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EEG biomarkers of cognitive load: Insights from incremental element encoding in short-term working memory

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ABSTRACT

Cognitive load refers to the mental effort required to encode, maintain, and manipulate information. Although previous electroencephalography (EEG) research has examined spectral biomarkers of cognitive load, most studies employed static task paradigms that average neural activity across entire difficulty levels. Such an approach presupposes that cognitive load remains constant within each level, thereby neglecting transient fluctuations that may arise during information processing. To address this limitation, we implemented a novel EEG-based incremental encoding paradigm to track dynamic changes in cognitive load over time. EEG was recorded from 24 healthy young adults performing the Corsi Block-Tapping Test, a visuospatial short-term memory task with sequential stimulus presentation. Items were added one by one to working memory, simulating real-world cognitive demands. Spectral absolute power was estimated across theta (4–8 Hz), alpha (8–13 Hz), low beta (13–20 Hz), high beta (20–30 Hz), and gamma (> 30 Hz) bands in frontal and parietal regions. Independently of the number of encoded elements, spectral power increased relative to rest: frontal theta by 80.52%, parietal theta by 139.66%, and frontal alpha by 17.72%, reflecting general attention engagement. In contrast, low beta power decreased consistently as more items were encoded ($p < 0.01$, $r > 0.5$), arising as the most reliable biomarker of incremental memory load. A spectral shift toward higher beta frequencies was also observed with increased load. These results challenge the conventional understanding of theta as a biomarker of working memory and highlight beta-band dynamics as key to real-time cognitive monitoring in adaptive systems.

1. Introduction

Cognitive load refers to the mental effort required to perform a task, encompassing the amount of cognitive resources that must be mobilized to achieve a given objective [1]. Although definitions of cognitive load vary between disciplines, it is broadly understood as the demand placed on working memory, a limited-capacity system responsible for temporarily storing, maintaining, and manipulating information during task execution [2]. As task demands increase, the finite capacity of the brain to manage and allocate resources becomes a limiting factor [3]. This limitation means that as more cognitive resources are consumed by a task, fewer remain available for other processes or challenges. The cognitive load, therefore, results from the inherent demands of a given task in addition to the interaction between these demands and the individual's cognitive capacity [4]. When the resources required for a task or multiple tasks simultaneously exceed this capacity, cognitive overload occurs. This overload state decreases the individual's ability to complete tasks effectively, as cognitive resources become saturated and cannot be efficiently redistributed [3,5]. Cognitive overload is particularly evident in modern societies, where the complexity and volume of information have increased dramatically. This phenomenon can have serious implications for both the worker's mental health and workplace safety [6,7], as sustained overload may lead to chronic stress and cognitive fatigue. In professional settings that require precision and quick decision making, such as air traffic control, healthcare, and military operations, the risks of cognitive overload are even more pronounced. In these fields, human errors due to cognitive saturation can result in severe or even fatal outcomes [8,9]. Moreover, cognitive overload is not limited to professional environments. It also affects

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daily life activities, such as driving [10], or recreational tasks like video gaming [11]. In these contexts, monitoring cognitive load can enhance performance, improve safety, and optimize user experiences. Therefore, identifying biomarkers to monitor cognitive load in real-time is of great interest across multiple domains.

Traditionally, cognitive load has been assessed using mental effort scales, among which the NASA Task Load Index (NASA-TLX) [12] and the Subjective Workload Assessment Technique (SWAT) [13] stand out. These tools are administered to subjects immediately after completing a task to rate perceived cognitive effort. In addition, its quick and simple implementation has contributed to their widespread use [1]. However, they present a series of limitations. Firstly, they are entirely subjective, since the perception of difficulty depends on personal factors that do not necessarily correlate with the actual cognitive load [14]. Furthermore, they do not provide real-time information, offering only a snapshot of the cognitive load after the task has been completed. This limitation complicates their use to prevent potential problems caused by cognitive overload during task execution.

In response to these limitations, physiological measures have emerged as promising alternatives to obtain more accurate real-time data on cognitive load during task execution. These measures exploit the physiological responses of the human body, which are closely linked to cognitive processes [15]. For instance, heart rate variability provides insight into autonomic nervous system activity, reflecting stress levels. Eye tracking measures, such as pupil size and blink rate, offer information on attention and effort. Body temperature and skin conductance can also indicate stress-related changes [15]. However, to capture rapid and moment-to-moment changes in cognitive load, brain-derived metrics are particularly valuable [16]. Among these, electroencephalography (EEG) stands out as a highly effective tool as it allows the non-invasive and real-time recording of brain electrical activity through electrodes placed on the scalp. Although EEG presents certain limitations, such as low spatial resolution and susceptibility to artifacts that require appropriate pre-processing, its high temporal resolution, lower cost compared to other neuroimage techniques, and portability, make it a highly useful technique for studying cognitive load [16].

The investigation of cognitive load using EEG commonly involves the application of two primary paradigms: (1) single task and (2) multiple task. The single task paradigm involves completing a single activity varying difficulty levels, while multitasks paradigms require participants to perform multiple tasks simultaneously [17]. Single task paradigms often rely on tasks that manipulate working memory demands, such as the N-Back test or the Corsi Block-Tapping test [18,19]. In the former, cognitive load is adjusted by increasing the number of items participants must recall and compare [18]. Many studies using this approach report an increase in theta power in the frontal regions as task difficulty rises, along with a decrease in alpha power in the parietal areas [20,21]. Similar findings regarding the theta power have been noted in other single task paradigm. For example, Galkin et al. [22] opted to use the Corsi Block-Tapping test, which involves recalling and reproducing a sequence of spatial locations [19], also reporting increases in frontal theta power corresponding to rising task difficulty. However, results for the alpha power are mixed in literature. While some studies report alpha power decreases under high cognitive load [20,21], others, such as Mak et al. [23], have observed the opposite effect. In their investigation, participants performed increasingly complex mirror-drawing tasks and they observed an increment in upper alpha power in frontal regions during high-demand conditions. On the other hand, multitask paradigms (2) induce cognitive load by requiring participants to manage multiple concurrent activities. For example, Puma et al. [24] studied multitasking environments, progressively increasing the number of sub-tasks participants needed to complete simultaneously. Their results revealed an increase in frontal theta power and in parietal alpha power as cognitive load intensified. While both approaches are valuable, the single task paradigm allows for more controlled study of cognitive load by minimizing confounding factors [25]. Moreover, the single task paradigm is more commonly used in the literature due to its ability to offer a more controlled assessment of cognitive load [25].

