Eur. Phys. J. Spec. Top. (2026) 235:8011–8018
https://doi.org/10.1140/epjs/s11734-026-02309-8

THE EUROPEAN PHYSICAL JOURNAL SPECIAL TOPICS

Regular Article

Aging effects on the dynamic network interactions of cortical rhythms during different sleep stages: evidence from a network theory-based approach

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Received 7 March 2026 / Accepted 3 April 2026 / Published online 9 April 2026
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Abstract The limitations of analyzing physiological states based solely on dominant rhythms or isolated pairwise interactions have become increasingly apparent. In response, a novel conceptual framework grounded in complex network theory has recently been developed. Rather than dismissing traditional views, this approach enriches them by elucidating the cooperative dynamics of brain rhythms, thereby enhancing diagnostic capabilities. Adopting this framework, the present study investigates age-related features of such interactions across the entire sleep–wake cycle. It identifies the most significant changes occurring within each phase and demonstrates that advancing age is associated with distinct and progressive alterations in cortical correlations.

1 Introduction

The study of characteristic electroencephalographic (EEG) rhythms remains a cornerstone of modern neurophysiology, providing crucial insights into the brain's complex electrical activity [1, 2]. Variations in the parameters of specific rhythms, particularly their amplitudes, are extensively utilized across a wide spectrum of applications, from fundamental research to clinical diagnostics, for evaluating the functional states of the body. Thus, the alpha rhythm represents the dominant background activity of the healthy, awake brain [3]. Oscillations within this range are typically observed during periods of physical rest and muscular relaxation, particularly when the eyes are closed. Opening the eyes or engaging in heightened attention and mental concentration tends to suppress these oscillatory patterns. The beta rhythm becomes prominent during episodes of active information processing and emotional arousal [4]. This faster, lower-amplitude activity is often observed during decision-making, active concentration, and motor planning. The transition from wakefulness to sleep is accompanied by changes in the brain's electrical activity. Various sleep phases are marked by a progressive rise in slow-wave oscillations, encompassing the delta and theta ranges. Deep sleep is dominated by high-amplitude delta oscillations, which are crucial for restorative processes, memory consolidation, and metabolic clearance from brain tissue [5]. Theta activity, on the other hand, is prominent during lighter sleep stages [6]. It should be emphasized that the behavior of these rhythms is highly dynamic and context-dependent. For instance, healthy aging is typically associated with a slowing of the dominant posterior alpha rhythm and a reduction in its amplitude, along with a general increase in slower frequency components. Given their sensitivity to physiological and pathological states, analyzing these dominant oscillations remains a standard procedure.

While the analysis of dominant EEG rhythms remains fundamental to neurophysiology, it is also important to understand that an exclusive focus on these prominent oscillations significantly constrains our understanding of the brain's complex electrical activity [7–9]. In recent decades, many studies have shown that the coordinated response of different rhythm pairs during critical states such as perception, consciousness, and cognition provides insights that cannot be obtained from analyzing only the dominant rhythms [10–12]. For instance, the precise timing and phase relationships between theta and gamma oscillations have been implicated in working memory

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processes, while alpha–beta interactions are thought to play a role in predictive coding and attentional gating. Subsequent investigations have advanced the field by demonstrating that a comprehensive description of physiological states requires investigating cross-communication between multiple pairs of rhythms within the framework of their dynamic network interactions [13, 14]. This network perspective acknowledges that brain rhythms do not operate independently but rather form complex, interconnected systems whose properties transcend simple additive models. Importantly, alterations in functional state involve more than just quantitative modifications in rhythm dynamics, such as the strengthening or weakening of correlations. Qualitative transformations also occur, including changes in the types of correlations between specific rhythm pairs.

