) has emerged as a valuable non-invasive tool for monitoring cognitive processes in real time due to its high temporal resolution and practical applicability. EEG records electrical brain activity and is commonly analyzed through frequency bands associated with specific cognitive and physiological states. The delta band (0.5–4 Hz) is mainly related to deep sleep, but it may also increase during high cognitive demand. Theta activity (4–7 Hz), particularly in frontal regions, is strongly associated with working memory load, sustained attention, and mental effort. The alpha band (8–12 Hz) is related to relaxed wakefulness and typically decreases during active cognitive processing, especially in parietal and occipital regions. Beta activity (13–30 Hz) is associated with active thinking, concentration, and alertness, while gamma activity (>30 Hz) reflects higher-order cognitive processing and information integration.

Previous studies have demonstrated that EEG-based measures, particularly theta and alpha activity, are reliable indicators of cognitive load and mental workload [3–5]. Increased frontal theta power and reduced posterior alpha activity are frequently associated with higher cognitive demand, while changes in beta power and band ratios such as theta/alpha may reflect mental fatigue and learning efficiency. These objective neurophysiological markers provide valuable insight into how the brain responds to different educational conditions and learning modalities.

Compared to subjective questionnaires, EEG enables continuous real-time monitoring of cognitive strain without interrupting the learning process, making it particularly useful for educational environments [4]. Nevertheless, the practical application of EEG in educational environments remains challenging because recordings are susceptible to motion artifacts, inter-individual variability, electrode placement, and differences in signal preprocessing.

The aim of this systematic review is to summarize current evidence on EEG-based markers of cognitive load and mental fatigue in university students, with a focus on identifying the most consistent neurophysiological patterns and methodological challenges in this field.

2. Materials and Methods

2.1. Search Strategy

This systematic review was conducted in accordance with the PRISMA 2020 statement (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [6]. The literature search was conducted in March 2026 and included studies published between January 2010 and March 2026. The search strategy was adapted for each database using combinations of the following terms: (“EEG” OR “electroencephalography”) AND (“cognitive load” OR “mental fatigue”) AND (“university students” OR “learning”). Titles and abstracts were screened by a single reviewer, followed by full-text assessment according to the predefined eligibility criteria.

Following title, abstract and full-text screening according to the eligibility criteria, seven studies were included in the qualitative synthesis. No duplicate records were identified among the retrieved studies. The study selection process is illustrated in Figure 1.

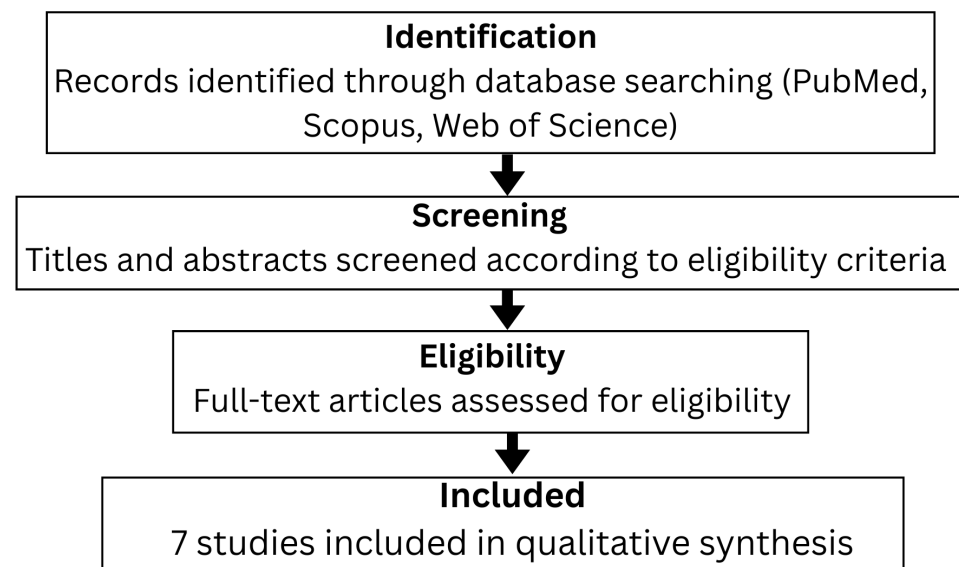


Figure 1. Simplified Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) workflow illustrating the study selection process.