Beyond the distinction between single- and multitask paradigms, another important dimension in cognitive load research lies in how task difficulty is labeled and analyzed. Most studies adopt traditional paradigms [21,23,26]. These traditional paradigms, such as the N-Back or standard implementations of the Corsi Block-Tapping test, typically manipulate difficulty through discrete levels [27,28]. In the N-Back, for instance, participants must compare the current stimulus to one presented N steps earlier, with cognitive demand increasing as N rises. In the Corsi task, participants observe a sequence of spatial locations that light up in a fixed order and are required to reproduce the same sequence [29]. Task difficulty increases by adding more elements to the sequence (for example, 5, 6, or 7 locations to remember). Each of these levels is treated as a distinct condition, and EEG data are segmented into short epochs within each trial and then averaged across repetitions of that level [27,28]. This approach assumes that the cognitive load remains stable throughout the entire level. However, this assumption overlooks the fact that mental effort often changes dynamically within a single level [30]. In the Corsi task, for example, the participant starts with an empty working memory and sequentially adds new items as they appear. Encoding the second or third element is generally less demanding than encoding the sixth or seventh. Yet, under the traditional static grading approach, all EEG epochs within that trial are treated as equally difficult, thereby masking the gradual buildup of cognitive load over time. To better capture these internal fluctuations, dynamic paradigms have been proposed [30,31]. Instead of aggregating EEG data by level, these paradigms track how cognitive load evolves during the sequential encoding of information. By aligning EEG signals to the moment each new item is introduced, researchers can examine how neural activity changes at finer temporal resolutions. This enables the identification of time-specific patterns that reflect the incremental demands placed on working memory [30,31]. Recent work by Liu et al. [32] reinforces the importance of this approach. With their study, they demonstrated that analyzing EEG signals at short timescales significantly improves cognitive load prediction.

Despite the advancements in cognitive load research, several limitations remain within the existing literature. One prominent issue is the high inter- and intra- subject variability in EEG recordings. This is influenced by individual cognitive responses and variability in electrode placement, impedance, and other manual aspects of EEG setup [33–35]. In addition, anatomical differences such as head shape, skull thickness, and tissue conductivity further affect the recorded EEG signals [36]. All these factors influence the EEG signal responses, hindering the development of a universal cognitive load index and limiting the generalizability of the results. To address this, implementing a consistent referencing method that accounts for each subject's baseline cognitive state could help to reduce this variability. For instance, Kakkos et al. [37] demonstrated that specific EEG spectral and connectivity features can successfully discriminate mental workload levels across different working memory tasks, revealing common neural mechanisms underlying cognitive demand. Their findings highlight the feasibility of developing general-purpose workload biomarkers that are robust across tasks. In this direction, implementing a consistent referencing method that accounts for each subject's baseline cognitive state could help reduce variability and enhance the robustness of EEG-based workload assessment. However, to date, this approach remains largely unexplored in cognitive load literature.

Another significant limitation in the study of cognitive load lies in the predominant reliance on traditional paradigms [21,23,27,28]. For example, in the N-Back test, epochs for levels $N = 2$ or $N = 3$ are grouped, EEG features are extracted, and comparisons are made across these difficulty levels [20,21,27]. However, real-world scenarios, such as performing a surgical procedure, driving in a complex traffic

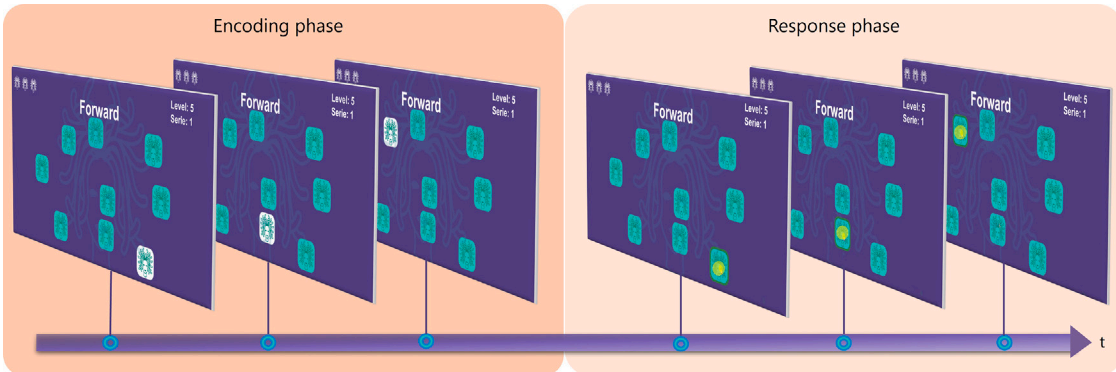

Fig. 1. Snapshot of the Corsi-Block Tapping test in ITACA [38].

environment, or managing air traffic, often involve rapidly fluctuating cognitive demands rather than sustained difficulty over time [30]. In these contexts, cognitive load can increase quickly as more information must be retained and processed in working memory. For instance, a surgeon may need to remember a sequence of steps while simultaneously adapting to unexpected complications, or an air traffic controller must track an increasing number of aircraft within their sector. To enable real-time monitoring of cognitive load in such dynamic scenarios, it is important to identify biomarkers capable of assessing the sequential integration of new information into working memory. Consequently, exploring tests with finer resolution, which enable a more detailed examination of these incremental encoding processes, could significantly enhance their suitability for practical, real-time use. Nevertheless, to the best of our knowledge, this type of analysis, focused on the development of biomarkers capable of tracking rapid changes in cognitive load, remains underexplored.

Based on the identified limitations in previous studies, we hypothesized that the use of EEG to study incremental element encoding could lead to the identification of highly sensitive biomarkers of rapidly cognitive load fluctuations. These biomarkers would offer improved resolution for monitoring real-time changes in cognitive load, making them particularly valuable for real-world applications. Thus, the main objective of this study is to examine spectral changes in EEG activity in response to incremental encoding of short-term memory elements during the Corsi Block-Tapping test. To achieve this goal, we analyzed EEG data from a cohort of 24 young, healthy subjects using a methodology designed to reduce inter-subject variability. The main novelties and contributions of this study are twofold: (1) the identification of highly sensitive spectral EEG biomarkers that provide a detailed representation of cognitive load fluctuations during incremental element encoding; and (2) the reduction of inter-subject variability by leveraging baseline EEG parameters from resting-state recordings. This framework lays the groundwork for real-time cognitive load monitoring in complex, high-demand environments.