Building upon the conceptual framework and methodological approach proposed in [13, 14], the present study addresses age-related aspects in the dynamics of brain rhythms. The aging process induces a cascade of structural, neurochemical, and functional transformations that profoundly affect neural dynamics. Even healthy aging is accompanied by significant changes, including gradual reductions in processing speed, working memory capacity, and cognitive flexibility, as well as prolonged reaction times and reduced fine motor control, all of which impact daily functioning and quality of life [15–17]. Importantly, the aging brain does not simply deteriorate passively but actively reorganizes to maintain function. A key phenomenon in cognitive neuroscience is the recruitment of additional brain areas during task performance in older adults [18, 19]. This is widely interpreted as a form of compensatory mechanism: the aging brain engages extended neural resources to overcome structural and functional decline, thereby maintaining performance levels comparable to those of younger individuals [20, 21]. These age-related differences in neural recruitment and network organization have important implications for understanding both normal aging and the transition to pathology. Recent advances in network neuroscience, particularly the application of functional brain network analysis, have provided powerful tools for investigating age-related changes in brain organization [22–26].The conventional approach, which analyzes pairwise interactions, has uncovered fundamental principles of brain organization. However, this method rests on a reductionist assumption that all neural communication is dyadic. This paradigm is fundamentally limited, overlooking collective phenomena where the relationship between two nodes is influenced by the broader network state. Such higher-order interactions are now hypothesized to be critical for supporting complex cognitive processes [27].

This study focuses on age-related effects on the dynamics of brain rhythms across all sleep–wake cycle phases. It aims to establish the most pronounced changes occurring in different phases and to identify the pairs of rhythms in which these changes are most significant in the older age group. It is important to note that the study of sleep is inextricably linked to that of epilepsy. The two phenomena share common neurophysiological substrates and are known to modulate one another, with sleep architecture significantly influencing the occurrence of epileptiform activity, and vice versa [28]. This relationship is well-documented: non-rapid eye movement (NREM) sleep, particularly slow-wave sleep, facilitates the generation and propagation of interictal epileptiform discharges and seizures due to enhanced neuronal synchrony in thalamocortical networks. Conversely, rapid eye movement (REM) sleep suppresses epileptic activity through its characteristic desynchronization of neural firing. Simultaneously, epilepsy itself disrupts normal sleep architecture, reducing sleep efficiency, fragmenting sleep, and impairing critical physiological oscillations such as sleep spindles. The paper is structured as follows. Section 2 provides a concise description of the experimental data and the methodological approach employed, including the cross-correlation analysis of brain waves based on normalized relative spectral power. This section details the participant groups and the signal processing techniques used to quantify rhythm interactions. Section 3 presents and discusses the main findings of the study, examining how the cooperative dynamics of specific rhythm pairs differ between three age groups. Section 4 summarizes the principal findings of the research.

2 Materials and methods

2.1 Subjects and experimental data

Our research was conducted using the SIESTA EEG database [29], a well-established polysomnographic resource that includes high-quality recordings of healthy subjects obtained during night-time sleep at various sleep centers across the European Union. The database is particularly valuable for aging studies due to its broad age range and standardized data acquisition protocols.

For the present analysis, a total of 68 multichannel EEG recordings were selected from both male and female subjects, ensuring a balanced representation across age groups. All recordings were sampled at a frequency of 200 Hz. Each recording contained continuous, artifact-free fragments of at least 5-min duration for the following states: wakefulness (W); sleep stages N1, N2, N3, and N4; and REM sleep. The selection of 5-min epochs ensures stationarity of the signal while providing enough data points for robust cross-correlation analysis.

It is important to note that under current American Academy of Sleep Medicine scoring guidelines, stages N3 and N4 are merged into a single stage (N3) due to their shared physiological characteristics as slow-wave sleep. Nevertheless, the original SIESTA database retains the distinction between these stages, allowing for a more

granular investigation. Therefore, in this study, we analyze possible differences in rhythm correlations separately for N3 and N4, aiming to determine whether the subtle physiological distinctions between these stages are reflected in the dynamic network interactions of brain waves.

To examine age-related effects, the subjects were stratified into three age groups: (1) young adults (under 40 years), (2) middle-aged adults (40–60 years), and (3) older adults (over 60 years). The number of subjects in each group was 25, 21, and 22, respectively, providing sufficient statistical power for between-group comparisons. The analysis was focused on the O_1 and O_2 electrodes, which are optimally positioned to capture occipital cortical activity and are particularly sensitive to alpha rhythm dynamics, though they also provide reliable recordings of slower oscillatory activity during sleep.

