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ORIGINAL PAPER

Comparing online cognitive load on mobile versus PC-based devices

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Abstract
Navigating the web represents a complex cognitive activity that requires effective integration of different stimuli and the correct functioning of numerous cognitive abilities (including attention, perception, and working memory). Despite the potential relevance of the topic, numerous limitations are present throughout the literature about the cognitive load during online activities. The main aim of this study is to investigate cognitive load during comprehension and information-seeking tasks. In particular, we here focus on the comparison of the cognitive load required while performing those tasks using mobile or PC-based devices. This topic has become even more crucial due to the massive adoption of smart working and distance learning during the COVID-19 pandemic. A great effort is nowadays devoted to the detection and quantification of stressful states induced by working and learning activities. Continuous stress and excessive cognitive load are two of the main causes of mental and physical illnesses such as depression or anxiety. Cognitive load was measured through electroencephalography (EEG), acquired via a low-cost wireless EEG headset. Two different tasks were considered: reading comprehension (CO) of online text and online information-seeking (IS). Moreover, two experimental conditions were compared, administering the two tasks using mobile (MB) and desktop (PC) devices. Eleven participants were involved in each experimental condition, MB and PC, performing both the tasks on the same device, for a total of twenty-two people, recruited from students, researchers, and employees of the university. The following two research questions were investigated: Q1: Is there a difference in the cognitive load while performing the comprehension and the information-seeking tasks? Q2: Does the adopted device influence the cognitive load? The results obtained show that the baseline (BL) requires the lower cognitive load in both the conditions, while in IS task, the requirement reaches its highest value, especially using a mobile phone. In general, the power of all the brain wave bands increased in all conditions (MB and PC) during the two tasks (CO and IS), except for alpha, which is usually high in a state of relaxation and low cognitive load. People include website navigation into their daily routines, and for this, it is important to create an interaction that is as easy and barrier-free as possible. An effective design allows a user to focus on interesting information: many website architectures, instead, are an obstacle to be overcome; they impose a high cognitive load and poor user experience. All these aspects draw cognitive resources away from the user's primary task of finding and comprehending the site's information. Having information about how the cognitive load varies based on the device adopted and the considered task can provide useful indicators in this direction. This work suggests that using an EEG low-cost wearable device could be useful to quantify the cognitive load induced, allowing the development of new experiments to analyse these dependencies deeper, and to provide suggestions for better interaction with the web.

Keywords Cognitive load · User experience · Web experience · Online behaviour · EEG

1 Introduction

In recent years, we have witnessed a significant and extremely rapid mobile internet diffusion, to the point where the amount of mobile internet users almost equals the PC-based internet accesses. For what is more, data showed that mobile is the only means, or the only affordable means, by which novel internet users access the internet, particularly those with lower incomes and possibly living in developing countries. A consistent number of findings suggest that mobile devices provide a wider range of contexts in which they can be used to access the internet [1–6, and references therein]. Because of the considerable

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spread of such mobile device usage to access, it is therefore of great interest to gain a comprehensive understanding of its specific characteristics if compared to PC-based web use, in particular in terms of ease of use (and related cognitive load) during different cognitive tasks like, for example, online reading and online information-seeking. For instance, mobile information-seeking patterns are significantly more constrained if compared to PC-based web patterns. Besides, substantial costs in terms of attentiveness and productivity [7] and higher search costs have been recorded on mobile platforms [8].

It is well known that human cognitive capacity can only process a few elements of information at a given time because the cognitive resources available during the execution of a task are limited, and they are used selectively and limited towards achieving a specific goal [9–11]. The Cognitive Load Theory is based on the idea that the intervention of cognitive processes that are closely connected to the memory happens while processing information or performing a task [9]. A heavy cognitive load may hinder information processing, perception of stimuli, and learning intended as study and memorization, particularly during complex activities that require processing a lot of information [9, 12].

Navigating the web represents a complex cognitive activity, similar to many activities carried out offline. Nonetheless, tasks such as reading, buying products, or seeking information online require a correct processing and integration of a variety of different stimuli, as well as the correct functioning of several cognitive capacities, including attention, perception, and working memory [13–15]. The availability of cognitive resources during the execution of a task is limited, and such resources are selectively used to achieve an aim or a specific objective [9–11]. Some studies [14, 16, 17] have pointed out that the web generally requires a high cognitive effort, and, therefore, it is often the cause of cognitive load increase [18, 19]. Previous literature has drawn a link between the Cognitive Load Theory and the principles of web usability. Among other things, usability has been shown to improve accessibility, defined as "the extent to which an environment, product, or service removes barriers and allows equal access to all components, irrespective of characteristics and difficulties/disabilities" [20], for various categories of users with sensory disabilities [21]. Therefore, a website design should take into consideration the principles of usability to be appealing to users with and without a disability or any special needs. For instance, there is consensus about usability requiring consistency in layouts and constitutive features of the webpages, ease of navigation [22], and simplicity, that is, the elimination of all unnecessary objects [23].

For these reasons, several studies have investigated the users' cognitive load during navigation on the web, in particular referring to the diverse tasks that can be carried out online (e.g. information-seeking and text reading) and to how web design can positively or negatively affect cognitive load [16, 24–29]. Among the most frequently studied activities, information-seeking resulted to be particularly relevant in the examination of users' behaviour on the web and of their cognitive load [14, 17, 30–33].

Despite the existing knowledge and the potential relevance of the topic, numerous limitations are still present throughout the literature about cognitive load and web usability during online information-seeking activities. First of all, the methodology for the evaluation of both during web navigation has so far been mainly subjective (e.g. self-report questionnaires, interviews, and thinking-aloud protocols). On the contrary, very few studies have included physiological measures in their data, such as brain activation, ocular movements, heart rate, or skin conductance. Moreover, even though people access the web from different devices, in particular mobile and PC-based devices, studies have mainly been directed towards the assessment of cognitive load during the navigation on PC [17, 19, 32, 34, 35]. Most research on cognitive load and internet access to date has lacked comparative analyses, in which the usage patterns of mobile platforms are analysed alongside those of desktop devices.