2. Materials and methods

2.1. Subjects and signals

For this research, we utilized a database compiled for the validation of ITACA, an application intended to design, conduct, and evaluate neurofeedback studies [38]. The database includes EEG recordings obtained during cognitive tests in 24 healthy participants (14 women, 10 men) with an average age of 24.47 ± 4.17 years. All participants received a full explanation of the study procedures, the type of data to be collected, how their data would be analyzed, and the measures in place to protect their privacy. Each participant provided written informed consent prior to participation. All experimental procedures were carried out under a strict internal protocol in accordance with the Declaration of Helsinki [37], ensuring participant safety, data confidentiality, and adherence to recognized international ethical standards. The EEG signals were recorded using a g.USBamp amplifier (g.TEC, Austria) equipped with 16 active Ag/AgCl electrodes located in F7, F3, Fz, F4, F8, FCz, C3, Cz, CPz, P3, Pz, P4, PO7, POz, and PO8, according to the international 10-10 system [39], with a sampling frequency of 256 Hz. There are two types of recordings in this database: (1) resting-state data, during which participants remained with their eyes open for three minutes without engaging in any cognitive tasks; and (2) EEG synchronized with events presented during the execution of each cognitive test. All recordings were carried out using MEDUSA© Platform [40], specifically employing the publicly available Recorder [41] and ITACA Corsi Block-Tapping Test [42] applications.

2.2. Corsi block-tapping test

Among the different cognitive psychology tests, the Corsi Block-Tapping test, which assesses visuo-spatial short term working memory, was selected as the central focus of the study [29]. Fig. 1 shows a screenshot of the implementation of this test in MEDUSA© Platform. This test involves two stages. First, the application presents the sequence of blocks that the user has to memorize by highlighting them in a specific order. The stimulus duration was 500 ms, and the inter-stimulus interval was set to 1000 ms. Once the whole sequence has been presented, the user has to repeat the sequence in the same order by clicking the corresponding blocks. As users respond correctly, the length of the presented sequence increases, thereby progressively increasing the maximum cognitive demands. This gradual increase forces users to encode more information until they reach the limit of their working memory capacity. At that point their resources become saturated, making it impossible to retain all the information [3]. The decision to focus on the Corsi Block-Tapping test lies in that its structure allows for a controlled progression of cognitive load through discrete, countable events. This enables to study how cognitive load evolves not only as general task difficulty increases, but also within a fixed difficulty level, as new elements are sequentially encoded. These characteristics of the Corsi Block-Tapping test make it particularly suitable for studying how cognitive load evolves in response to incremental element encoding.

In the implementation provided by the ITACA framework, the test is structured into levels, series, and trials, following the same approach as described in [43]. Each difficulty level (i.e., each sequence length) consists of three series, and each series comprises three trials. To pass a series, the user must correctly complete at least two of the three trials. Then, to advance to the next level, the user must successfully complete all three series. This means correctly answering at least six trials out of nine (two per series). Additionally, in ITACA's default implementation, the test starts with an initial sequence length of 4, which progressively increases. Due to these rules, not all users reach the same level, as memory capacity varies between individuals, with 9 being the maximum possible number of items to remember.

Table 1
Distribution of available epochs per subject and class following the preprocessing stage.

Subject	Class 0	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
S01	170	25	25	25	25	17	8	0	–
S02	141	16	16	16	16	7	–	–	–
S03	144	7	7	7	7	–	–	–	–
S04	160	28	28	28	28	19	10	3	–
S05	156	20	20	20	20	11	4	–	–
S06	137	24	24	24	24	15	7	–	–
S07	169	15	15	15	15	8	1	–	–
S08	174	21	21	21	21	12	3	–	–
S09	163	17	17	17	17	8	1	–	–
S10	156	30	30	30	30	21	12	6	–
S11	150	17	17	17	17	8	1	–	–
S12	167	36	36	36	36	27	18	10	3
S13	172	23	23	23	23	14	8	0	–
S14	154	19	19	19	19	10	1	–	–
S15	132	22	22	22	22	14	6	–	–
S16	149	27	27	27	27	18	10	1	–
S17	168	24	24	24	24	10	1	–	–
S18	164	19	19	19	19	10	1	–	–
S19	137	34	34	34	34	25	16	8	1
S20	154	17	17	17	17	8	0	–	–
S21	143	30	30	30	30	21	13	6	–
S22	136	25	25	25	25	17	8	0	–
S23	164	23	23	23	23	14	5	–	–
S24	143	28	28	28	28	19	11	3	–
Total	**3703**	**547**	**547**	**547**	**547**	**333**	**145**	**37**	**4**

2.3. EEG preprocessing

Before characterizing cognitive load during task execution, it is necessary to preprocess the signal to remove noise and artifacts, thereby ensuring data quality. For this purpose, MEDUSA© software was used [40]. First, a finite impulse response (FIR) band-pass filter of order 1000 was applied between 0.5 and 60 Hz to encompass relevant brain activity, along with a notch filter of order 1001 between 49 and 51 Hz to eliminate power line interferences [44].

Next, the signal was segmented into 1-s epochs starting from the onset of each stimuli, marking the timestamp when the brain's response is triggered. This approach is designed to capture cognitive processes related to the discrete encoding and storage of information. Resting-state recordings were similarly segmented into 1-s epochs for consistency. To ensure artifact-free data, epochs were automatically rejected if the amplitude exceeded a threshold of $\sigma = 4$ times the standard deviation in at least two samples within one or more channels, following the guidelines in [45]. This method accounts for a broad range of artifacts, including eye blinks, muscle activity, and electrode noise, by directly removing contaminated epochs. The artifact rejection process was implemented using the MEDUSA© software, which includes validated routines for signal preprocessing [40]. The remaining clean epochs were then categorized into different groups for subsequent analysis. Resting-state epochs were assigned to class 0, representing the reference condition with absence of cognitive load. For the Corsi Block-Tapping test, cognitive load was modeled based on the number of elements that have been encoded in working memory during an specific trial, as illustrated in Fig. 2. For example, epochs corresponding to the first stimulus were assigned to class 1, reflecting minimal cognitive load since no prior elements had been encoded. Similarly, epochs related to the second stimulus were assigned to class 2, reflecting the encoding of one prior element, and so on. This segmentation strategy is a key methodological contribution of our study, as it has not been applied in previous cognitive load research, and enables a more precise analysis of how cognitive load evolves as additional elements are encoded.

It is worth noting that not all participants reached the higher task difficulty levels, leading to a class imbalance. Classes 8 and 9 had very few epochs available and were therefore excluded from the analysis. Likewise, only epochs associated with correctly responded trials were included, as errors could introduce confounding factors. For instance, incorrect trials may reflect lapses in attention or other cognitive processes unrelated to the encoding of additional elements. For this reason, all epochs from incorrect trials were discarded, as done in [20]. The final number of epochs available for each class and each subject after the preprocessing stage can be seen in Table 1.