2.2. Inclusion and Exclusion Criteria

Studies were included if they met the following criteria: (1) involved healthy university students as participants; (2) used EEG as the primary tool for assessing cognitive load, mental fatigue, or learning-related cognitive effort; (3) included tasks related to learning, academic performance, multimedia learning, examination stress, or classroom-based activities; and (4) were published as peer-reviewed full-text articles in English.

Studies were excluded if they involved clinical populations, neurological or psychiatric disorders, non-EEG neuroimaging methods without EEG analysis, purely theoretical papers without experimental data, or studies not directly related to cognitive load or mental fatigue during learning activities.

2.3. Data Extraction

Relevant data were extracted from all included studies, including sample size, participant characteristics, experimental paradigm, EEG recording protocol, analyzed EEG frequency bands, reported EEG markers, and the main findings related to cognitive load and mental fatigue.

Special attention was given to changes in theta, alpha, beta, and delta activity, as well as commonly reported band ratios such as theta/alpha and beta/(theta + alpha), since these measures were most frequently associated with cognitive effort and fatigue across the reviewed studies.

The selected studies showed considerable heterogeneity in experimental design, EEG preprocessing methods, and reported outcome measures, which limited the possibility of direct quantitative comparison.

3. Results and Discussion

3.1. Characteristics of Included Studies

A total of seven studies met the inclusion criteria, comprising 179 participants, with sample sizes ranging from 7 to 43 participants per study. Most studies involved healthy

university students exposed to cognitively demanding tasks such as examination stress, multimedia learning, language-based learning, classroom activities, and comparison of different educational modalities such as text-based versus video-based learning. The characteristics of the included studies are summarized in Table 1.

Table 1. Summary of included studies and main electroencephalography (EEG) findings.

Author (Year)	Sample (n)	Experimental Task	EEG Markers	EEG System/Channels	Age	Main Findings	Main Limitations
Rajendran et al. (2022) [2]	14	Pre/post examination stress	Theta, alpha, beta	Enobio 8 channels	18–24 years	EEG activity changed with examination stress	Small sample size
Negi & Mitra (2018) [3]	7	Arithmetic cognitive load task	Theta/alpha ratio	Muse EEG headset	20–28 years	Theta/alpha reflected cognitive load	Pilot study; very small sample
Lee (2014) [4]	43	Documentary learning (English vs. Korean)	Beta activity at T3	EEG (T3 analysis)	Mean age not reported	Beta correlated with perceived difficulty	Single EEG region analyzed (T3)
Farkish et al. (2023) [7]	28	With/without multimedia principles	Theta, alpha	32-channel EEG	Mean 22.8 ± 2.6 years	Better design reduced load	Laboratory-based multimedia task
Guo et al. (2022) [8]	38	Color/grayscale multimedia	Beta/(theta + alpha), entropy	EEG with entropy analysis	Mean 21.3 ± 1.5 years	Higher load related to reduced emotional activity	Case-study design/limited generalizability
Sarailoo et al. (2022) [9]	30	Low/high-load videos	Alpha, theta	29-channel EEG	18–25 years	EEG classified load in 3 s segments	Controlled laboratory environment
Ramírez-Moreno et al. (2021) [5]	19	Text/video learning	Theta/alpha, delta	EEG system (reported theta/alpha, delta)	Not reported	Fatigue markers related to lower performance	Small sample; classroom simulation

Although increased frontal theta activity and decreased posterior alpha activity were consistently reported across several studies, the robustness of these findings should be interpreted cautiously. Considerable methodological heterogeneity exists regarding EEG acquisition systems, electrode configurations, preprocessing pipelines, experimental paradigms, and outcome measures, limiting direct comparison across studies. Consequently, these biomarkers should currently be regarded as promising indicators rather than universally established measures of cognitive load.

