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Impact of mobile phone use on the brain activity: Audio call vs video call

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ABSTRACT

The growing dependence on mobile phones for communication has raised concerns regarding the neurological impact of radio-frequency electromagnetic fields, especially in audio and video calls. This research investigates the impact of WhatsApp audio and video calls on cognitive load and mental fatigue using non-invasive electroencephalography (EEG) signals. EEG signals were recorded from 28 healthy participants during baseline, 3-minute, and 4-minute call sessions, with participants equally distributed between audio and video call groups. The signals were preprocessed using bandpass filtering, continuous wavelet transform, and independent component analysis to isolate theta and alpha frequency bands. Cognitive load was assessed using the theta–alpha ratio (TAR), and mental fatigue was measured using Mahalanobis distance-based analysis of theta and alpha rhythms. The findings reveal that video calls impose significantly more cognitive load (e.g., TAR mean: 0.78 (SD: 0.36) for 3-minute video call and mean: 0.76 (SD: 0.37) for 3-minute audio call, $p < 0.05$) and mental fatigue (e.g., 42.11 microvolts for 4-minute video call and 38.84 microvolts for 4-minute audio call) than audio calls, and both effects become stronger for prolonged durations. Machine learning (ML) classification also demonstrated high separability, with receiver operating characteristic analysis exhibiting area under the curve values above 0.90 for distinguishing call conditions. These results demonstrate that video communication places higher cognitive and fatigue demands as compared to audio communication. By integrating EEG indices, self-report measures, and ML classification, this study exhibits convergent evidence for the cognitive impact of mobile phone calls and illustrates the necessity to consider communication modality when assessing workload and fatigue in real-world contexts.

1. Background and literature review

Today, people are significantly affected by technology because everybody uses wireless devices such as mobile phones for personal and business use. Smartphones have increased memory and processing speed, enabling them to be connected to the Internet at all times. Their popularity has been so great that they are nearly ubiquitous. As a result, exposure to radio-frequency radiation has significantly increased (Miller et al., 2019). Such rapid evolution and exposure have raised concerns about possible health effects. Previous studies have shown that mobile phone use is likely to change brain activity, affect cognitive processes and cause mental fatigue (Ji Jeong et al., 2015; Redmayne, 2013). Mental fatigue emerges frequently in contemporary daily life and results in deteriorating cognitive performance at work (Van Cutsem et al., 2017). Considering that mobile phones are used for long-duration communications such as audio and video calls, it is important to understand how daily activities impact cognitive load and fatigue.

Electroencephalography (EEG) is one of the techniques for investigating brain activity while performing such tasks non-invasively (Cabañero et al., 2019; Tamanna & Parvez, 2021), and much research has investigated EEG-based cognitive load and fatigue metrics using smartphones (Anderson et al., 2011; Friedman et al., 2019). The quantity of information that can be processed by our working memory at any given time is referred to as cognitive load (Paas et al., 2003). Cognitive load is an important metric in evaluating mental effort when performing various tasks, including phone calls. Most of the available research has evaluated overall mobile phone exposure (Ishihara et al., 2020) or individual single tasks (Nodoushan et al., 2021), but few have investigated comparisons between video and audio calls. Although video calls have become more prevalent and entail higher visual demands than audio calls, little is known about translating such differences into quantifiable neural and subjective workload. Moreover, previous studies tended to use EEG markers alone (Kunasegaran et al., 2023) or self-report measures alone (Estes, 2015), with few using both as a means to offer convergent evidence. This is a significant omission in determining whether physiological measures like the theta–alpha ratio (TAR) (Puma et al., 2018) and markers of fatigue (Tran et al., 2020) exist that relate to participants' self-assessment of mental state.

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In order to address these gaps, this study utilizes EEG signals to investigate the impact of WhatsApp audio and video calls on cognitive load and mental fatigue. Cognitive load was measured by the TAR, a well-validated electrophysiological measure (Antonenko et al., 2010; Raufi & Longo, 2022), whereas fatigue detection relied on the Mahalanobis distance of theta and alpha rhythms (Tyas et al., 2020; Wascher et al., 2014). Participants also performed a self-report questionnaire on perceived fatigue and mental effort after each session in order to strengthen the interpretation. The measures from the brain and participants' self-reports were combined to better understand how communication methods shape cognitive processing. By adapting this multimodal approach, our study explores whether video calls are more mentally demanding than audio calls and how those demands develop over time. In accordance with earlier research, we postulated that (i) both audio and video calls would result in increased cognitive load and fatigue when compared with rest; (ii) video calls would be more demanding than audio calls because they require more visual processing; and (iii) longer call durations would intensify the effects.

The growth in electromagnetic radiation from mobile phones has raised concerns about its impact on the human body. Several studies have investigated the neurological impact of mobile phone use through EEG, specifically looking at changes in brain wave activity. In Li et al. (2021), authors studied the effects of mobile phone addiction tendency (MPAT) on the resting-state EEG microstates, which are indicators of spontaneous brain activity patterns. Mobile phone addiction tendency scale and temporal property measurement of four EEG microstates (MS1-MS4). The study compared MPAT score with neural dynamics. Higher MS1 and lower MS2/MS4 durations corresponded to higher MPAT scores, suggesting adverse effects on sensory and attention brain systems. In Henz et al. (2018), the authors investigated whether the mobile phone chip could mitigate the effect of EMFs generated by mobile phones on brain activity. EEG signals were recorded from 30 participants in three conditions (mobile phone chip, placebo chip, no chip), both at rest and during an attention task. Results indicated that the chip strongly inhibited the EMF-induced increase in theta, alpha, beta and gamma activities.

The authors utilized smartphones and wearables such as portable EEG headbands to capture brain activity remotely in clinical trials in Byrom et al. (2018). And the study suggested that the devices were able to capture continuous EEG recordings and other cognitive or behavioral parameters, such as sleep, gait, or attention, in real-life environments. By utilizing the parameters the study investigated pain, epilepsy and cognitive impairment. In order to define the influence of mobile phone use on brain activity, EEG recordings were collected from 21 students while performing daily activities in Parmar et al. (2019). It found that phone use increased brainwave frequencies, suppressed amplitudes and caused slow waves in some parts of the brain. Moreover, they felt sleepy and experienced headaches that could be detrimental to their health. The researchers investigated the effects of MPR on brain activity in epilepsy patients and healthy controls in Azmy et al. (2020). The results showed that the healthy control subjects exhibited no unusual brain activity. But the epilepsy patients had a noticeable spike in abnormal brainwave events, specifically epileptiform discharges when they were exposed to MPR. Thus, more research is needed to determine how to use MPR devices safely and effectively.

The authors in Qiao et al. (2023) investigated the temporo-spatial dynamics of visual search in EEG cortical connectivity by utilizing wavelet coherence and source localization analyses. By training a machine learning classifier with theta-band coherence features during the N2pc time window (200–400 ms), the authors found differences between left and right visual fields for functional connectivity. This study found that theta-band synchronization plays a crucial role in visual attention processing, as demonstrated by 87% accuracy. The authors in Xu et al. (2025) designed a transformer-based deep learning model (TS-former), which was used to classify motor imagery EEG signals from individuals with spinal cord injury. First, the model leveraged the spatial features extracted by a filter bank common spatial pattern with transfer learning. Then, it captured temporal features by employing mechanisms of attention to personalize the model. TS-former achieved an accuracy of 95.09% on spinal cord injury patient data, outperforming all classical machine learning and deep learning baselines. The authors in Li et al. (2024) presented a multi-scale swin transformer network, a deep learning model for cognitive load measurement by utilizing EEG signals through a system that integrates both multi-scale parallel convolution and swin transformer. The study utilized both local and public datasets. By extracting features from spatial patterns and spectral as well as temporal dimensions, the model was able to classify cognitive load into three levels with an accuracy of 89.1% and 83.19%. Employing EEG, the authors compared the brain activity in older adults with subjective cognitive impairment and healthy controls (Cave et al., 2025). The results presented that participants with subjective cognitive impairment showed higher theta-alpha and beta but lower delta-theta and alpha-beta activity, particularly in the eyes-closed condition.

The authors also investigated the effect of mental fatigue on performance during laparoscopic surgical simulation using EEG signals in Ndaro and Wang (2018). The real-time fatigue monitoring system was implemented, investigating alpha and theta rhythms in 20 subjects' brains who performed peg transfer tasks. The result showed better efficiency and accuracy up to trial 13, beyond which a further decrease caused by fatigue occurred. The impact of mental fatigue on EEG signals was investigated in Trejo et al. (2015). They developed a classifier to detect fatigue from short EEG segments. A total of 22 participants performed math problems in 3-hour-long sessions, and their EEG and mood data were collected. Based on power spectral densities of theta and alpha bands, their model obtained 91% to 100% classification accuracy, indicating that EEG is suitable for real-time fatigue monitoring. In Cabañero et al. (2020), cognitive load during smartphone interactions is explored to aid in the early detection of cognitive impairments. Using EEG, the brain activity of 26 users performing 12 typical tasks was monitored, which reveals that audio-related tasks required the highest cognitive demand. These findings provide insights into identifying metrics for diagnosing cognitive pathologies. In Caldiroli et al. (2023), researchers compared online cognitive load for information searching and reading comprehension tasks on mobile and PC devices with EEG. 22 users participated in the experiment. It was identified that information searching took more cognitive load than the comprehension task, especially on mobile devices.

Multiple studies have been conducted to understand the effects of mobile phone use on the brain, but most of them are limited in scope and methodology. Studies have either focused on the effects of radio-frequency radiation emitted by mobile phones or examined the use of mobile phones in a specific task. Additionally, several studies rely solely on EEG markers and self-report measures without multimodal validation, which limits the robustness of findings. Moreover, previous studies have not conducted a comparative analysis of different communication modalities, such as audio and video calling.

The current study provides a unique contribution to the fast-growing research on mobile phone-related cognitive effects by directly contrasting audio versus video calls, which are two of the most widely used communication modalities rarely evaluated side-by-side regarding cognitive workload and accompanying fatigue. Whereas many previous studies have looked at mobile phone exposure in general or specific tasks in isolation, this study offers a controlled modality-specific assessment of WhatsApp calls using a multimodal methodological design. With the help of integrating EEG-based indices, regional frequency analysis, ML-based classification and parallel self-report measures, our study provides converging evidence that video calls impose measurably higher neural and subjective demands compared to audio calls. Moreover, these effects also strengthen with call duration. Our study constitutes an incremental methodological advance by incorporating brain patterns, statistical, behavioral and ML-derived insights over

Table 1
Participant demographics (N = 28).

Age (years)	Educational level	Vision problems	Handedness
19–25 (M = 22.1, SD = 1.9)	Undergraduate: 25 (89.3%) Graduate: 3 (10.7%)	Yes: 2 (7.1%) No: 26 (92.9%)	Right: 28 (100%)

earlier studies, which relied on a single type of measure and illustrates the need to consider communication modality when assessing workload and fatigue in real-world contexts. Key contributions of our research with theoretical, methodological and practical implications are summarized below.

- Theoretical: Video calls, compared to audio calls, create a higher cognitive load and more mental fatigue. This is consistent with the concepts of dual-task interference and cognitive theory.
- Methodological: This approach will highlight the effectiveness of combined EEG-based indices, such as TAR and the fatigue index, with self-report questionnaires in assessing cognitive load.
- Practical: Prolonged video interactions increase fatigue, which affects remote learning and workplace meetings.
- Clinical/Health: EEG and self-report could be used to identify individuals at risk of excessive cognitive load.
- Future research: This will provide the groundwork for higher-density EEG studies across diverse populations to improve findings' generalizability.