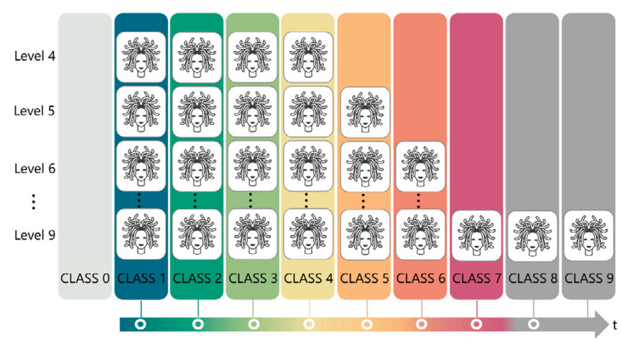

Fig. 2. Epoch labeling based on the number of stimuli encoded in working memory within each trial, corresponding to each level of difficulty. Classes 8 and 9 were excluded from analysis due to an insufficient number of observations.

2.4. Spectral analysis for cognitive load characterization

To analyze and characterize how cognitive load impacts information encoding, this study focused on features extracted from the spectral domain of EEG signals in the frontal and parietal regions, as these areas are known to be highly involved in cognitive processes [46]. The frontal region, primarily responsible for executive control and attentional regulation, and the parietal region, critical for visuospatial processing [46]. In particular, we examined the absolute power within five frequency bands: theta (4–8 Hz), alpha (8–13 Hz), low beta (13–20 Hz), high beta (20–30 Hz), and gamma (>30 Hz) [47]. Although relative power is commonly used in EEG studies, we opted for absolute power because it allows for a more precise identification of where changes in activity occur [48]. Relative power, by normalizing the power within a specific frequency band to the total power across bands, can obscure the interpretation of changes. For instance, a decrease in one band's relative power might result not from an actual reduction in activity within that band but from an increase in another band's absolute power, while the original band remains unchanged.

To obtain absolute power values, we first calculated the power spectral density (PSD) for each EEG channel using the Welch method. To do so, a Hanning window of 500 ms was applied with 80% segment overlap. With a sampling rate of 256 Hz, this corresponds to 128 points per window in the Fast Fourier Transform (FFT), yielding a frequency resolution of 1 Hz. From the resulting PSD, we extracted absolute power values for each frequency band. We then averaged these values across frontal electrodes (F7, F3, Fz, F4, F8, FCz) and parietal electrodes (P3, Pz, P4, PO7, POz, PO8), which are key regions involved in attention and working memory processes [46]. The delta band (<4 Hz) was excluded from the analysis due to the limited segment length used for spectral estimation. Reliable power estimation typically requires at least 3–4 cycles per frequency within each epoch [49]. At 4 Hz, we observed 4 cycles per second, barely meeting this threshold, whereas lower frequencies like 1–3 Hz yield fewer than 4 cycles. This makes the estimation unreliable. Thus, to ensure spectral accuracy, we restricted our analysis to frequencies above 4 Hz. In addition, delta activity is predominantly associated with sleep and non-cognitive processes, and thus has limited relevance for the analysis of task-related cognitive load in awake, healthy participants [50,51].

We performed two types of analyses using the absolute power data. First, we analyzed overall power differences between the resting state and task conditions within the frontal and parietal regions. Specifically, the power values were averaged across all epochs recorded during the task, regardless of the class. This approach aimed to capture general cognitive engagement by comparing the resting state with the overall brain activity during task execution. Second, we explored cognitive load dynamics during the encoding of discrete information in working memory. The aim was to focus on differences across individual task classes in the frontal and parietal regions. Given the inherent inter-subject variability in EEG power [33], normalization was used to adjust for baseline differences in each participant's resting-state power [52]. Specifically, mean power in each frequency band during resting state was subtracted from task-based power values for each class and expressed as a percentage increment relative to the resting-state power. This procedure reduces individual variability, providing a more reliable basis for assessing cognitive load changes across task classes.

Following these analyses, statistical tests were performed for each approach. Firstly, we applied the Shapiro–Wilk test to assess the normality of the data distributions. As most bands returned p-values below 0.05, normality was rejected. Consequently, for the comparison between resting and task conditions, we applied the Wilcoxon signed-rank test to absolute power values across all frequency bands in the frontal and parietal regions to assess overall cognitive engagement. For the analysis across task classes, we applied the same test to normalized power increments for each frequency band, evaluating changes associated with the increasing number of encoded elements. In both cases, we set a significance level of 0.05 and applied a false discovery rate (FDR) correction using the Benjamini–Hochberg method to account for multiple comparisons [53]. Additionally, to quantify the magnitude of the observed effects, we estimated the effect size using the rank-based correlation coefficient r, which is appropriate for non-parametric data [54]. According to established thresholds, $r > 0.5$ indicates a large effect size, while $r > 0.3$ is considered a medium effect [54].

3. Results

In this section, we present the findings from the spectral power analysis for both approaches: overall power differences between the resting state and task conditions, and power variations with incremental element encoding. Table 2 summarizes the results for both the frontal and parietal regions. In this table, we report the absolute power in each band for both the resting state and task conditions. Additionally, corrected p-values are displayed. These p-values indicate statistically significant differences across all frequency bands between the resting and task conditions, which suggests a general power increase due to cognitive engagement during task execution.

For the analysis of cognitive load dynamics in the encoding of discrete information elements, each frequency band is represented in Fig. 3. In the theta band, no statistically significant differences were found between the cognitive load classes, where each class corresponds to the number of elements being encoded into working memory (Fig. 3A). Similarly, in the alpha band, hardly any significant differences were observed as the number of encoded elements increased (Fig. 3B). For the low beta band, we observed a clear downward trend in baseline-normalized power as cognitive load increased, with statistically significant differences identified between nearly all classes (Fig. 3C). In the high beta band, baseline-normalized power also showed a downward trend in the frontal and parietal channels, with statistically significant differences appearing primarily between lower and higher classes (Fig. 3D). Lastly, in the gamma band we also found statistically significant differences in absolute power distributions in both regions (Fig. 3E). The most differences are observed in the classes where fewer elements are encoded.

4. Discussion

4.1. Cognitive load characterization

We investigated the spectral power changes across various EEG frequency bands during the encoding of information in a working memory task, focusing specifically on frontal and parietal regions. Unlike traditional paradigms that rely on fixed difficulty levels, our study was designed to emulate the dynamic nature of cognitive load as experienced in real-world tasks. Specifically, EEG dynamics is analyzed in response to the incremental encoding of individual elements with the Corsi Block-Tapping test. This fine-grained analysis offers novel insights into the neural mechanism underlying cognitive load fluctuations and highlights potential biomarkers for real-time monitoring. A summary of the findings from other relevant studies alongside our results is presented in Table 3.