Despite its considerable potential, the practical implementation of EEG in educational environments remains challenging. Reliable EEG acquisition requires specialized equipment, trained personnel, careful electrode placement, artifact correction, and extensive signal preprocessing. Furthermore, most available studies were conducted under controlled laboratory conditions using relatively simple experimental paradigms. Therefore, the ecological validity and scalability of EEG-based cognitive load monitoring in authentic classroom settings remain limited and require further investigation.

The reviewed studies showed considerable methodological heterogeneity. EEG recordings ranged from portable 8-channel systems to more advanced 29-channel and 32-channel devices. The most commonly analyzed frequency bands were theta, alpha, beta, and delta, while some studies also included gamma activity and frequency band ratios such as theta/alpha, alpha/gamma, and beta/(theta + alpha). In addition to EEG, several studies used subjective measures such as NASA-TLX questionnaires and performance-based outcomes including comprehension tests, recall tasks, and academic performance scores.

Despite differences in study design, most studies aimed to identify objective EEG markers associated with increased cognitive load, mental fatigue, and learning efficiency.

Although increased frontal theta and decreased posterior alpha activity were the most consistently reported findings, these biomarkers were not observed under identical experimental conditions. Differences in EEG hardware, preprocessing pipelines, cognitive tasks, and analytical methods may partly explain the variability across studies. Therefore,

current evidence supports these EEG features as promising indicators rather than definitive biomarkers of cognitive load.

3.2. EEG Markers of Cognitive Load and Mental Fatigue

Cognitive load was most consistently reflected through changes in theta, alpha, and beta activity. Increased frontal theta power was frequently associated with higher working memory demands, sustained attention, and mental effort. Several studies reported that prolonged cognitive tasks and examination stress were accompanied by increased theta activity, suggesting greater cognitive strain and mental fatigue [2].

Alpha activity, particularly in parietal and occipital regions, was commonly reduced during periods of increased cognitive processing. Lower alpha power was generally associated with higher cognitive load, while higher alpha activity was observed in more efficient learning conditions and lower mental workload states. Studies evaluating multimedia learning showed that educational materials designed according to multimedia principles produced lower cognitive load indicators and better learning outcomes compared to poorly designed materials [7–9].

Beta activity was also associated with task difficulty and perceived mental effort. One study reported a significant positive correlation between self-reported difficulty and beta activity in the T3 region ($r = 0.309$, $p < 0.05$), while difficulty ratings were negatively correlated with learning performance ($r = -0.391$, $p < 0.01$) [4]. Additionally, higher theta/alpha ratios and increased delta power were linked to mental fatigue, drowsiness, and poorer academic performance [5].

Machine learning approaches were applied in some studies to classify cognitive load based on EEG features [2,6]. However, the main importance of these findings lies in confirming that EEG can serve as an objective physiological marker of cognitive strain during learning tasks rather than only as a predictive tool.

3.3. Methodological Limitations and Future Directions

Although the findings support the usefulness of EEG in assessing cognitive load and mental fatigue, several methodological limitations remain. Sample sizes were generally small, which reduces statistical power and limits generalizability. Experimental paradigms varied substantially across studies, including differences in task duration, learning modality, EEG devices, preprocessing pipelines, and feature extraction methods.

The lack of standardized protocols makes direct comparison between studies difficult and limits the development of robust universal EEG markers. In addition, many studies focused primarily on spectral power analysis without considering functional connectivity or more advanced network-based approaches that may provide additional insight into cognitive processing.

Future research should focus on larger participant cohorts, standardized experimental designs, and more transparent reporting of EEG preprocessing and analysis methods to improve reproducibility and clinical applicability.

In addition, the available evidence should be interpreted cautiously because most studies included relatively small samples, heterogeneous EEG acquisition systems, different preprocessing pipelines, and diverse experimental paradigms, limiting direct comparison across studies.

Furthermore, a formal methodological quality assessment or risk-of-bias evaluation was not performed because of the concise proceedings format. The present findings should be interpreted considering the methodological heterogeneity of the included studies. Therefore, the present findings should be interpreted as indicative rather than definitive evidence.