2.2 Relative spectral power

To quantify the contributions of individual oscillatory components, we employed the concept of relative spectral power as introduced in [13]. In that study, the authors proposed incorporating 0.5 Hz frequency gaps between conventional EEG bands to achieve a more reliable separation of neighboring brain rhythms. Following this approach, band-pass filtering of the selected EEG fragments was performed for the following frequency ranges: delta (0.5−3.5 Hz), theta (4.0−7.5 Hz), alpha (8.0−11.5 Hz), sigma (12.0−15.5 Hz), and beta (16.0−19.5 Hz). It is worth noting that the introduction of these gaps does not substantially alter the computed spectral characteristics compared to conventional filtering without gaps, while providing a cleaner dissociation between adjacent oscillatory activities. It should be noted that, in line with previous studies [13, 14], we consider the sigma rhythm among the key brain rhythms. The sigma rhythm is a specific pattern of electrical brain activity that appears during the initial stage of slow-wave sleep, immediately following drowsiness (stage N2). This rhythm is thought to block external stimuli, helping the brain remain asleep even in the presence of background noise, and is considered one of the important mechanisms underlying memory consolidation [30, 31]. During wakefulness, this frequency range is typically classified as low-frequency beta activity.

For each frequency band, the normalized relative spectral power S was then computed. This value represents the ratio of the spectral power of a given rhythm to the total spectral power integrated over the entire 0.5−19.5 Hz range. The computations were performed using a sliding window approach. Specifically, a 2 s moving window was applied, followed by additional averaging with a 14 s window and a 1 s resolution. Subsequently, correlation analysis was carried out on 30 s segments of the resulting S time series.

2.3 Correlation analysis

To quantify the dynamic interactions between cortical rhythms, we employed a variant of moving-window analysis of the linear (Pearson) correlation coefficient

$$C = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}}. \tag{1}$$

Specifically, the correlation coefficient C was computed over consecutive 30 s segments of the normalized relative spectral power S for each pair of brain rhythms. This approach allowed us to track temporal variations in rhythm correlations during transitions between sleep and wakefulness states. For two given brain rhythms, x_i and y_i are the time series of their respective relative spectral power S within a 30 s window, and $\overline{x}$ and $\overline{y}$ represent the mean values of the signals. The coefficient C ranges between -1 and $+1$, where $C = +1$ indicates perfect positive correlation, $C = -1$ indicates perfect negative correlation (anti-correlation), and $C = 0$ implies the absence of a linear relationship. By examining the dynamics of C across successive windows, we were able to identify patterns of rhythm correlations throughout the sleep–wake cycle.

3 Results and discussion

Transitions between wakefulness and various sleep stages lead to significant changes in EEG rhythm characteristics, reflected in the relative spectral power S of each oscillatory component. Figure 1 illustrates representative examples of these changes for a subject from the second group and all five rhythms under study across different functional states of the body: wakefulness (W), sleep stages N1, N2, N3, N4, and REM sleep. For illustrative purposes, we selected arbitrary 5-minute fragments from a single subject (channel O_1), which demonstrate pronounced differences in S values between wakefulness and deep sleep stages. Visual inspection of the dynamics reveals a clear opposite (anti-correlated) behavior between the alpha and delta rhythms. Specifically, delta rhythm

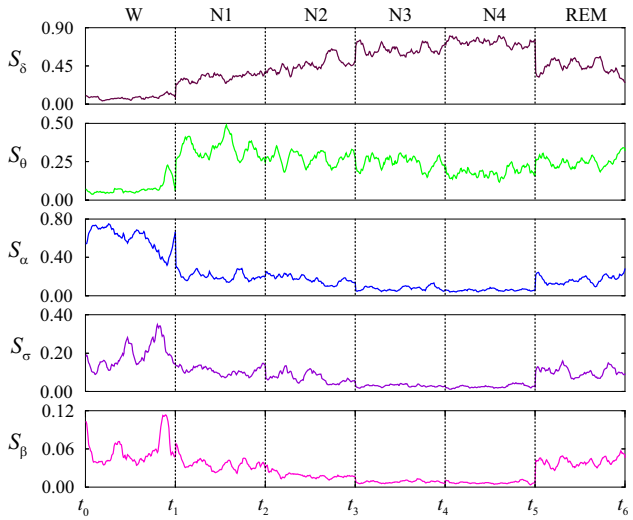


Fig. 1 Relative spectral power changes for the five analyzed rhythms across different stages of the sleep–wake cycle (a representative example)