The primary strength of our approach is the dynamic analysis of cognitive load fluctuations. Traditional methods typically assign a uniform difficulty label to entire levels and average EEG activity across them to extract general patterns of cognitive demand [20,21,23,27,55]. While this strategy is useful for identifying broad trends, it inherently assumes that cognitive load remains stable throughout the task level, overlooking the fact that mental effort often varies significantly as information is progressively encoded. In contrast, our approach captures the evolving nature of cognitive load by aligning the EEG analysis with the temporal structure of the task itself, specifically the sequential encoding of new elements in working memory. This allows for a finer-grained characterization of how mental effort increases within a single level, providing greater sensitivity to subtle neural fluctuations. Moreover, our approach aligns with recent findings from [32], who emphasize the importance of tracking EEG changes on a moment-to-moment basis to better detect variations in cognitive demand. Their results support the broader view that EEG signals reflect fast, transient mental states that unfold over short time windows. This validates our approach of analyzing within-level dynamics, as opposed to aggregating across fixed difficulty levels, because it provides a more precise way to assess how cognitive load evolves throughout the task. In addition, this is particularly valuable for applications requiring dynamic monitoring, as it reflects the rapid shifts in mental effort often overlooked by conventional approaches. This granularity aligns more closely with real-life tasks that demand continuous adaptation and dynamic allocation of cognitive resources.

Our findings regarding the theta band (4–8 Hz) align with the existing literature, showing an statistically significant increase in theta power relative to the resting state in the frontal and parietal regions.

Table 2
Comparison of averaged EEG absolution power values between resting state and cognitive tasks within frontal and parietal regions.

Frequency band	Resting (μV^2)	Cognitive task (μV^2)	*p-value*	Percentage variation
Frontal region				
Theta (4–8 Hz)	0.077	0.139	3.58e−06	80.52%
Alpha (8–13 Hz)	0.079	0.093	0.033	17.72%
Low Beta (13–20 Hz)	0.042	0.049	0.033	16.67%
High Beta (20–30 Hz)	0.044	0.053	0.033	20.45%
Gamma (>30 Hz)	0.047	0.070	0.004	48.94%
Parietal region				
Theta (4–8 Hz)	0.058	0.139	1.19e−06	139.66%
Alpha (8–13 Hz)	0.071	0.107	1.11e−04	50.70%
Low Beta (13–20 Hz)	0.048	0.069	1.81e−04	43.75%
High Beta (20–30 Hz)	0.038	0.062	3.50e−05	63.16%
Gamma (>30 Hz)	0.050	0.100	1.13e−05	100.00%

P-values were calculated using the Wilcoxon signed-rank test and corrected for multiple comparisons using the Benjamini–Hochberg method. All comparisons are statistically significant (p-value < 0.05).