The rest of this paper is organized as follows. Section 2 outlines subjects, experimental protocol, EEG recordings, data preprocessing, feature extraction, and self-report assessment. Section 3 presents the EEG and self-report analysis results, and Section 3.7 discusses the findings in the context of background literature, identifying implications. Finally, Section 4 concludes this paper and outlines directions for future research.

2. Materials and methods

In this section, we discuss the impact of mobile phone use on brain activity by comparing EEG signals during audio and video calls. At first, we recorded and preprocessed the EEG signals. Then, we extracted significant features from the signals and conducted diverse analyses to investigate brain activity. The proposed methodology to investigate the impact of audio and video calls on brain activity is depicted in Fig. 1, and a step-by-step description of the methodology is provided in the following subsections.

2.1. Subjects

Twenty-eight right-handed university students aged 19–25 years with a mean (M) = 22.1 and a standard deviation (SD) = 1.9 volunteered in the experiment, mostly being undergraduate level (n = 25) and some graduates (n = 3). The sample was drawn from a range of academic fields, and all the subjects were neurotypical with no history of neurological or psychiatric pathology and had normal or corrected-to-normal vision (except for two with minor vision impairment). Demographics are listed in Table 1.

2.2. Experimental protocol

We collected three EEG recordings from each participant: a 2-minute baseline, a 3-minute call, and a 4-minute call. Participants were distributed randomly into video call and audio call groups, based on the call type they experienced. Six distinct analysis labels were developed across the study due to the defined recording types, which included BaselineA, Audio3min, and Audio4min for the audio group and BaselineV, Video3min, and Video4min for the video group. The baseline recordings for audio and video groups were designated as BaselineA and BaselineV, showing participants in a relaxed position with open eyes who did not engage in deep thinking during the two-minute durations. The terms Audio3min and Audio4min represent a 3-minute audio session and a 4-minute audio session, respectively, for the audio call participant group. On the other hand, the terms Video3min and Video4min represent a 3-minute video session and a 4-minute video session, respectively, for the video call participant group. A 30-second break was given between sessions when no EEG data were recorded. For the call sessions, the subjects were told to listen carefully but not speak. Both a 3-minute and a 4-minute audio call were conducted for the audio call group, and the same procedure was conducted for the video call group. The experimental protocol for both groups is illustrated in Fig. 2, with the timeline of the baseline, rest, and call sessions.

2.3. EEG recordings

Twenty-eight participants were split into two groups and labeled as one with an audio call group and another with a video call group, each consisting of 14 individuals. The reason, purpose, and procedures of the research were clearly explained to each participant before conducting the experiment. Written consent from each participant was taken with the information regarding their name, gender, age, educational qualifications, and state of mental health. Data collection only commenced after they had given written consent. All the recordings took place in a quiet and well-lit soundproof room. Participants were asked to be quiet, relax in a resting position, and provide undivided attention for the experiment so that artifacts would not be created in the recorded EEG signals. They were comfortably seated on a chair approximately 55 cm from the smartphone and instructed to remain as still as possible in order to minimize muscle and movement artifacts. Background noise was kept to a minimum, and only the participant and experimenter were present during the session. We utilized the Emotiv Epoc X EEG headset to record data in our research. The device contains 14 electrodes that capture brain signals and 2 reference electrodes used to hold the device in position. Out of the 14 electrodes, 8 are located on the frontal section of the brain. While the AF3, F7, F3, and FC5 electrodes capture data from the left hemisphere, the FC6, F4, F8, and AF4 electrodes capture data from the right hemisphere. T7 and T8 electrodes track the temporal region of the brain. Data is collected from the occipital region by the O1 and O2 electrodes and the parietal region by the P7 and P8 electrodes. The headset records the brain signals at a sampling rate of 128 Hz, and it captures the EEG signals using Emotiv Pro software. We employed the Emotiv Epoc X headset since it provided a validated, portable, and non-invasive method of obtaining EEG in naturalistic environments. In previous work (Cabañero et al., 2019, 2020), it had been shown that even though the Emotiv system has fewer channels than laboratory-quality EEG, it provides a trustworthy data source for measuring cognitive load and fatigue when evaluating tasks and mobile environments. The quality of the signal is confirmed, and recording is started only when both the connection and the strength of the signal are 100%. Two mobile phones were employed for the video and audio call sessions via WhatsApp.

2.4. Data preprocessing

EEG signals of 28 participants were captured using the Emotiv Pro software and exported in CSV and EDF formats. A total of 84 EEG recordings (3 recordings per participant × 28 participants) were obtained. Each participant performed three tasks, and the recordings

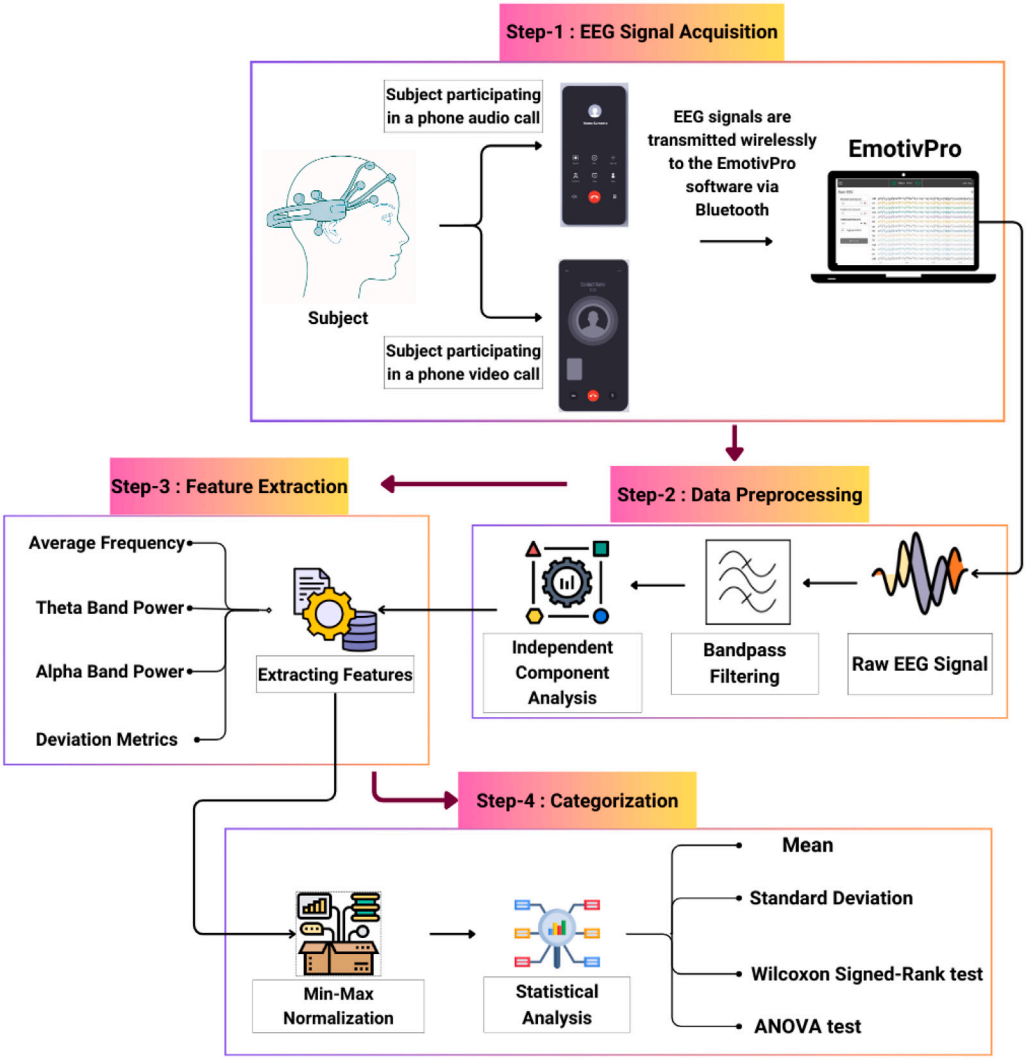


Fig. 1. Proposed methodology for investigating the impact of audio and video calls on brain activity.

correspond to the 2-minute baseline, 3-minute call, and 4-minute call tasks of the audio and video call groups. EEG recordings are mostly prone to artifacts and noisy signals due to eye movements, muscle activity, and even environmental interference, usually requiring preprocessing for improvement in the quality of the data before analysis. Preprocessing was hence adapted to the needs of cognitive load and mental fatigue analysis, and it also varied between CSV and EDF file types.

We processed the CSV files using eeglib (Cabañero-Gomez et al., 2021), which is a Python library for EEG signal processing in order to quantify cognitive load. This library is convenient to read EEG data from CSV files and allow to import data from NumPy (Harris et al., 2020) and Python, compliant for statistical processing. The EEG signals are divided into different frequency bands; each is associated with specific brain processes and states of mind. These frequency bands include δ (1–4 Hz), θ (4–8 Hz), α (8–13 Hz), β (13–35 Hz), and γ (>35 Hz) (Miller, 2007). In order to assess cognitive load and mental fatigue, the theta (4–8 Hz) and alpha (8–13 Hz) bands are most relevant among these bands. Theta waves are associated with working memory and the initial stages of sleep. Also, these waves rise with mental fatigue, which suggests decreased cognitive ability (Wolinski et al., 2018). On the other hand, alpha waves are most prominent during resting wakefulness, associated with attention. These waves increase as fatigue begins, suggesting lowered alertness (Chen et al., 2020). We applied a 2–15 Hz band-pass filtering to get the θ (4–8 Hz) and α (8–13 Hz) frequency bands related to cognitive workload. This filtering removed both low-frequency drifts and high-frequency noise, removing the artifacts outside our band of interest and leaving us with the components of interest of the signal. The signals were segmented into 6-second segments after bandpass filtering, every 768 samples at a sampling rate of 128 Hz (i.e., 6 s × 128 Hz = 768 samples). The segments were created with an overlap of 50%, or by a step size of 3 s or 64 samples (i.e., 128 Hz/2 = 64 samples). A 14-channel window of EEG activity, each 6-second segment, was created as an input matrix of dimensions 768 × 14 (768 samples × 14 EEG channels) for cognitive load estimation. The overlapping segmentation technique was able to achieve proper temporal resolution and continuity in following the dynamics of cognitive load during the performance of the audio and video call tasks. Fig. 3 depicts a sample EEG signal and corresponding theta and alpha band components, as well as the impact of the bandpass filter.