activity progressively increases with the deepening of NREM sleep, reaching its maximum in stages N3 and N4, precisely where alpha activity is most strongly suppressed. This inverse relationship highlights the fundamental reorganization of cortical oscillatory activity during sleep onset and maintenance. Theta rhythm exhibits a distinct pattern, with maximum power observed during the initial sleep stages (N1 and N2), followed by a gradual decline as sleep deepens. This is consistent with the role of theta activity in the transition from wakefulness to sleep and its association with drowsiness and light sleep. The remaining rhythms, particularly beta, show relatively low activity across all sleep stages, which is an expected finding given that beta oscillations are typically associated with active wakefulness, alertness, and cognitive processing. Their suppression during sleep confirms the general reduction of cortical activation in the sleeping brain. These observations provide a qualitative foundation for the subsequent quantitative analysis of rhythm dynamics.

Analyzing the local estimates of the correlation coefficient C computed over consecutive 30 s segments of relative spectral power reveals notable variations both within individual states and, more prominently, during transitions between states. Figure 2 illustrates representative examples of these dynamics for five rhythm pairs, derived from the same signals presented in Fig. 1. Their consideration yields the following observations:

– Delta–theta pair: Strong positive correlations observed during wakefulness (W) abruptly shift to strong negative correlations (anti-correlations) during sleep onset (stage N1). Subsequently, the correlations exhibit a mixed pattern during stages N2 and N3 as well as REM sleep, returning to pronounced anti-correlations in deepest sleep (stage N4).
– Delta–sigma pair: Pronounced anti-correlations are consistently observed in the three states (W, N3, and N4), while the remaining three states (N1, N2, and REM) are characterized by mixed correlation patterns.

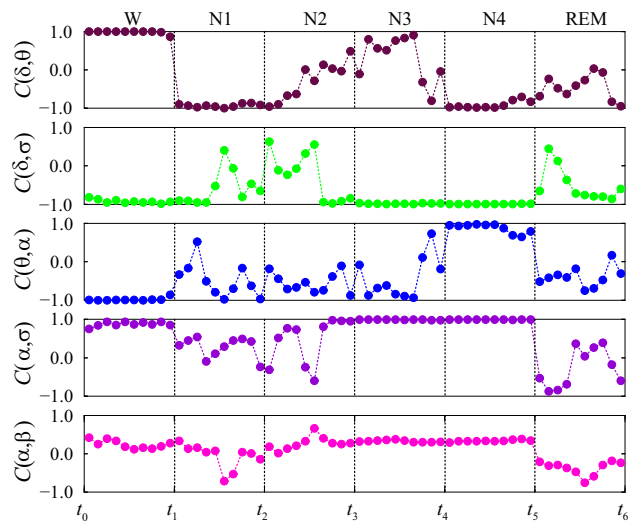


Fig. 2 Local estimates of the correlation coefficient C for the signals presented in Fig. 1

– Delta–alpha pair: Strong anti-correlations during wakefulness are changed by strong positive correlations in stage N4. The intermediate stages display either mixed correlations or predominantly anti-correlated behavior.
– Alpha–sigma pair: Strong positive correlations are characteristic of three states: wakefulness (W) and the deep sleep stages N3 and N4.
– Alpha–beta pair: The measure C takes on intermediate values across most states, which may be attributable to the generally low amplitude of beta rhythm activity during sleep, as noted earlier.