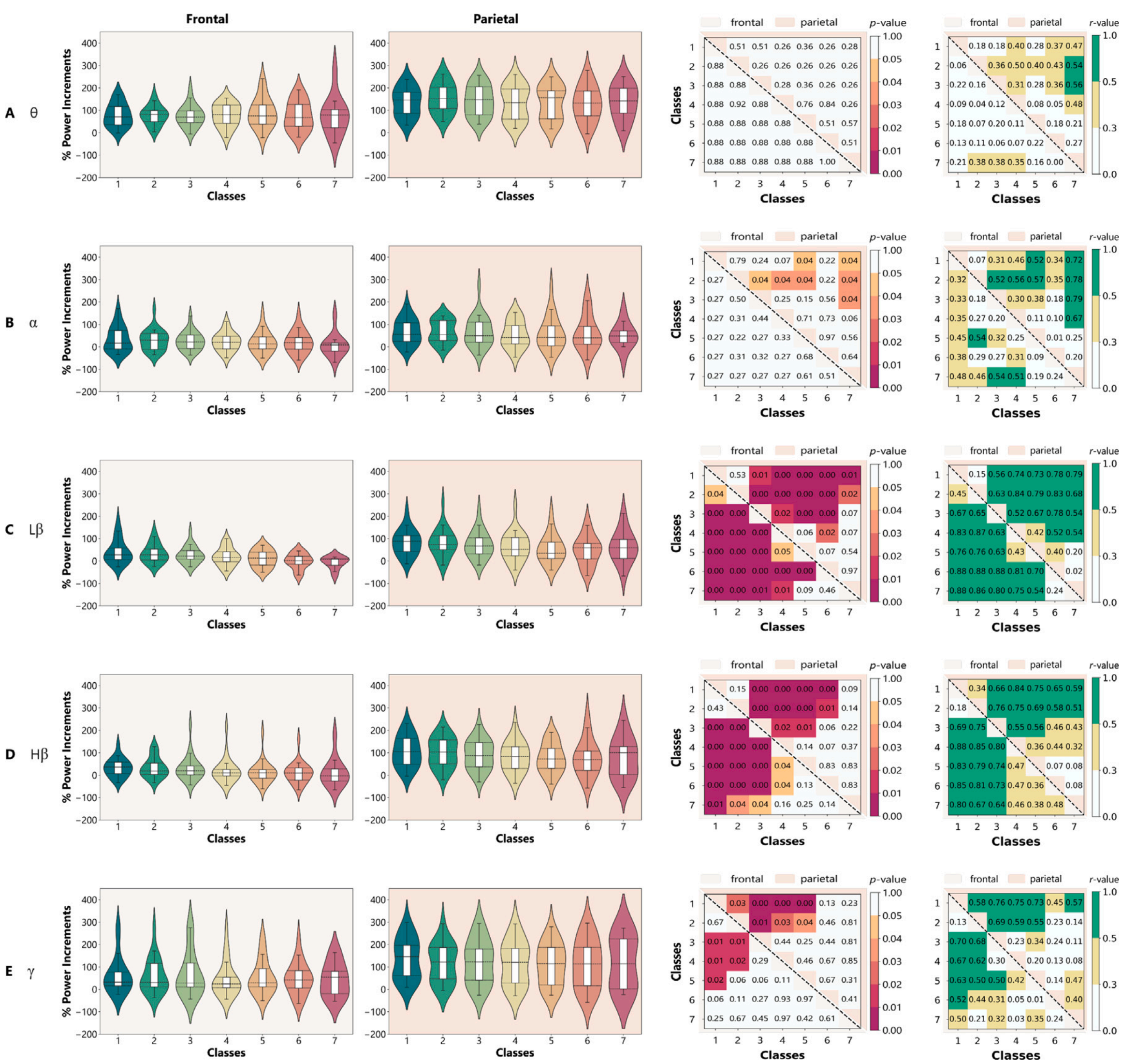

Fig. 3. Analysis of baseline-normalized power across frequency bands and task classes. Each row corresponds to a specific frequency band. **A**: theta (θ, 4–8 Hz); **B**: alpha (α, 8–13 Hz); **C**: low beta ($L\beta$, 13–20 Hz); **D**: high beta ($H\beta$, 20–30 Hz); **E**: and gamma (γ, >30 Hz). For each band, the left display violin plots and overlaid boxplots of absolute baseline-normalized power increments in the frontal (left plot) and parietal regions (right plot). The violin plots illustrate the distribution shapes for each class, while the central line within the boxplots represents the median power increment, and the upper and lower lines indicate the interquartile range. The central panel presents matrices of corrected *p*-values from pairwise statistical comparisons between classes. Each matrix is divided into two triangular regions: the lower-left triangle corresponds to comparisons within the frontal region, and the upper-right triangle corresponds to comparisons within the parietal region. Non-white cells in the matrices indicate statistically significant differences ($p < 0.05$) between classes. Statistical comparisons were performed using the Wilcoxon rank-sum test with a Benjamini–Hochberg FDR correction for multiple comparisons. The rightmost panel shows the corresponding effect size matrices (r-values), allowing interpretation of the magnitude of these differences. Darker shades represent larger effect sizes, with values above 0.5 indicating large effects and values above 0.3 representing medium effects.

Table 3
Summary of findings from the literature analyzing cognitive load through EEG and extracting frequency features.

Authors	Task	Cognitive domain	Signal analysis	Extracted features	Results
Pergher et al. [20]	N-Back Test	Visuospatial	Task level averaging	P300 amplitude ERPs, power in θ and α	↑ Power in θ with CL in F region ↓ Power in α with CL in P region
Brouwer et al. [27]	N-Back Test	Visuospatial	Task level averaging	ERPs, power between 2 and 20 Hz	↓ Power in α with CL in Pz
Plechawska et al. [28]	Arithmetic tasks	Arithmetic	Task level averaging	Power in δ, θ, α, low β, and high β	Higher correlation between CL level and β-band characteristics
Mak et al. [23]	Mirror drawing	Motor planning	Task level averaging	Power in δ, θ, α, β, γ bands	↑ Power in α and θ with CL in F region
So et al. [55]	Arithmetic, visual-motor, and linguistic tasks	Arithmetic, verbal and motor planning	Task level averaging	Power in θ, α, β, and γ bands	↑ Power in θ with CL in F region
Puma et al. [24]	Priority Management Task	Sustained attention	Task level averaging	Mean power at θ and α	↑ Power in θ with CL in F region ↑ Power in α with CL in P region
Wang et al. [21]	N-Back Test	Visuospatial	Task level averaging	Mean, variance, skewness and kurtosis; θ, α, β, and γ powers	↑ Power in θ with CL in F region ↓ Power in α with CL in P region
Galkin et al. [22]	Corsi Block-Tapping Test	Visuospatial	Task level averaging	θ, α, and β powers	↑ Power in θ with CL in F region ↓ Power in α with CL in C and P regions
Schapkin et al. [56]	Multiple stimulus–response mappings	Sustained attention and motor planning	Task level averaging	θ, α, low β, and high β powers	↑ Power in θ with CL widespread ↓ Power in α with CL widespread ↑ Power low β with performance decline in T ↑ Power high β with performance decline in C, P, and PT regions
Zammit et al. [57]	Matching-to-sample task	Visuospatial	Task level averaging	α and β powers	↓ Power in α with CL in F and P regions ↓ Power in β with CL in F and P regions
Pavlov et al. [58]	Memorizing 5-6-7 elements forward and backwards	Visuospatial	Task level averaging	θ, α, low β, and high β powers	↑ Power in θ with CL in the midline ↓ Power in low α with CL in P and F regions ↓ Power in low β with CL in PO regions ↑ Power in high β with CL in F and P regions
This work	Corsi Block-Tapping Test	Visuospatial	IEE[a]	Baseline-normalized power in θ, α, low β, high β, and γ bands	No variation in θ&α powers with IEE in F and P ↓ Power in low β with IEE in F and P regions ↓ Power high β with IEE in F and P regions ↑ γ-power variability in F and P regions

[a] Note that all studies except this one averaged epochs across stimuli per task level, instead of considering the number of elements being encoded in real-time. CL: cognitive load. ERPs: Event related potentials. Frequency bands: θ (theta), α (alpha), β (beta), γ (gamma). Regions: F (Frontal), P (Parietal), C (Central), T (Temporal), O (Occipital). IEE: incremental element encoding.

This rise in theta power has been associated with cognitive engagement, particularly in tasks that involve working memory and mental effort [46]. However, while previous studies demonstrated theta power increases with overall task difficulty [20,21,23,55], our results reveal that frontal theta power remains stable during incremental element encoding (Fig. 3A). This suggest that theta power reflects general task engagement but does not track the stepwise increases in cognitive demand associated with encoding additional items. This distinction implies that theta activity may be more closely related to task initiation and sustained attention than to dynamic encoding processes. Thus theta band may have a limited utility as a biomarker for detecting rapid cognitive load fluctuations in real-time.

The dynamics of alpha power in working memory tasks have shown mixed results in the literature, as summarized in Table 3. Some studies report alpha desynchronization (i.e., decreased alpha power) with increasing task difficulty, especially in visuospatial memory tasks such as the N-Back or Corsi Block-Tapping test [20–22,27]. This has been linked to increased cognitive effort during encoding and maintenance. Others, however, find alpha synchronization (i.e., increased alpha power) under higher load, particularly in tasks involving attentional control or motor planning, such as mirror drawing [23] or priority management [24]. These increases are interpreted as reflecting inhibitory processes that suppress distractions and help maintain task focus. Still, other task types, such as arithmetic or language-based paradigms, show more variable alpha responses depending on whether they involve verbal or spatial processing [28,55]. In our study, we observed a statistically significant increase in alpha power (8–13 Hz) during task conditions relative to the resting state in both frontal and parietal regions, as shown in Table 2. However, when examining alpha power across individual elements being encoded, significant differences were minimal. Only a slight trend of decreasing alpha power in the parietal region has been shown as the number of encoded elements increased (Fig. 3B). This trend is consistent with prior visuospatial memory findings, linking alpha desynchronization to the retention of information in working memory [20–22,27]. These results suggest that alpha-band responses are highly sensitive to the specific cognitive demands of a task, whether spatial, verbal, motor, or attentional, rather than to general task difficulty alone. In our case, alpha modulation was aligned with the expected pattern for visuospatial tasks but failed to reflect dynamic changes in cognitive load. Therefore, based on our results, alpha power does not appear to be a suitable biomarker for real-time monitoring of cognitive load, as it fails to track the rapid changes associated with encoding additional elements.