4. Conclusions

This systematic review highlights the growing potential of electroencephalography (EEG) as an objective tool for assessing cognitive load and mental fatigue in university students. Across the reviewed studies, the most consistent findings were related to increased frontal theta activity, reduced posterior alpha power, and changes in beta activity and frequency band ratios such as theta/alpha, which were associated with higher cognitive demand, mental fatigue, and reduced learning efficiency.

Studies involving multimedia learning, examination stress, and classroom-based tasks showed that EEG markers can successfully reflect differences in mental effort and learning conditions. Educational materials designed according to multimedia learning principles were generally associated with lower cognitive load indicators and improved performance outcomes, supporting the practical value of EEG-based monitoring in educational settings.

However, significant methodological heterogeneity and relatively small sample sizes limit the generalizability of current findings. Differences in EEG devices, preprocessing methods, experimental paradigms, and outcome measures make direct comparisons difficult and prevent the establishment of standardized neurophysiological markers.

Overall, EEG-based biomarkers demonstrate considerable potential for monitoring cognitive load and mental fatigue in university students. However, methodological heterogeneity, small sample sizes, and practical limitations currently restrict their routine implementation in educational settings. Future studies should prioritize standardized methodologies, larger participant cohorts, and ecologically valid learning environments to improve reproducibility and facilitate translation into educational practice.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The author declares no conflict of interest.

References

1. Petrović, N.; Spahić, L.; Mandić, S.; Sovilj, P. Decoding cognitive processes in arithmetic tasks: An EEG-based convolutional neural network model. In *Proceedings of the 26th IMEKO TC4 International Symposium and 24th International Workshop on ADC and DAC Modelling and Testing (IMEKO TC-4 2023)*, Pordenone, Italy, 20–21 September 2023; IMEKO: Budapest, Hungary, 2023; pp. 154–159.
2. Rajendran, V.G.; Jayalalitha, S.; Adalarasu, K. EEG based evaluation of examination stress and test anxiety among college students. *IRBM* **2022**, *43*, 349–361. [\[CrossRef\]](#)
3. Negi, S.; Mitra, R. EEG metrics to determine cognitive load and affective states: A pilot study. In *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the ACM International Symposium on Wearable Computers (UbiComp/ISWC Adjunct)*, Singapore, 8–12 October 2018; Association for Computing Machinery: New York, NY, USA, 2018; pp. 182–185. [\[CrossRef\]](#)
4. Lee, H. Measuring cognitive load with electroencephalography and self-report: Focus on the effect of English-medium learning for Korean students. *Educ. Psychol.* **2014**, *34*, 838–848. [\[CrossRef\]](#)
5. Ramírez-Moreno, M.A.; Díaz-Padilla, M.; Valenzuela-Gómez, K.D.; Vargas-Martínez, A.; Tudón-Martínez, J.C.; Morales-Menendez, R.; Ramírez-Mendoza, R.A.; Pérez-Henríquez, B.L.; Lozoya-Santos, J.d.J. EEG-based tool for prediction of university students' cognitive performance in the classroom. *Brain Sci.* **2021**, *11*, 698. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [\[CrossRef\]](#) [\[PubMed\]](#)
7. Farkish, A.; Bosaghzadeh, A.; Amiri, S.H.; Ebrahimpour, R. Evaluating the effects of educational multimedia design principles on cognitive load using EEG signal analysis. *Educ. Inf. Technol.* **2023**, *28*, 2827–2843. [\[CrossRef\]](#)

8. Guo, X.; Zhu, T.; Wu, C.; Bao, Z.; Liu, Y. Emotional activity is negatively associated with cognitive load in multimedia learning: A case study with EEG signals. *Front. Psychol.* **2022**, *13*, 889427. [[CrossRef](#)] [[PubMed](#)]
9. Sarailoo, R.; Latifzadeh, K.; Amiri, S.H.; Bosaghzadeh, A.; Ebrahimpour, R. Assessment of instantaneous cognitive load imposed by educational multimedia using electroencephalography signals. *Front. Neurosci.* **2022**, *16*, 744737. [[CrossRef](#)] [[PubMed](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.