For the analysis of mean frequency and mental fatigue across various areas of the brain, the EDF files were preprocessed by the MNE-Python library (Gramfort et al., 2014), which is a widely used library for EEG signal processing. Signals were re-referenced to the average, the preprocessing started with applying a wider bandpass filter in the range 1–50 Hz to maintain a wider band of neural activity for fatigue analysis. A 50 Hz notch filter was subsequently used to remove powerline noise, a ubiquitous artifact in EEG recordings. Independent component analysis (ICA) was subsequently used to remove artifacts

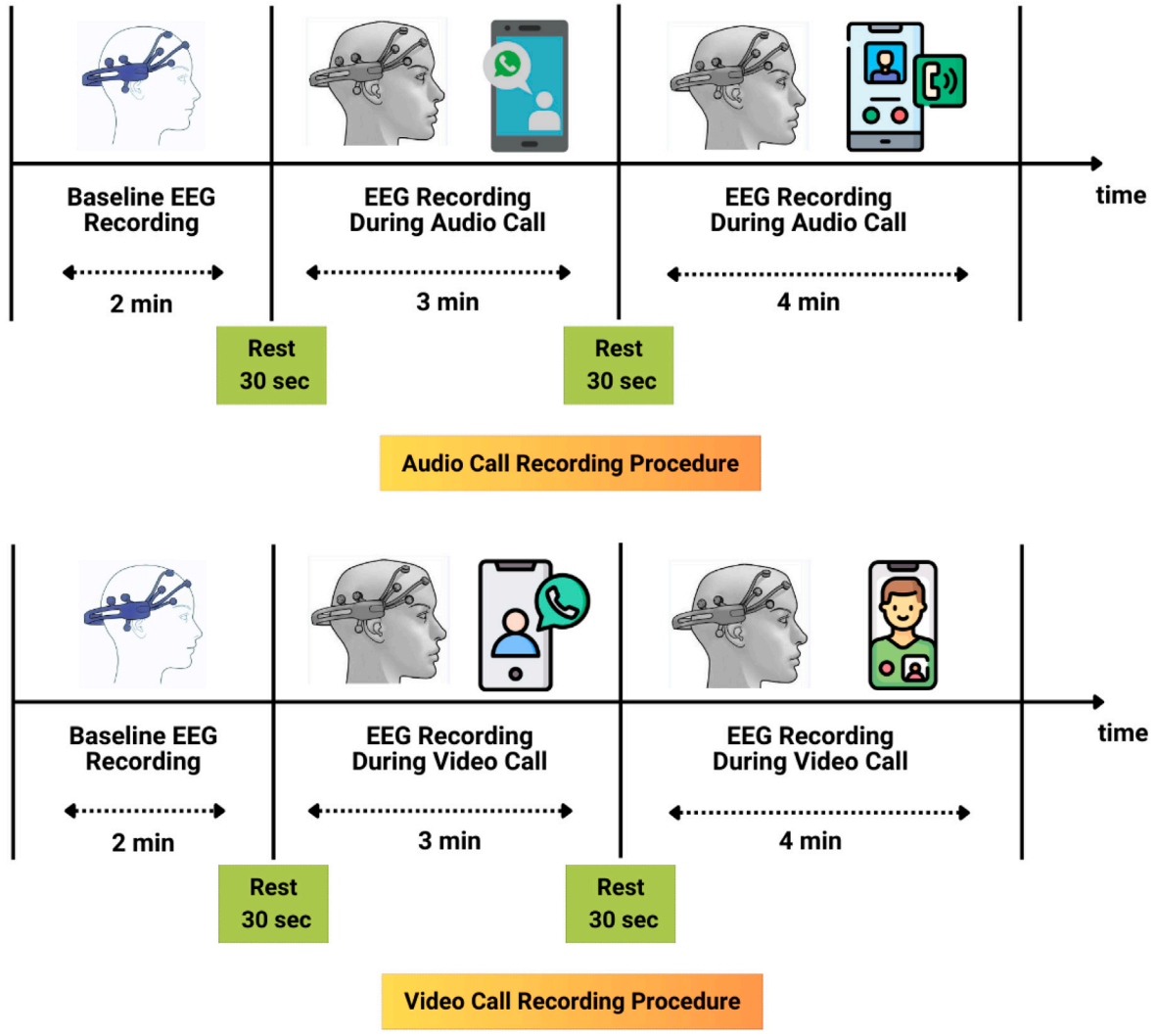


Fig. 2. Protocol for EEG-based evaluation of audio and video calls.

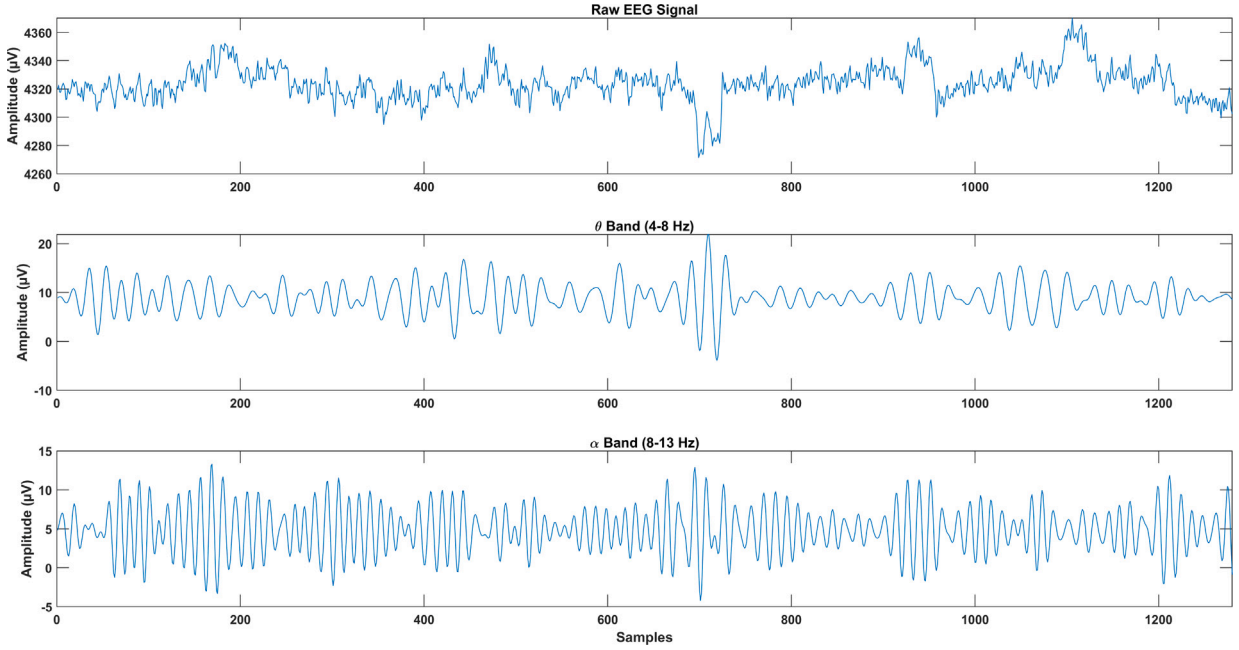


Fig. 3. Raw EEG signal and corresponding theta and alpha band components after bandpass filtering.

further, e.g., due to eye blinks and muscle activity. ICA separates the EEG signals into independent sources that can be removed based on their spatial and temporal features if artifactual in origin. ICA (14 components, random state = 97, default parameters) with the FastICA algorithm was used for artifact removal. We identified and excluded 2–3 components per participant based on these criteria before reconstructing the cleaned EEG. After artifact rejection, filtered EEG signals were utilized in mental fatigue estimation and regional frequency analysis.

2.5. Feature extraction

The preprocessed EEG signals were transformed into measurable features to identify the impact of audio and video call tasks on brain activity. Feature extraction was applied to derive measurements of cognitive load, mental fatigue, and regional brain activity. This section describes the extraction process, beginning with the estimation of cognitive load, followed by mental fatigue and average EEG frequency analyses.

2.5.1. Cognitive load estimation

The mental effort employed in information processing during a task, or cognitive load, was estimated through the TAR, which is a common measure derived from EEG signals. TAR is calculated from the spectral power of theta (4–8 Hz) and alpha (8–13 Hz) bands. The theta band and the alpha band are defined to represent cognitive demand and relaxation states, respectively. The next subsections describe TAR extraction, normalization to facilitate inter-participant comparability, and statistical measures used to compare the results.

Theta-alpha ratio (TAR). Preprocessed EEG data were divided into 6-second windows with an overlap of 0.5 s so that a good temporal resolution would be available without an inordinate computational burden to calculate the TAR. Spectral power was estimated in the theta and alpha frequency bands for each subject and task, respectively-e.g., BaselineA, Audio3min, Audio4min for an audio call group, BaselineV, Video3min, and Video4min for a video call group. More precisely, theta band power (4–8 Hz) was recorded from F3 and F4 electrodes over both hemispheres' frontal areas, sensitive to working memory and attentional load. On the other hand, alpha band power (8–13 Hz) was recorded from the P7 and P8 electrodes over the parietal regions famous for being related to resting cognitive states. The TAR was then calculated as follows

$$\mathrm{TAR} = \frac{\mathrm{Theta}_{\mathrm{F3}} + \mathrm{Theta}_{\mathrm{F4}}}{\mathrm{Alpha}_{\mathrm{P7}} + \mathrm{Alpha}_{\mathrm{P8}}}, \tag{1}$$

where $\mathrm{Theta}_{\mathrm{F3}}$ and $\mathrm{Theta}_{\mathrm{F4}}$ represent the spectral power of the theta band at the F3 and F4 electrodes, respectively. Moreover, $\mathrm{Alpha}_{\mathrm{P7}}$ and $\mathrm{Alpha}_{\mathrm{P8}}$ denote the alpha band power at the P7 and P8 electrodes, respectively.

Normalization. Because of the natural variability in EEG signals across participants with respect to inconsistency in skull thickness, electrode placements, and baseline activity, raw comparisons of TAR among individuals are prone to misinterpretation. To counter this, we applied min–max normalization to normalize the TAR values of each individual to a common range [0, 1]. This was done separately for the audio call condition (over BaselineA, Audio3min, and Audio4min) and the video call condition (over BaselineV, Video3min, and Video4min). The normalization formula is given by

$$\text{Normalized TAR}_i = \frac{\mathrm{TAR}_i - \min(\mathrm{TAR})}{\max(\mathrm{TAR}) - \min(\mathrm{TAR})}, \tag{2}$$

where TAR_i is the TAR value for a specific task, and $\min(\mathrm{TAR})$ and $\max(\mathrm{TAR})$ are the minimum and maximum TAR values across all tasks for that participant. Such normalization preserves relative cognitive load differences across data from any specific subject while being flexible regarding comparison and aggregation across the group. It must be pointed out that this kind of normalization greatly alters the distribution of the data, from a Gaussian to a bimodal one, because there are a lot of extreme values (0 and 1).

Mean. Mean TAR is a standard measure of cognitive load for each of the tasks and thus serves as a reference point against which any subsequent statistical comparison is made. For each participant and for each task, the mean TAR was calculated over all 6-second windows as follows

$$\text{Mean TAR} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{TAR}_i, \tag{3}$$

where TAR_i represents the TAR value for the ith window of the EEG signal, and N is the total number of windows in the recording. The mean TAR was calculated for all 28 participants over their respective tasks, producing a set of averaged cognitive load values. These scores were then combined for subjects within a group (audio and video) to obtain an overview of the average cognitive load caused by each condition.

Standard deviation. To provide an estimation of cognitive load task variance, the SD of TAR per task and participant was calculated. It describes mental effort variation over time, estimating persistent attention or shifting cognitive demands. The SD was computed as

$$\mathrm{SD} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathrm{TAR}_i - \text{Mean TAR})^2}, \tag{4}$$

where TAR_i is the TAR value for the ith window, Mean TAR is the mean TAR calculated for the task, and N is the total number of windows in the recording. The SD is a measure of cognitive load consistency in performing the call tasks, with a greater SD being an indicator of greater inconsistency of mental effort. Similar to the mean, SD values were added up for subjects within groups for comparison.

2.5.2. Mental fatigue assessment

The approach developed by Ndaro and Wang (2018) was adapted in this study for EEG-based estimation of fatigue using audio and video call tasks to analyze the effect of participants' cognitive state. Dealing with variations of alpha (8–13 Hz) and theta (4–8 Hz) rhythms as the primary feature of fatigue, the method focuses mainly on rhythm isolation and computation of the fatigue index in feature extraction after applying the preprocessing operations discussed above. The continuous wavelet transform (CWT) using the Morlet wavelet was used to extract alpha and theta rhythms from the preprocessed EEG data. For every EEG channel, CWT was performed over scales 1 to 128 at a sampling rate of 128 Hz. Alpha band power and theta band power were calculated by time-averaging wavelet coefficients over these bands. The calculation provided channel-wise alpha and theta rhythm results for 3-min call, and 4-min call for all 28 subjects.