It should be emphasized that Fig. 2 is primarily illustrative, as it presents rhythm correlations patterns derived from relatively short fragments of a single subject. Nevertheless, these observations are consistent with the findings of previous studies, reinforcing the notion that statistical analysis of cross-rhythm communications can provide valuable insights for characterizing the functional states of the organism. The dynamic reorganization of correlation patterns across states, particularly the abrupt changes during state transitions, suggests that cross-rhythm interactions are highly sensitive to alterations in brain state and may serve as robust markers of sleep–wake dynamics.

Let us now turn to the results of the statistical analysis performed across the subject groups. Figure 3 presents two representative examples illustrating the calculations of the linear correlation coefficient, averaged within each group of subjects (data are shown as mean values ± standard error of the mean). In Fig. 3a, a shift in the type of correlation is observed for the theta-alpha pair across different stages of the sleep–wake cycle. Negative correlations (anti-correlations) predominantly persist during wakefulness (W), as well as in sleep stages N1 and N2. These are subsequently replaced by positive correlations during deep sleep stages N3 and N4, while the correlation becomes non-significant during REM sleep, which may reflect the distinct neurophysiological mechanisms underlying this state. Differences between the groups are generally subtle. For instance, statistically significant differences between groups 1 and 3 (Mann–Whitney test, $p < 0.01$) were detected only in stage N4. Figure 3b shows a notably different scenario. Here, no shift in the type of correlation is observed; instead, correlated behavior for measure (1) persists across all sleep stages. In this case, intergroup differences are more pronounced. Statistically significant differences between groups 1 and 3 (Mann–Whitney test, $p < 0.01$) were identified in four distinct stages: W, N2, N3, and REM. Both scenarios are typical for different pairs of rhythms and have comparable probabilities.

Given the relatively modest sample sizes of the groups, these limitations may influence the robustness of the estimates. Rather small group sizes can increase the variability of results, particularly when analyzing individual stages separately. Therefore, to address the question of which specific rhythm pairs exhibit the most pronounced age-related changes, we opted not to analyze individual sleep stages. Instead, we performed an integrated assessment averaged across all states. To achieve this, we estimated the following measure:

$$\Delta C_j = \sqrt{\frac{1}{6}\sum_{i=1}^{6}\left(C_j^i - C_1^i\right)^2}, \tag{2}$$

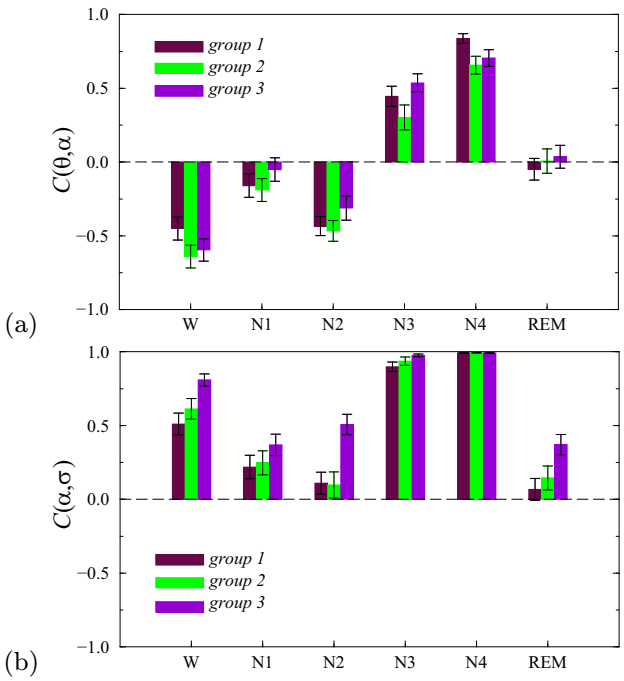


Fig. 3 Different types of correlations between pairs of rhythms in three age groups: change in the sign of C (**a**) and only qualitative changes (**b**).