The most significant findings in our study were observed in the beta bands, especially in the frontal region, which is known for its role in executive functions, attention, and working memory control [50]. With the incremental element encoding approach, we identified a progressive decrease in baseline-normalized power within the low beta band (13–20 Hz) as more elements were encoded. This trend exhibited statistically significant differences across nearly all levels of encoded elements (Fig. 3C), with large effect sizes ($r > 0.5$) observed in most comparisons, both in frontal and parietal regions, reinforcing the robustness of the observed pattern. This frontal low beta desynchronization has been linked in previous work to the flexible reconfiguration of large-scale neural circuits supporting cognitive control. Specifically, it is thought to reflect a release of network inhibition, enabling transient communication between task-relevant brain regions [59,60]. The prefrontal cortex plays a central role in this process by coordinating distributed activity as cognitive load increases. In our task, as more spatial locations were encoded, reduced beta synchrony may reflect a greater need for dynamic allocation of resources across the frontoparietal network. This would be consistent with the involvement of prefrontal mechanisms in managing increasing memory demands. All these findings are aligned with prior literature. For instance, Zammit et al. [57] observed a reduction in beta power during a matching-to-sample task, while Pavlov et al. [58] reported a decrease in low beta power during the retention of 5–7 elements in working memory. However, a key distinction lies in our methodological approach: instead of averaging brain activity across broad task difficulty levels, we incrementally analyzed the EEG signal within levels. This approach enhances sensitivity to the neural changes accompanying gradual increases in cognitive load and highlights the utility of low beta power as a fine-grained indicator of encoding demands. We hypothesize that these changes allow cognitive resources to be allocated efficiently as task demands increase. Importantly, this finding shows that low beta desynchronization is highly sensitive to incremental cognitive load. This interpretation is consistent with findings by Kakkos et al. [37], who identified task-independent EEG spectral fingerprints that reliable distinguish between levels of mental workload. Therefore, the results support the notion that beta desynchronization may be a potential biomarker for detecting rapid fluctuations in cognitive load and applying in real-time monitoring.

Respectively, high beta (20–30 Hz) showed a statistically significant but less pronounced power decrease, particularly between encoding early and later elements. In the corrected p-values matrix for frontal and parietal regions (Fig. 3D), the frontal region shows clear significant decreases in power for classes 1–3 compared to classes 4–7. A similar but less marked pattern appears in the parietal region. Moreover, effect size analysis revealed medium to large effects in both regions. These results align with Chikhi et al. [46], who reviewed evidence showing low beta is more sensitive to cognitive load than high beta. However, our findings suggest a progressive shift in neural desynchronization, with higher-frequency beta bands becoming more engaged as cognitive demands increase. This likely reflects a redistribution of neural activity, where desynchronization transitions from low to high beta to recruit additional resources for higher cognitive processing. Interestingly, our results contrast with Schapkin et al. [56]. They observed an increase in high beta power during complex stimulus–response tasks and attributed it to motor cortex activations and challenges in response preparations. Their task involved multiple stimulus–response mappings combined with the inhibition of irrelevant stimulus–response mappings, likely engaging additional motor processes [61]. In contrast, the Corsi Block-Tapping task primarily involves cognitive processes, as it focuses on encoding and retaining spatial information without significant motor demands [19,62]. This distinction suggests that the high beta power decrease in our study reflects a role in higher-order cognitive demands rather than motor-related processes.

Regarding gamma activity (>30 Hz), a distinct pattern emerged in the parietal regions. Significant gamma power desynchronization was observed in classes 3, 4, and 5 compared to classes 1 and 2. In contrast, classes 6 and 7 showed a notable increase in gamma power variability. This may be due to the noisier nature of the gamma band [63] and the smaller number of examples in these higher classes. In the frontal region, median gamma power remained stable, but its variability across epochs increased (Fig. 3E). This suggests that frontal gamma activity does not directly scale with the number of encoded elements. Instead, the variability may reflect diverse strategies used by individuals to manage the cognitive load of encoding multiple items. While few studies have analyzed gamma power in working memory tasks, our findings align with Xu et al. [64], who linked gamma dynamics to subjective perceptions of cognitive load. Unlike their focus on functional connectivity, our results emphasizes spectral power changes, suggesting that gamma variability could reflect the heterogeneity of cognitive strategies rather than consistent neural activations patterns.

Our results also reveal important differences in the level of granularity at which different frequency bands reflect cognitive load. Theta and alpha power increased significantly when comparing task performance to the resting state, indicating general task engagement and attentional processes. However, they did not reliably track transient changes during the encoding phase. In contrast, both low and high beta bands showed progressive modulation as more items were encoded, capturing fine-grained, within-level variations in cognitive load. Among them, low beta power emerged as the most sensitive marker for distinguishing between successive encoding steps, making it a robust candidate for dynamic load monitoring. Gamma activity, on the other hand, exhibited increased variability under higher cognitive demands. As previously discussed, this may reflect the involvement of gamma oscillations in individual encoding strategies, which likely vary across participants. These results underscore the importance of adopting high-resolution temporal analysis when studying cognitive load.

All these findings highlight the involvement of both frontal and parietal regions in the encoding process, each contributing according to its specific functional role. Significant changes in EEG signal power are observed in these regions when compared to resting state, indicating their activation during the task. Notably, this broader shift in neural activity may suggests that these regions synchronize during the encoding of multiple items, which may reflect increased connectivity between them.

4.2. Contributions

In summary, the primary contributions of this study are as follows:

- Innovative methodological approach for dynamic analysis of cognitive load: this study represents the first analysis of EEG activity specifically during incremental element encoding in working memory. This approach simulates real-life scenarios where cognitive demands change dynamically, offering a more granular perspective compared to traditional methods. Additionally, EEG power was referenced to a resting state baseline, allowing for the normalization of inter-subject variability and providing a clearer assessment of task-related neural dynamics.
- Frontal low beta (13–20 Hz) desynchronization as a biomarker for cognitive load: our results indicate that low beta band could serve as a key biomarker for tracking cognitive load in real-time during working memory tasks. The sensitivity of low beta power to the number of elements encoded suggests it reflects the brain's neural adjustments as more cognitive resources are allocated for information processing.