The mental fatigue was measured by computing the combined deviation of alpha and theta rhythms EEG spectra in terms of Mahalanobis distance. For each subject and task condition, Mahalanobis distance was computed separately for alpha (D_α) and theta (D_θ) rhythms as follows (Ndaro & Wang, 2018)

$$\begin{aligned} D(x_\alpha) &= \sqrt{(x_\alpha - \mu)^T \mathbf{C}^{-1}(x_\alpha - \mu)}, \\ D(x_\theta) &= \sqrt{(x_\theta - \mu)^T \mathbf{N}^{-1}(x_\theta - \mu)}. \end{aligned} \tag{5}$$

Here, x_α and x_θ denote the alpha and theta rhythm data, respectively, for a given task condition; μ is the mean vector of the rhythm data; and $\mathbf{C}$ and $\mathbf{N}$ are the covariance matrices of the alpha and theta rhythms, respectively. Inverse covariance matrices were used to account for inter-channel correlations. Combined deviation (D_C) was subsequently determined as a weighted summation of individual distances by

$$D_C = \sigma \cdot D(x_\alpha) + (1-\sigma)\cdot D(x_\theta), \quad 0 \le \sigma \le 1, \tag{6}$$

where σ is a constant weighting factor equilibrating the alpha and theta rhythms' contributions. The calculated D_C values determined in this way were used as an index of fatigue, with large values reflecting higher mental fatigue, and were calculated for video and audio call groups for 3-min and 4-min task durations in preparation for subsequent comparative and temporal analysis.

Table 2
Cognitive load results for BaselineA, Audio3min, and Audio4min using normalized TAR.

Task	BaselineA	Audio3min	Audio4min
Mean	0.175474	0.763272	0.524796
Standard deviation	0.318339	0.371262	0.444624

Table 3
Cognitive load results for BaselineV, Video3min, and Video4min using normalized TAR.

Task	BaselineV	Video3min	Video4min
Mean	0.181581	0.777588	0.585826
Standard deviation	0.325674	0.359495	0.400775

Table 4
Results of a one-way ANOVA analysis for audio call.

	Degrees of Freedom	Sum of squares	Mean Sum of squares	F	p-value
Task	2	2.447216	1.223608	8.402642	0.000924
Residual	39	5.679250	0.145622		

Table 5
Results of a one-way ANOVA analysis for video call.

	Degrees of freedom	Sum of squares	Mean Sum of squares	F	p-value
Task	2	2.591924	1.295962	9.819852	0.000352
Residual	39	5.146974	0.131974		

2.5.3. Average frequency analysis

To examine the regional variations of brain activity owing to audio and video call tasks, average frequency analysis in relation to the peak alpha frequency (8–13 Hz) was performed across the different brain areas. This parameter indicates variations of cognitive and attentional states according to task requirements. The analysis was performed on preprocessed EEG data collected at a sampling frequency of 128 Hz from 28 subjects (14 per condition), as stated earlier.

EEG signals were divided into Audio3min, Audio4min and Video3min, Video4min in the audio and video call groups, respectively, depending on the condition. Eight brain areas were chosen based on the 10–20 system: left frontal (AF3, F7, F3, FC5), right frontal (AF4, F8, F4, FC6), left temporal (T7), right temporal (T8), left parietal (P7), right parietal (P8), left occipital (O1), and right occipital (O2). The Welch method was employed to estimate power spectral density (PSD) in the 8–13 Hz range to identify peak alpha frequencies across all subjects and conditions. We averaged PSD per channel within each region and determined the frequency with the highest power. The Wilcoxon signed-rank test was employed to compare the difference between peak frequency under the 3-min and 4-min conditions within regions. Hemispheric differences were compared by comparing peak frequency between corresponding left and right regions for each condition with the same test.

2.5.4. Machine learning-based feature selection and classification

After extracting EEG band-power and statistical features from baseline, 3-min, and 4-min sessions (for both audio and video groups), we also implemented a machine learning (ML) based pipeline to extract additional features in order to enhance the investigation of discriminative patterns within the data. A total of 56 features, including statistical features, derivative features, interval/period features, Hjorth parameters, frequency-domain features, and wavelet-based features, were extracted from the EEG signals and saved in CSV format for each pairwise condition (Baseline vs. 3 min, Baseline vs. 4 min and 3 min vs. 4 min). The features were normalized to decrease the inter-subject variability and allow a direct comparison between the participants. To determine the subset of features that carries the most information, three complementary feature importance approaches were used:

- Extra trees classifier, a tree ensemble technique that assigns significance measures to the features through random splitting.
- Extreme gradient boosting (XGBoost), a boosting method, which estimates feature contributions in iterative decision-tree construction.
- Correlation-based ranking, in which features that were strongly correlated with the target labels but relatively less correlated among each other ranked first.

The three rankings were averaged, and the top-15 features were selected for further evaluation. This method ensured that three perspectives (tree-based, boosting, and statistical) were employed in the implementations. Subsequently, both the entire set of features (56 features) and the top-15 selected features were utilized to train and test various classifiers: k-Nearest neighbors (KNN), random forest, decision tree, support vector machines (linear and RBF kernel), multi-layer perceptron (MLP), linear discriminant analysis (LDA), and XGBoost. Five-fold stratified cross-validation was performed, and the mean accuracy and F1-scores were computed for each classifier. This machine learning analysis allowed us to validate whether it is possible to distinguish the call conditions and durations based on EEG features and whether feature selection improved classification efficiency. All machine learning analyses were implemented in Python using scikit-learn (Pedregosa et al., 2011), XGBoost (Chen & Guestrin, 2016), Pandas (McKinney et al., 2011), and NumPy.

2.6. Self-report assessment

In addition to the EEG measures, a subjective evaluation of cognitive load and fatigue was collected at the end of each experimental session (Baseline, 3 min call, and 4 min call). Participants filled out a seven-item questionnaire aimed at assessing their perceived workload and physiological state. Each item was scored on a 7-point Likert scale (1 = not at all, 7 = extremely). The items assessed: mental demand, mental fatigue/tiredness, sleepiness, stress, attention, headache, and eye strain. The questionnaire was adapted from studies and the NASA Task Load Index (NASA-TLX) (Hoonakker et al., 2011) to measure cognitive workload. It was meant to complement EEG-derived indices and allow the convergence of neural and self-report outcomes relevant to call-based communication. The scores from the audio and video sessions were averaged accordingly (audio or visual group) and reported as mean ± standard deviation across participants.

3. Results

This section explores the effects of audio and video call tasks on cognitive processing, fatigue, and brain regional activity, based on EEG-based measurements for 28 participants. The results are presented in three subsections. First, Section 3.1 compares cognitive load differences between baseline, 3-min, and 4-min task conditions based on TAR and one-way analysis of variance (ANOVA) to compare statistical significance. Second, Section 3.2 verifies the presence of mental fatigue during the tasks by displaying dot plots of individual participants' fatigue score with mean fatigue value for the 3-min and 4-min conditions and curves of change in fatigue over time. Lastly, regional variation in peak alpha frequencies is discussed in Section 3.3 based on mean frequency, *p*-value tables, and bar plots of left–right hemisphere comparisons. Section 3.4 highlights the ML-based classification results, and lastly, self-report measures are discussed in Section 3.5.

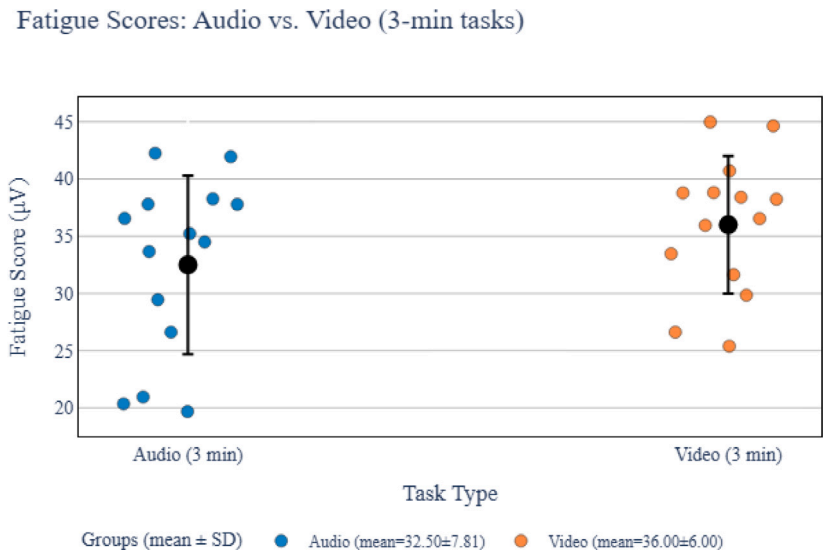


Fig. 4. Comparison of average fatigue scores between Audio (M = 32.50, SD = 7.81) and Video (M = 36.00, SD = 6.00) 3-minute tasks. Error bars represent SD.

3.1. Cognitive load estimation results

Cognitive load is examined using the normalized TAR for baseline, 3-minute, and 4-minute task conditions in 28 individuals divided into audio and video call groups. In the case of the audio call group, the mean normalized TAR is increased from 0.18 ± 0.32 during BaselineA to 0.76 ± 0.37 during Audio3min and is decreased further to 0.53 ± 0.45 during Audio4min (Table 2), indicating increased cognitive load at 3 min and a decline thereafter. And, in the video call condition, the mean normalized TAR is increased from 0.18 ± 0.33 at BaselineV to 0.78 ± 0.36 at Video3min. Then it is decreased to 0.59 ± 0.40 at Video4min (Table 3), showing a similar tendency but comparatively higher cognitive load in the video group. The standard deviations indicate moderate variability of cognitive load with higher values for the 4-min conditions.

The one-way ANOVA test is used to determine if mean TAR values are significantly different under different conditions. In the audio call category, p-value is 0.000924 (Table 4) and shows a significant difference ($p < 0.05$). In the video call category, p-value is 0.000352 (Table 5), which shows a significant difference ($p < 0.05$). Such conclusions highlight that the audio call as well as the video call are evidenced to have significant differences in the cognitive load; however, in the case of a video call, the effect is a bit stronger, which could be due to augmented visual demands.

Table 6
Average EEG frequencies for audio group across brain regions (Hz).

Region	Audio3min Mean ± SD	Audio4min Mean ± SD	p (Audio3min vs. Audio4min)
Left frontal	9.643 ± 0.882	9.902 ± 1.178	0.108
Right frontal	9.750 ± 1.000	10.018 ± 1.088	0.070
Left temporal	10.259 ± 0.922	10.312 ± 1.109	0.408
Right temporal	10.188 ± 0.742	10.384 ± 0.645	0.261
Left parietal	10.116 ± 1.047	9.777 ± 1.060	0.327
Right parietal	10.241 ± 0.980	10.134 ± 0.919	0.507
Left occipital	10.170 ± 0.869	10.554 ± 0.939	0.107
Right occipital	10.152 ± 0.976	10.545 ± 0.752	0.262

Table 7
Average EEG frequencies for video group across brain regions (Hz).