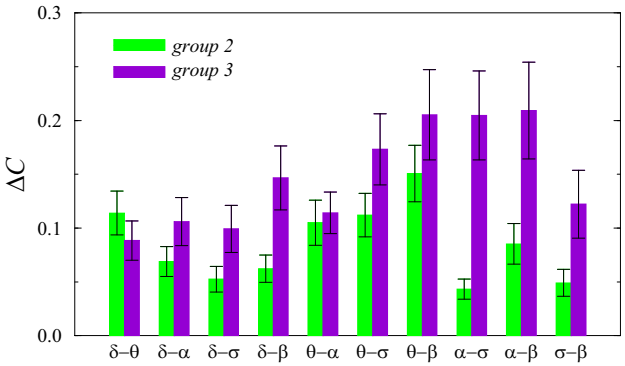


Fig. 4 Values of the measure (2) quantifying age-related changes in rhythm correlations for groups 2 and 3 (mean values ± SE). The ΔC quantitatively evaluates changes for group 2 or group 3 compared to group 1.

where j denotes the subject group index, and i represents the state index ranging from 1 to 6 (corresponding to W, N1, N2, N3, N4, and REM sleep stages). This measure quantifies the root mean square deviation of the group-averaged correlation coefficients for group 2 or group 3 from the corresponding baseline values observed in group 1. These estimations were performed separately for each pair of EEG rhythms.

The results of this analysis are summarized in Fig. 4. Based on the data presented in this figure, several distinct patterns of age-related changes in cortical rhythm interactions can be identified. In group 2 (middle-aged adults) compared to group 1 (young adults), the most pronounced differences are observed for rhythm pairs involving theta activity, specifically theta–beta, delta–theta, theta–sigma, and theta–alpha. This suggests that alterations in theta-related correlations may be an early indicator of age-related cortical reorganization. In group 3 (older adults) compared to group 1, the pairs showing the strongest changes include theta–beta, alpha–sigma, alpha–beta, and theta–sigma, indicating that both theta and alpha rhythms become increasingly involved in age-related network modifications. When comparing group 3 directly with group 2, the most prominent differences emerge in pairs that do not involve theta, namely alpha–sigma, alpha–beta, delta–beta, and sigma–beta, suggesting a progressive and widespread reorganization of the functional network architecture. Importantly, Fig. 4 demonstrates that age-related changes are not confined to a few pairs but occur across all rhythm pairs, implicating the entire network of dynamic interactions among cortical oscillations. This global pattern of change underscores the importance of analyzing the full network when assessing the physiological state of the organism and searching for potential biomarkers, including those indicative of pathological alterations in brain dynamics. A network-level perspective may therefore provide a more comprehensive understanding of aging effects on cortical function and facilitate the identification of early markers for age-related neurological conditions.

4 Conclusion

This study investigated age-related effects on correlations of EEG oscillations, grounded in the conceptual framework of dynamic network interactions between various brain rhythms. In contrast to previous research [32], the present work places particular emphasis on a detailed examination of all stages comprising the sleep–wake cycle, with the specific aim of identifying rhythm pairs that exhibit the most pronounced age-related differences. The findings demonstrate that advancing age is associated with distinct and progressive alterations in rhythm correlations. We suppose that these results can be interpreted in terms of cortical coupling. The most prominent changes initially involve theta-related interactions, followed by rhythm pairs that include both theta and alpha electrical activity. Furthermore, a broader reorganization of the interaction network is observed, encompassing other cortical rhythms as well. These results are of considerable interest not only for understanding the effects of healthy aging on brain dynamics but also for investigating various pathological alterations in the brain's electrical activity, potentially contributing to the development of diagnostic markers for age-related neurological conditions.

Acknowledgements This work was supported by the Russian Science Foundation, Russia, Grant No. 23-71-30010.

Author contribution statement

Authors contributions are as follows: conceptualization, A.P.; methodology, A.P.; software, V.A.; formal analysis, V.A.; investigation, V.A.; writing—original draft preparation, V.A. and A.P.; writing—review and editing, A.P.; visualization, V.A.; supervision, A.P. All authors have read and agreed to the published version of the manuscript.

Data availability The datasets analyzed in the current study are available through the advisory board of the SIESTA Group (https://www.thesiestagroup.com) upon request.

Declarations

Conflict of interest The authors have no conflict of interest to declare that are relevant to the content of this article.

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