– High beta (20–30 Hz) power modulation as an indicator of cognitive demands: We observed that high beta power exhibited a decrease with increasing cognitive load, particularly during the encoding of later elements. This suggests that high beta may play a role in higher-order cognitive processing, potentially reflecting the brain's allocation of resources for managing complex tasks.
– Theta (4–8 Hz) and alpha (8–13 Hz) bands as biomarkers of cognitive engagement:we observed statistically significant power increments relative to the resting state, but no further differences as additional elements were encoded. This suggests that these bands are primarily associated with general cognitive engagement, reflecting heightened attentional processes. However, there are not directly linked to the complexity of encoding multiple elements.

4.3. Limitations and future work

While our study provides valuable insights into the relationship between EEG spectral power and information encoding, several limitations should be addressed. First, there was a class imbalance in the data, particularly in the encoding of the fifth, sixth, and seventh elements, as not all subjects reached these stages in the Corsi Block-Tapping test. Future studies could mitigate this imbalance ensuring that all participants attempt the same number of elements regardless of performance (e.g., continuing the series even after errors). This approach would allow for more robust conclusions. Another important limitation is the individual variability in cognitive load responses, as the same task may represent a high load for one person while being minimal for another. This variability can affect the consistency of results, as different participants may show distinct neural patterns under the same conditions. Implementing individualized analysis strategies could help identify more accurate and sensitive cognitive load biomarkers. Moreover, we did not explore functional or effective connectivity, such as prefrontal–parietal interactions, nor did we assess dynamic connectivity using approaches like meta-state analysis. These measures could offer complementary insights into how inter-regional communication supports encoding, especially in relation to the low beta desynchronization we observed. Future studies could integrate phase-based or information flow metrics to better understand the functional role of low beta oscillations in cognitive load regulation. This would enrich the interpretation of spectral findings and provide a more mechanistic understanding of encoding dynamics. Additionally, we did not test the proposed EEG biomarkers in clinical setups. This limits their generalizability and prevents conclusions about their diagnostic or therapeutic value. Future studies should examine whether these spectral features show differences between healthy individuals and patients, such as mild cognitive impairment, Alzheimer's disease or schizophrenia. Future work could also investigate cognitive load under alternative paradigms, such as dual-task scenarios, to determine whether the observed patterns generalize across tasks with differing demands. Furthermore, it would be valuable to explore how low beta desynchronization correlates with other qualitative metrics, such as self-reported measures of workload (e.g., NASA-TLX questionnaires), and quantitative markers, such as pupil diameter changes measured through eye tracking. These additional measures could strengthen the interpretation of EEG findings and provide a more comprehensive assessment of cognitive load. Finally, the controlled lab settings and the exclusive focus on young healthy participants limit the validity and applicability of the findings to real-world environments or more diverse populations.

Future research could build on our findings and explore real-time cognitive load monitoring in tasks with progressively increasing demands. In education, adaptive platforms could monitor student's mental effort during tasks like solving increasingly complex math problems or memorizing expanding sequences and personalize content accordingly [65]. In high-stakes fields, such as air traffic control or surgery, cognitive load tracking could be applied to scenarios where operators manage progressively larger sets of information or increasing task complexity [51]. This would help to prevent overload and optimize decision-making under stress. In the automotive sector, monitoring driver's cognitive load during progressively demanding driving conditions, such as increasing traffic density, multitasking with navigation systems, or managing vehicle automation levels, could enhance safety by detecting mental overload [10]. Similarly, in healthcare, tasks requiring incremental memory encoding could be used to identify early signs of cognitive decline. The EEG-based biomarkers proposed here could support early screening strategies complementing traditional neuropsychological tests by providing objective, real-time markers of working memory function [66,67]. Finally, in gaming and entertainment, cognitive load monitoring could personalize game difficulty as players progress through levels with increasing challenges, enriching engagement and user experience [68].

5. Conclusions

This research offers a different perspective on the neural dynamics of working memory. For this purpose, we focus on the incremental encoding of discrete elements; that is, the gradual accumulation and temporal storage of information in short-term working memory. Our analysis captures variations within a single task level, as the number of elements being encoded increases progressively, rather than examining static difficulty levels where cognitive demands remain constant. This dynamic approach would enable the identification of neural biomarkers for real-time cognitive load monitoring in practical applications, where cognitive load fluctuates rapidly. The findings, particularly the progressive desynchronization of low beta activity as more elements are encoded, highlight its role as a sensitive indicator of cognitive load variations. Moreover, beta desynchronization shifted towards higher frequencies as cognitive load increased. This suggests that the neural adjustments involved in managing greater memory demands may progressively move to higher beta frequencies. These insights emphasize the relevance of beta oscillations as biomarkers of working memory processes, with low beta providing continuous feedback on task demands and high beta signaling more substantial cognitive adjustments when demands reach higher levels. The results also highlight the stability of the theta and alpha activity, which appear more linked to general task engagement rather than the encoding of specific elements.

CRediT authorship contribution statement

B. Pascual-Roa: Methodology, Writing – original draft, Data curation, Formal analysis, Investigation. **E. Santamaría-Vázquez:** Writing – review & editing, Supervision, Methodology. **D. Marcos-Martínez:** Writing – review & editing. **S. Pérez-Velasco:** Writing – review & editing. **C.R. Ruiz-Gálvez:** Writing – review & editing. **V. Martínez-Cagigal:** Writing – review & editing. **R. Hornero:** Project administration, Funding acquisition, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: **Beatriz Pascual Roa** reports financial support was provided by NextGenerationEU via INVESTIGO Program. **Eduardo Santamaría-Vázquez** reports administrative support was provided by Biomedical Research Network Centre of Bioengineering Biomaterials and Nanomedicine. **Diego Marcos-Martínez** reports financial support was provided by Junta de Castilla y León Consejería de Educación. **Diego Marcos-Martínez** reports administrative support was provided by Biomedical Research Network Centre of Bioengineering Biomaterials and Nanomedicine. **Cristóbal Rubén Ruíz-Gálvez** reports financial support was provided by Junta de Castilla y León Consejería de Educación. **Víctor Martínez-Cagigal** reports administrative support was provided by Biomedical Research Network Centre of Bioengineering Biomaterials and Nanomedicine. **Sergio Pérez-Velasco** reports administrative support was provided by Biomedical Research Network Centre of Bioengineering Biomaterials and Nanomedicine. **Roberto Hornero** reports financial support was provided by Spain Ministry of Science and Innovation. **Roberto Hornero** reports administrative support was provided by Biomedical Research Network Centre of Bioengineering Biomaterials and Nanomedicine.

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Data availability

Data will be made available on request.

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