Region	Video3min Mean ± SD	Video4min Mean ± SD	p (Video3min vs. Video4min)
Left frontal	9.223 ± 1.385	9.688 ± 1.464	0.096
Right frontal	9.562 ± 1.444	9.393 ± 1.405	0.422
Left temporal	9.777 ± 1.327	9.857 ± 1.341	0.307
Right temporal	9.696 ± 1.412	9.777 ± 1.548	0.397
Left parietal	9.946 ± 1.299	10.089 ± 1.356	0.626
Right parietal	9.955 ± 1.286	9.938 ± 1.483	0.806
Left occipital	9.571 ± 1.328	9.795 ± 1.349	0.441
Right occipital	9.991 ± 1.246	10.062 ± 1.483	0.431

3.2. Mental fatigue results

Mental fatigue is quantified through the application of Mahalanobis distance (D_C) to estimate fatigue levels during audio and video calls. The average fatigue scores in microvolts (μV) are derived for 3-min and 4-min conditions within both groups, and temporal trends are assessed in order to capture how fatigue changes over time. Individual fatigue scores along with the average fatigue score for each condition were visualized using dot plots. From Fig. 4, it is observed that for the 3-minute tasks, the average fatigue score is 32.50 μV for the audio and 36.00 μV for the video group. From Fig. 5, it is seen that for the 4-min tasks, the fatigue score is increased to 38.84 μV for the audio group and 42.11 μV for the video group. These results indicate that video call tasks consistently induce higher fatigue levels than audio call tasks, with fatigue scores rising with task duration in both groups.

Line graphs are used to study how fatigue changes over time. In the case of audio call tasks, Fig. 6 compares Audio3min and Audio4min conditions. It is identified that fatigue keeps rising during both tasks, ending at 32.50 μV for the 3-minute call and 38.84 μV for the 4-minute call. For the video group, Fig. 7 is a comparison between Video3min and Video4min conditions and illustrates a similar pattern, where fatigue rises steadily in the 3-minute and 4-minute video calls, with the highest scores of 36.00 μV for Video3min and 42.11 μV for Video4min at the point of task completion. The fatigue score increases more quickly in the case of video tasks, particularly under the 4-min condition, suggesting that video calls impose an additional visual processing demand to induce higher levels of mental fatigue over time.

3.3. Analysis of mean EEG frequencies across brain regions

The peak frequency analysis examined alpha frequency changes in eight brain regions, from left frontal to right occipital, when individuals perform audio and video calls. Four different experimental conditions between Audio3min and Audio4min, along with Video3min and Video4min are assessed. The statistical comparison of peak alpha frequencies between Audio3min and Audio4min within the audio group

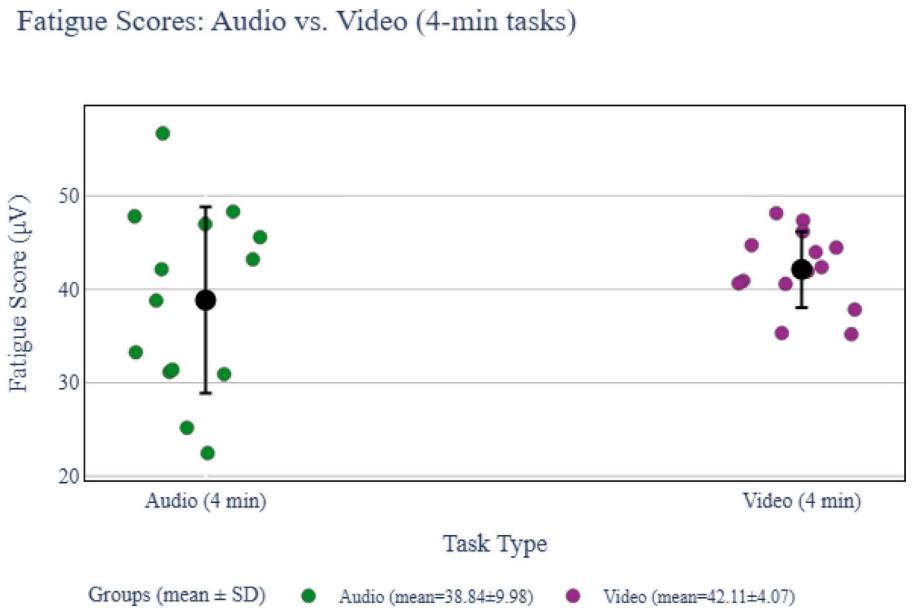


Fig. 5. Comparison of average fatigue scores between Audio (M = 38.84, SD = 9.98) and Video (M = 42.11, SD = 4.07) 4-minute tasks. Error bars represent SD.

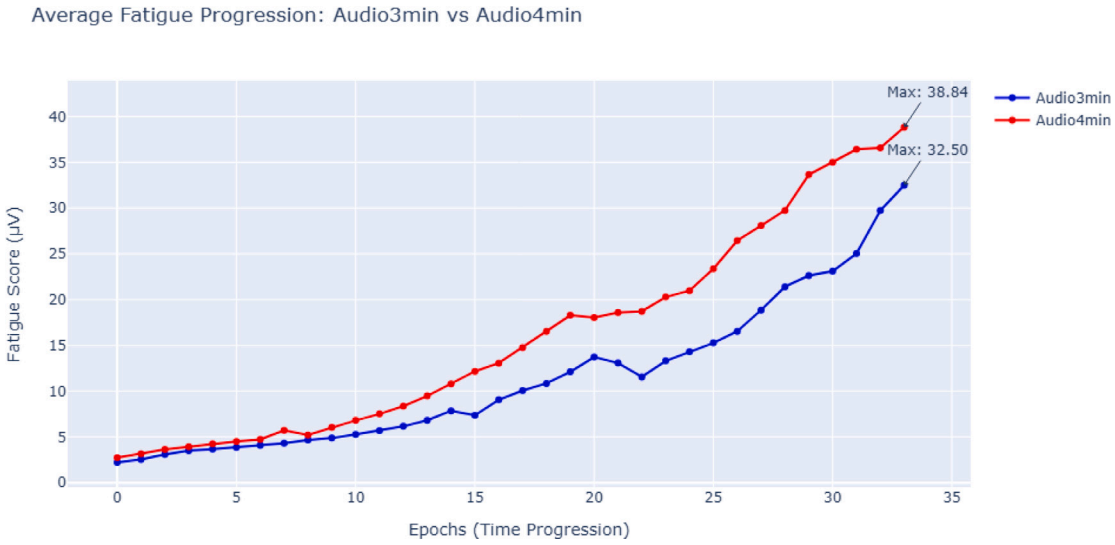


Fig. 6. Line plot illustrating the progression of average fatigue over time for Audio3min and Audio4min conditions.

and between Video3min and Video4min within the video group is conducted using Wilcoxon signed-rank tests.

For the audio group, mean frequencies are computed for Audio3min and Audio4min, as shown in Table 6. The mean frequency in the left frontal region is increased from 9.643 ± 0.882 Hz for Audio3min to 9.902 ± 1.178 Hz for Audio4min, although the difference is not statistically significant ($p = 0.108$, Wilcoxon signed-rank test). A similar trend is noted in the right frontal region as well, where mean frequency is increased from 9.750 ± 1.000 Hz to 10.018 ± 1.108 Hz with a p-value of 0.070. The right temporal region shows the highest increase; it is observed to change from 10.188 ± 0.742 Hz to 10.384 ± 0.645 Hz ($p = 0.261$), while the left parietal region shows a slight decrease; it is observed to change from 10.116 ± 1.047 Hz to 9.777 ± 1.060 Hz ($p = 0.327$). Across all regions, the p-values exceed 0.05, no significant differences are found. Mean frequencies in the video group follow a similar pattern, as shown in Table 7. The mean frequency in the left frontal region is increased from 9.223 ± 1.385 Hz (Video3min) to 9.688 ± 1.464 Hz (Video4min), with $p = 0.096$. The right occipital region shows the highest increase; it is observed to change from 9.991 ± 1.246 Hz to 10.062 ± 1.483 Hz ($p = 0.431$), while the right parietal region shows a slight decrease; it is observed to change from 10.116 ± 1.047 Hz to 9.777 ± 1.060 Hz ($p = 0.806$). Like in the audio group, no significant differences are seen ($p > 0.05$). It is noted that, in specific areas like the right and left parietal regions for the audio group and the right frontal and right parietal regions for the video group, slight decreases are recorded while other areas experience increases. The findings of this study align with previous research (Croft et al., 2010; Perentos et al., 2013; Roggeveen et al., 2015; Wallace et al., 2022), which also demonstrated inconsistent outcomes regarding the change in alpha power due to mobile phone exposure; some studies observed increased alpha power, others observed a decrease.

Both condition and region comparisons between left and right hemispheres showed minimal differences according to Figs. 8 and 9. Mean frequency in the right frontal region reached 10.02 Hz during Audio4min, while left frontal activity recorded 9.90 Hz ($p = 0.725$). Simultaneously, the left occipital region achieved 10.17 Hz during Audio3min when compared to 10.15 Hz in the right occipital area ($p = 0.875$). Right occipital frequencies in Video4min reached 10.06 Hz

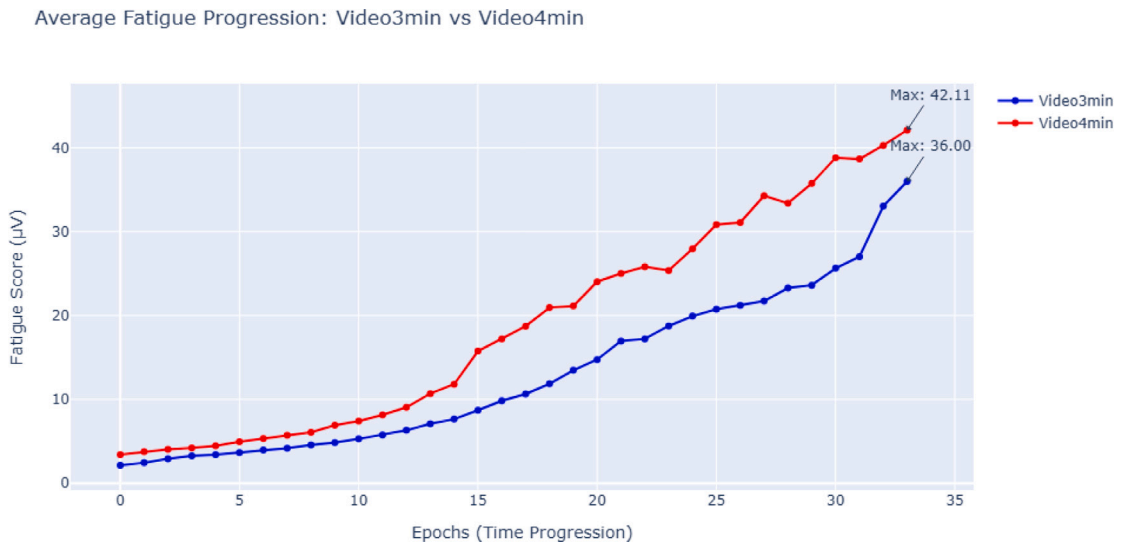


Fig. 7. Line plot illustrating the progression of average fatigue over time for Video3min and Video4min conditions.

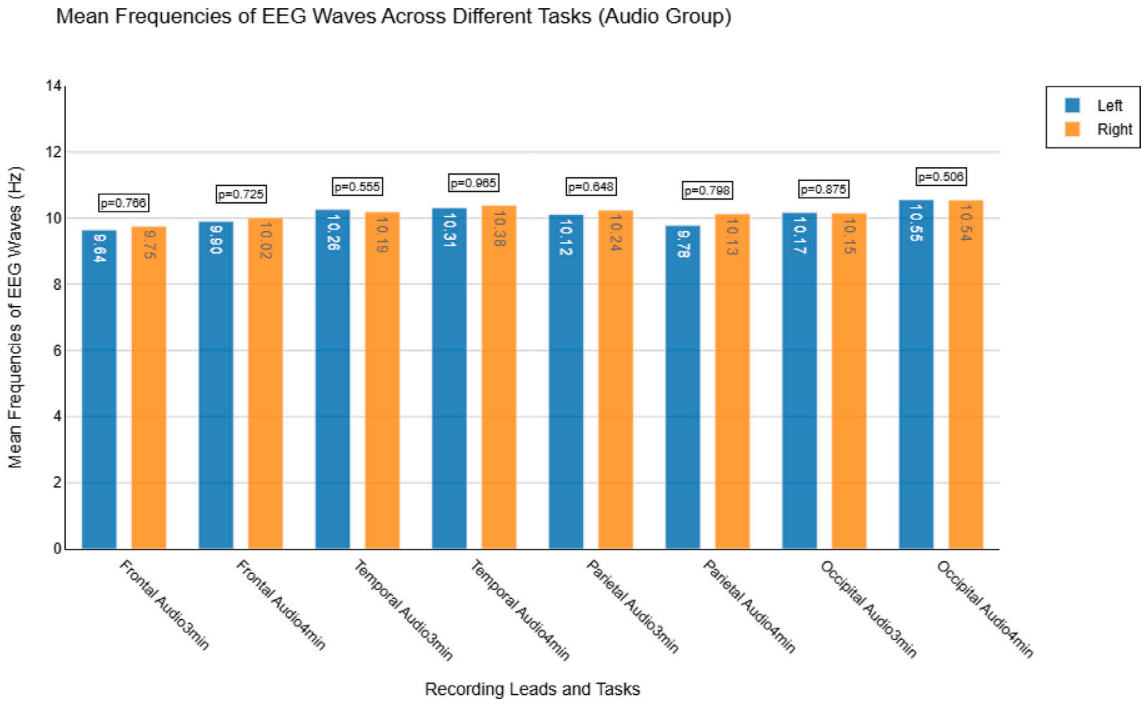


Fig. 8. Mean EEG frequencies (Hz) across brain regions for the audio group, comparing left and right hemispheres during Audio3min and Audio4min.

while left side frequencies maintained a lower rate of 9.79 Hz (p = 0.574).

3.4. Machine learning–based classification results

Classification analyses were carried out to assess whether EEG characteristics were capable of distinguishing between the conditions (Baseline vs. 3 min, Baseline vs. 4 min, and 3 min vs. 4 min) in both the audio and video groups. The models were tested on the full 56-feature set, as well as the top-15 selected features. Figs. 10, 11, 12, 13 present mean classification accuracies for the video and audio groups, respectively. Ensemble models (random forest, XGBoost) and SVM (RBF kernel) provided the best mean accuracies on all the datasets with consistency. Performance was maintained largely even after feature selection with little loss of accuracy, substantiating that the 15-feature set retains most of the discriminative information.

Fig. 14 illustrates the Receiver Operating Characteristic (ROC) curves of the 6 pair-wise comparisons, indicating improved discriminability in audio and video groups, as all Area Under the Curve (AUC) values were greater than 0.90. The highest separability was shown in baseline vs. 4-min comparisons, with Audio AUCs of 0.998 using all features and 0.989 with selected features and Video AUCs of 0.985 and 0.971, respectively. The next highest separability was found in the baseline vs. 3-min comparisons, with Audio AUCs of 0.988 and 0.960 and Video AUCs of 0.977 and 0.966. Moreover, the most difficult distinction was between 3-min vs. 4-min sessions, which still showed strong discrimination, with Audio AUCs of 0.957 and 0.930 and Video AUCs of 0.914 and 0.909. Feature selection consistently resulted in small AUC decreases (≈0.01–0.03), and it proved that the smaller feature set comprised much of the discriminative information without losing efficiency.

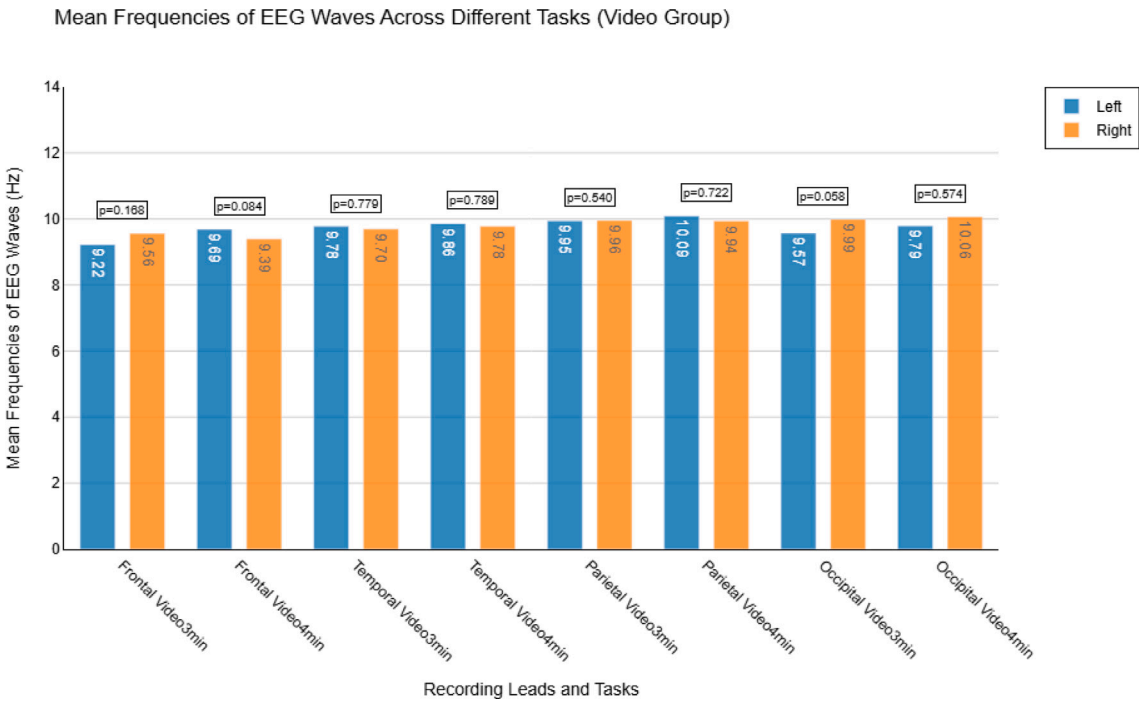


Fig. 9. Mean EEG frequencies (Hz) across brain regions for the video group, comparing left and right hemispheres during Video3min and Video4min.

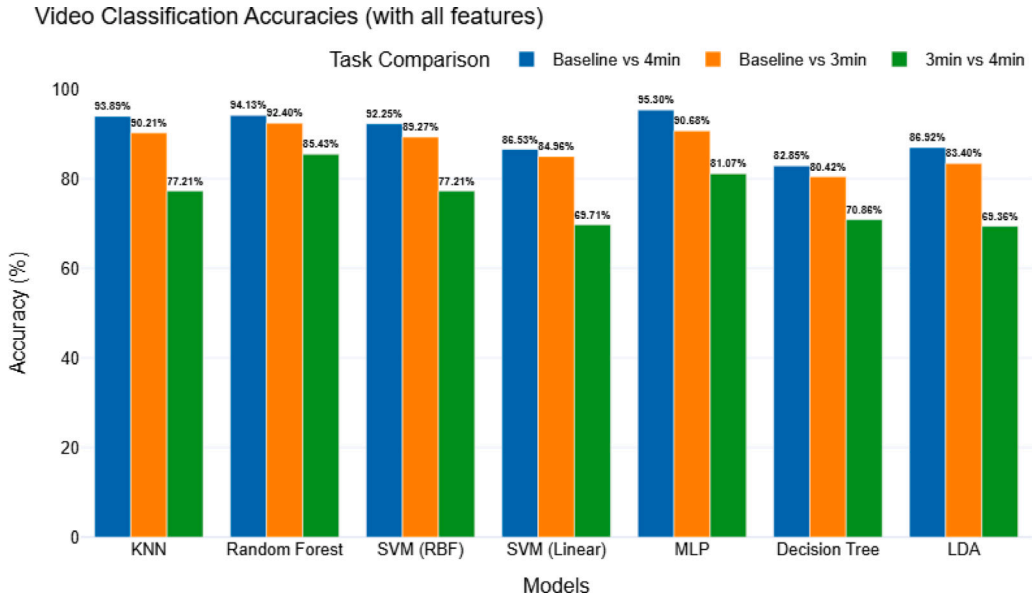


Fig. 10. Classification accuracies (all features) for video tasks across three comparisons (Baseline vs. 3-min, Baseline vs. 4-min, and 3-min vs. 4-min).

The classification results from the XGBoost model demonstrated good discriminative ability in both audio and video conditions in Table 8. Overall, baseline vs. task comparisons yielded higher accuracies than within-task (3 min vs. 4 min) comparisons. For the video tasks, the highest accuracy was obtained in the baseline vs. 4 min (94.1% for all and 92.2% for selected features) and audio tasks, especially baseline vs. 3 min (95.7% with all features). Within-task comparisons (3 min vs. 4 min) showed comparatively lower accuracies (83%–90%) due to the subtle differences between the task durations. Notably, feature selection slightly decreased accuracy in some cases, suggesting that reducing dimensionality can obtain more compact models with negligible classification performance loss.

3.5. Self-report measures

In addition to EEG results, we analyzed subjective ratings obtained immediately after each session (Baseline, 3-min call, and 4-min call). Participants rated seven dimensions (mental demand, fatigue, sleepiness, stress, attention, headache and eyestrain) on a 7-point Likert scale. Mean values (±SD) are plotted in Figs. 15 and 16. Repeated-measures ANOVA and Friedman tests indicated that all items significantly changed across the three conditions (baseline, 3-min, and 4-min) in both groups (all $p < .001$). Notably, both audio and video calls markedly increased self-reported mental demand and fatigue compared to baseline. Stress, attention, headache, and eyestrain also displayed

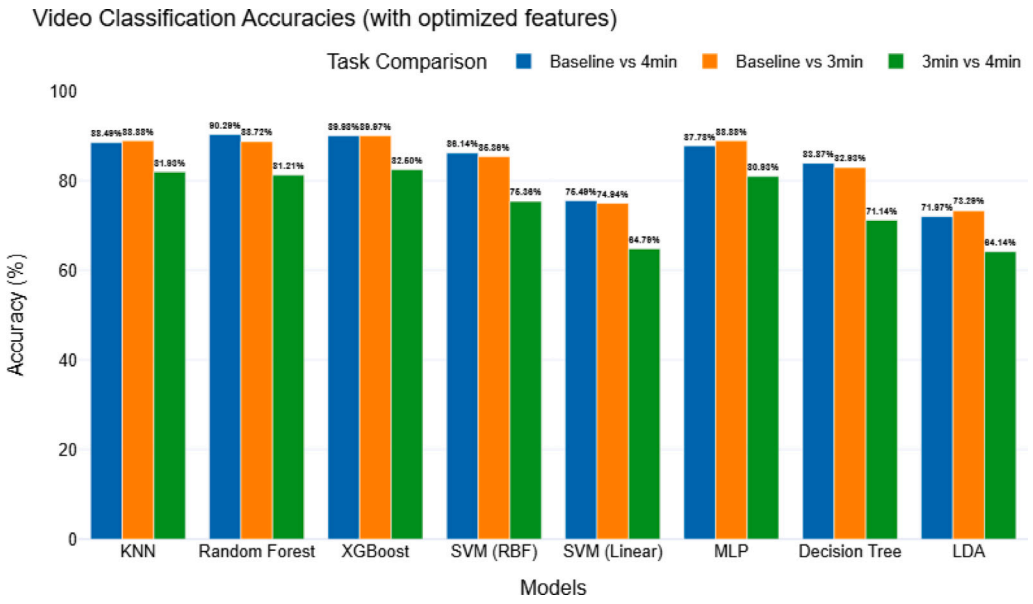


Fig. 11. Classification accuracies (selected features) for video tasks across three comparisons (Baseline vs. 3-min, Baseline vs. 4-min, and 3-min vs. 4-min).

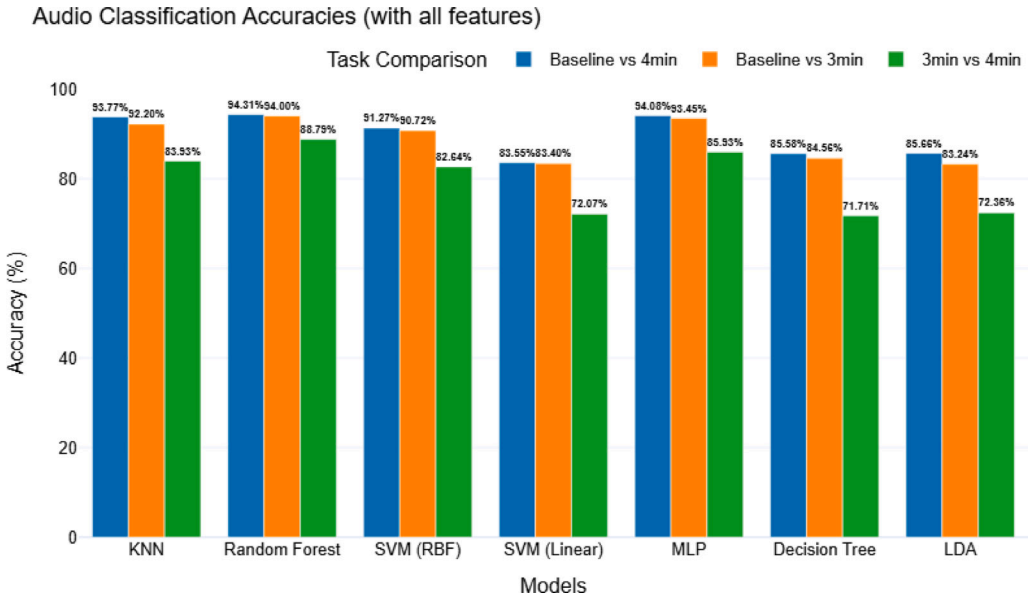


Fig. 12. Classification accuracies (all features) for audio tasks across three comparisons (Baseline vs. 3-min, Baseline vs. 4-min, and 3-min vs. 4-min).

Table 8
Performance of XGBoost classifier for Audio and Video conditions using all features vs. selected features. Metrics are reported as Accuracy and macro-averaged F1-score (in %).

Comparison	Feature set	Accuracy	Macro precision	Macro recall	Macro F1
Baseline vs. 3-min video	All features	90.23%	90.10%	90.26%	90.17%
	Selected features	91.02%	90.96%	90.90%	90.93%
Baseline vs. 4-min video	All features	94.14%	94.06%	94.13%	94.09%
	Selected features	92.19%	92.37%	91.90%	92.08%
3-min vs. 4-min video	All features	82.50%	82.50%	82.50%	82.50%
	Selected features	83.57%	83.60%	83.57%	83.57%
Baseline vs. 3-min audio	All features	95.72%	95.66%	95.72%	95.69%
	Selected features	92.22%	92.39%	91.94%	92.12%
Baseline vs. 4-min audio	All features	96.50%	96.69%	96.29%	96.46%
	Selected features	94.55%	94.46%	94.79%	94.53%
3-min vs. 4-min audio	All features	90.36%	90.61%	90.36%	90.34%
	Selected features	85.71%	85.98%	85.71%	85.69%

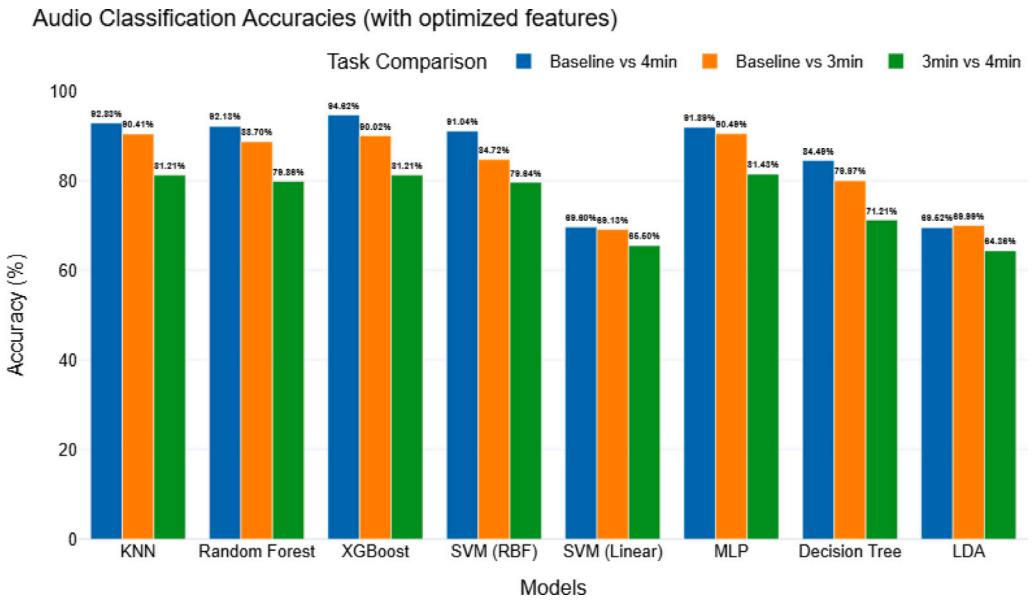


Fig. 13. Classification accuracies (selected features) for audio tasks across three comparisons (Baseline vs. 3-min, Baseline vs. 4-min, and 3-min vs. 4-min).

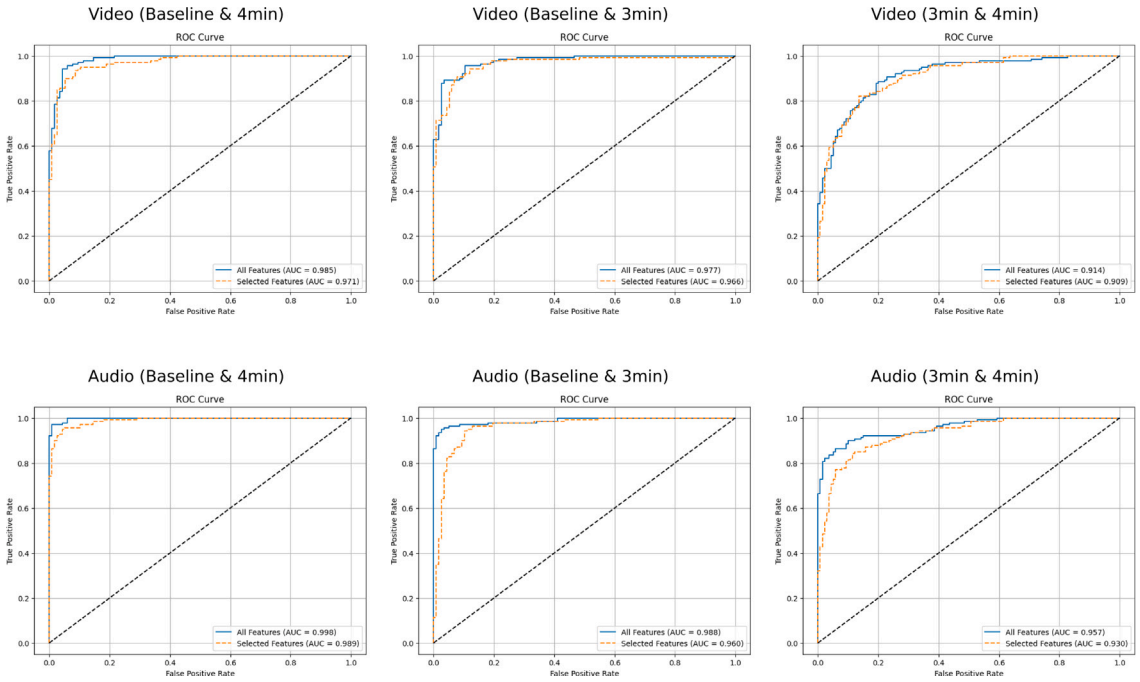


Fig. 14. ROC curves for six classification tasks.

significant within-group effects, indicating the progressive subjective strain induced by the call.

Independent-sample t-tests and nonparametric tests also identified significant modality effects on several measures. Video calls were rated as more cognitively demanding than audio calls at 3 min ($t(26) = -4.03$, $p < .001$, $d = -1.52$), and more fatigue was experienced at both 3 min ($t(26) = -3.94$, $p < .001$, $d = -1.49$) and at 4 min ($t(26) = -3.45$, $p = .003$, $d = -1.30$). Video calling also yielded much higher attention scores at 3 min ($t(26) = -2.62$, $p = .015$) and 4 min ($t(26) = -2.77$, $p = .010$), suggesting greater engagement with content. Stress was mildly variable at baseline, with the video participants reporting a little more stress than audio ($t(26) = 2.22$, $p = .035$). All details are summarized in Table 9. There were no significant between-group differences on sleepiness, headache, or eyestrain.

3.6. Comparative study with other proposed techniques

A comparison between the proposed model and prior EEG-based analyses that studied smartphone task-related cognitive load and fatigue levels is demonstrated in Table 10. Parmar et al. (2019) conducted research with 21 participants engaged in phone calls, lasting between five to fifteen minutes, through Wilcoxon and chi-square tests and established a correlation between call duration and frequency increases. Ndaro and Wang (2018) studied ICA alongside wavelet analysis with 20 participants completing a peg transfer task that lasted 5 min each trial to detect fatigue beginning at the 13th trial. Cabañero et al. (2020) utilized TAR alongside bandpass filtering (2–15 Hz) resulted in higher cognitive loads throughout voice messages during production tasks with 26 participants who completed 12 tasks that lasted almost

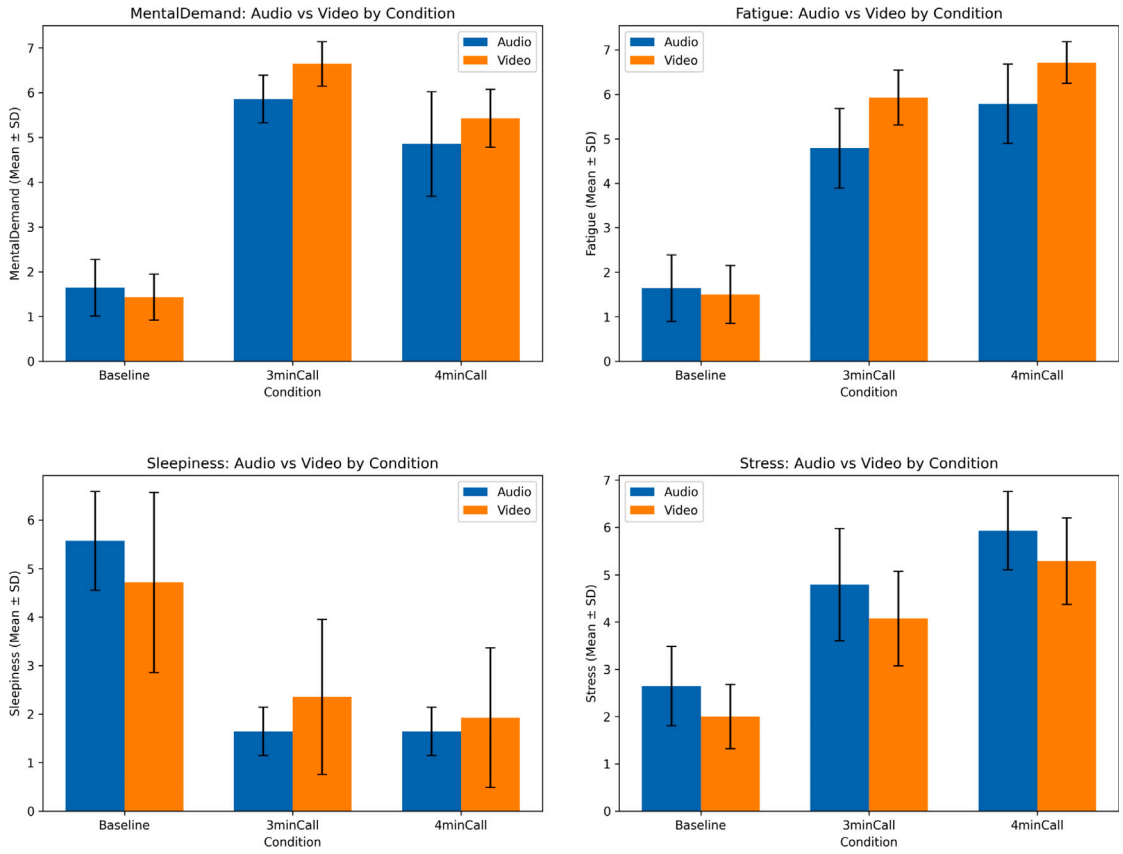


Fig. 15. Mean (±SD) self-reported ratings of mental demand, fatigue, sleepiness, and stress across conditions (baseline, 3-min call, 4-min call) for audio and video groups.

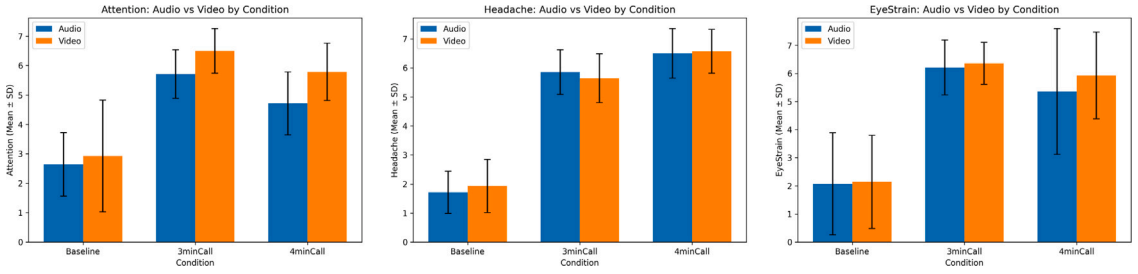


Fig. 16. Mean (±SD) self-reported ratings of attention, headache, and eyestrain across conditions (baseline, 3-min call, 4-min call) for audio and video groups.

Table 9
Significant between-group differences ($p < 0.05$) in self-reported measures (Audio vs. Video). Values are presented as mean ± SD, with corresponding t-test, Mann–Whitney U, and Cohen's d effect sizes.

Item	Condition	Audio (M ± SD)	Video (M ± SD)	t	p_t	U	p_u	Cohen's d
Mental demand	3minCall	5.86 ± 0.53	6.64 ± 0.50	−4.03	0.0004	34.5	0.0012	−1.52
Fatigue	3minCall	4.79 ± 0.89	5.93 ± 0.62	−3.94	0.0006	31.5	0.0013	−1.49
Fatigue	4minCall	5.79 ± 0.89	6.71 ± 0.47	−3.45	0.0026	36.0	0.0018	−1.30
Stress	Baseline	2.64 ± 0.84	2.00 ± 0.68	2.22	0.0355	139.5	0.0428	0.84
Attention	3minCall	5.71 ± 0.83	6.50 ± 0.76	−2.62	0.0145	49.5	0.0183	−0.99
Attention	4minCall	4.71 ± 1.07	5.79 ± 0.97	−2.77	0.0102	45.0	0.0127	−1.05

10 s each. Ding et al. (2020) tested whether EEG can measure smartphone user experience (UX) accurately for short-term interaction using PSD analysis, behavioral performance, and subjective ratings collectively. With 24 participants, they found that stronger alpha, delta, and gamma power for task activities like online shopping (62.04–117.24 s) was associated with better UX. The proposed model examined EEG data gathered from 28 participants during WhatsApp audio and video call sessions lasting 2 to 4 min each. We applied several processing techniques, including ICA, TAR, ANOVA, Mahalanobis Distance. The results indicated higher cognitive load and mental fatigue in video calls. Additionally, in order to improve the robustness and interpretability, two supplementary components were incorporated in the proposed model apart from the EEG-derived parameters. After each session, a self-report questionnaire was completed to determine subjective mental demand, tiredness, attention, stress, and discomfort.

Table 10
Comparative study with other methods.

Proposed by	Technique used	Tasks performed	Number of subjects	Outcomes	Time (per task-wise)
Parmar et al. (2019)	High-pass filter (1 Hz), low-pass filter (70 Hz), notch filter, Wilcoxon signed-rank test, chi-square test	Baseline recording, phone off, phone on without audio, phone on with audio	21	Frequencies increased with increasing call duration, amplitudes decreased	Baseline: 5 min, Phone off: 5 min, Phone on: 5 min, Phone on with audio: 5/10/15 min
Ndaro and Wang (2018)	BSS with ICA, Wavelet analysis (alpha, theta), Mahalanobis Distance	Peg transfer task on laparoscopic simulator (20 trials)	20	Fatigue increased after 13th trial	Each trial: 5 min
Cabañero et al. (2020)	Bandpass filtering (2–15 Hz), min–max normalization, Theta-Alpha Ratio (TAR)	12 tasks (e.g., add/move app shortcut, write excuse, voice message, listen to voice recording)	26	Production tasks (e.g., voice message) had highest cognitive load; audio tasks showed higher load	All tasks: ~10 s
Ding et al. (2020)	Power spectral density (PSD) in Delta, Theta, Alpha, Beta, Gamma bands, ICA, high-pass filter (1 Hz)	Online shopping (purchase movie ticket), map search (find bus route), social media (take selfie, post)	24 (12 per smartphone group)	Smartphone with higher UX scores evoked stronger Alpha, Delta, Gamma power, weaker Beta, Theta power	Rest: 62.04 s, Purchasing: 69.29 s, Route finding: 80.18 s, Social media: 117.24 s
Proposed model	Bandpass filtering (2–15 Hz, 1–50 Hz), ICA, notch filter, min–max normalization, Theta-Alpha Ratio (TAR), Mahalanobis Distance, Wilcoxon signed-rank test, ANOVA test, self report measurements, ML-based classification	Baseline recording, WhatsApp audio and video call	28 (14 audio, 14 video)	Increased cognitive load in calls (video > audio), higher fatigue in video group, frequencies increased with longer call duration (e.g., 4-min vs. 3-min)	Baseline: 2 min, audio call: 3 min and 4 min, video call: 3 min and 4 min

By correlating physiological indicators with participants' workload and fatigue perception, the measures offered convergent validity with EEG indices. Moreover, in order to investigate the discriminative power of EEG features across conditions, a machine learning based classification pipeline was utilized. Incorporating 56 extracted features (statistical, Hjorth, frequency, and wavelet-based) and a top-15 reduced feature set, models like XGBoost and random forest achieved high classification accuracies and AUC values (>0.90), indicating the feasibility of automatic workload detection.

3.7. Discussion

The study investigated cognitive load and fatigue during audio and video calls through EEG indices, regional analysis, machine learning classification of EEG data, and self-reports. Both audio and video calls showed an increase in the TAR from baseline, with a significantly larger increase in video calls. This is consistent with the previous findings that show that a higher TAR is associated with greater attentional demands and cognitive workload. Fatigue analysis confirmed that call engagement increased mental fatigue, with more pronounced effects during video than audio sessions. This agrees with previous studies, which have reported increased theta activity and altered alpha rhythms in task-induced fatigue. No consistent alpha frequency differences among regions were found between conditions. This implies that global EEG measures like TAR and fatigue indicators are more sensitive to modulation by calls about cognition, in agreement with previous mixed findings.

Classification analyses further confirmed that EEG features effectively discriminated between experimental conditions. Accuracies were greatest for baseline vs. call comparisons and somewhat lower but still strong values for 3-min vs. 4-min comparisons. ROC analysis evidenced high separability with all AUCs greater than 0.90. Feature selection had a minimal decrease in performance, indicating that a subset of features can maintain discriminability while optimizing efficiency. Subjective ratings yielded convergent evidence, as there were more reported mental demand, fatigue, and attention in video calls than in audio calls, especially for longer calls. These results are in line with the EEG measures and emphasize the perceived effect of video communication. Overall, these results validate our hypotheses. Both audio and video calls elevated cognitive load and fatigue from baseline, with larger effects for video calls. (Hypotheses 1 and 2). Longer call length magnified these differences, and self-report measures correlated with EEG-derived measures (Hypothesis 3).

4. Conclusion

This study investigated changes in brain activity due to the use of mobile phones in audio and video calls by performing an EEG analysis. Our results showed that both audio and video calls increased cognitive load, while video calls imposed a significantly higher cognitive burden, supported by greater TAR. The mental fatigue levels determined through Mahalanobis distance were also higher in the video call group. EEG frequency measures increased due to longer call duration (4 min compared to 3 min), yet no significant differences were noticed regionally ($p > 0.05$). The experimental findings show that video calls place a greater neural burden on users because participants are required to process visual information along with auditory information during video calls. The study provides quantitative evidence by showing increased mental workload during video calls, offering insight into the physiological effects of modern communication devices on human health for users who spend extended periods on mobile devices. TAR and Mahalanobis distance demonstrated strong effectiveness as cognitive load and fatigue assessment tools in EEG-based investigations that examine human-device interactions. The findings from this research enable future investigations into mobile phone effects on brain activity, which focus on identifying cognitive decline at early stages. This research lays the groundwork to use EEG-based analysis as a tool for cognitive health monitoring during the era of omnipresent mobile technology. However, the comparatively small, homogenous sample (young university students) limits generalizability, and higher-density EEG systems could provide more detailed spatial information. Additionally, although ICA was employed, the remaining artifacts cannot be entirely excluded. Despite these limitations, our EEG, self-report, and machine learning approach together show a new multimodal framework that can be applied to the real-world monitoring of mental workload in healthcare, education, and the workplace. Future investigations may explore the prolonged cognitive impact of audio and video call exposure using larger and more diverse participant groups.

CRediT authorship contribution statement

Mohammad Azmain Zahir Akas: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tanvir Hossain Ovi:** Writing – review & editing, Validation, Methodology. **Md. Fazlul Kader:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation.

Informed Consent Statement

All participants gave their written consent to record EEG data for the research purpose only, provided that the personal information would remain confidential.

Ethical Statement

The study adheres to the ethical principles outlined in the Declaration of Helsinki and the guidelines of the local ethics committee.

Declaration of Generative AI and AI-assisted technologies in the writing process

No generative artificial intelligence (AI) tools were used for the generation of content, research, or analysis in this paper.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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