Cognitive load comparison between mobile and desktop users is particularly important to build consciousness about the different effects that accessing the same information (i.e. learning material) can have on students with different equipment. Since excessive cognitive load is considered responsible for physical illnesses such as depression and anxiety [36], it is important to know if devices that permit the delivery of instruction to learners at any time and any place [37] actually have a different impact on cognitive load.

The novelty of the present study is in the methodology applied for analysing users' cognitive load during online tasks. Besides the traditional self-report questionnaires and interviews, we here address the issue through the electroencephalogram (EEG) users' response.

The EEG is a multichannel signal widely used for studying brain activation. Due to its high temporal resolution, it provides useful data for investigating human brain functioning. Specific brain activities induce changes in different brain wave potentials. These variations can thus be correlated with multiple functions, such as movement, perception, sensory registration, and tracking as well as cognitive processes related to learning, attention, and memory [38]. Previous works suggested that EEG may be useful to analyse different cognitive processes [39, 40]. In particular, previous studies have evidenced a decrease of alpha activity while cognitive load increases and an increase of theta activity with higher task difficulty [41–44]. In particular, Cabañero et al. [44] reported that the theta-alpha ratio (TAR) obtained by dividing the spectral power of theta band in the middle frontal area (Fz) by the spectral power of the alpha band in the central parietal area (Pz) significantly captures these spectral power variations for the theta and alpha bands. Other studies have shown that the decrease of alpha activity is counterbalanced by an increase of beta, related to workload complexity [45, 46]. Finally, Fitzgibbon et al. [47] have shown that cognitive tasks augment gamma EEG power.

It has thus been proven that during cognitive tasks, the spectral composition of EEG varies in response to changes in task difficulty or level of alertness [48]. However, precise workload estimation is an ongoing research challenge. Zarjam et al. [49] measured the entropy of wavelet coefficients extracted from EEG signals. In this way, the authors were able to distinguish seven different levels of workload induced using an arithmetic task.

Summarizing, in this article, we investigate if differences are observed from the EEG signal analysis when comparing users' cognitive load associated with two different tasks (comprehension, reading a text online vs. online information-seeking) and if these differences are affected by the device used (mobile vs. desktop). To this end, an experiment has been set up where EEG signals have been registered using a low-cost wireless EEG headset. Data will be made available upon request to the authors.

2 Materials and methods

2.1 Participants

Twenty-two participants, 14 females (63%) and 8 males (37%), age (years old) = 24.4 (SD 6.4), years of education = 17.6 (SD 1.9), were recruited among students and personnel of the University of Milano-Bicocca and other universities. No credits nor economic rewards were provided during the research. Before participating, each individual was informed by the researcher about the experiment's characteristics, both verbally and through a written information leaflet. To be included in the study, individuals had to meet the following criteria: (1) age between 18 and 35 years old, (2) no major medical disorders (heart disease or high blood pressure, neurological disorders, epilepsy), (3) no presence of pharmacotherapy (psychoactive drugs, anti-hypertensive, anti-depressants), (4) no significant visual impairment (all with normal or corrected-to-normal visual acuity), and (5) no left-handed.

2.2 Procedure

Before starting the experiment, each participant was asked to sign a written consent to participate in the study. Participants were asked to wear the EEG device, to record their electroencephalographic signals. A brief baseline (3 min long) was recorded for each participant at rest condition, with their eyes open. After recording the baseline, the experimental session began. The order of each condition was counterbalanced and randomized. During the execution of the two tasks, EEG data activities were recorded to evaluate the cognitive load of the users.

2.3 Experimental design

The two tasks of comprehension, performed by reading a text, and of information-seeking have been considered within two experimental conditions:

- Mobile condition (MB). During the MB condition, participants were seated at a desk and were given a mobile phone (Samsung S6) on which they were asked to complete the tasks;
- Desktop condition (PC). In the PC condition, individuals were seated at a desk in front of a computer monitor and asked to complete the tasks, using a mouse and a keyboard to interact with the PC.

Eleven participants were involved in each condition and performed both tasks on the same device.

2.3.1 Comprehension task

The comprehension task (CO) consisted of reading an online article selected in the "lanazione.it" website. The article was about the 1966 flood in Florence. An article about a historical event was chosen since it would not be affected by the passage of time and could be considered still relevant. For this stimulus, a 15-question test was devised.

2.3.2 Information-seeking task

The information-seeking (IS) task consisted of a search on the "Amazon.it" website. Participants explored this website to find the object (a computer) that best suited a set of characteristics stated by the researcher. Instructions were given to the participants including a list of characteristics that participants were required to find in a computer (i.e. display size, processor type, memory capacity, and maximum cost). Participants were asked to add the target product to their shopping cart, and the task was considered completed before subjects entered personal data in the online payment form. After completing the task, participants answered a questionnaire in which they indicated the result of their search. This questionnaire aimed to confirm that participants effectively scanned and explored the website [17, 31, 34]. The total time required to complete the information-seeking task by each participant was recorded.

2.4 Psychophysiological assessment

The electroencephalographic signals of each participant were recorded both in a resting condition (baseline) and during the experimental sessions.

EEG data were recorded using an Emotiv EPOC+16-channel EEG wireless recording headset (Emotiv Systems Inc., San Francisco, CA, USA). Emotiv EPOC is a low-cost commercial device particularly useful for BCI use. The electrode scheme of this device is arranged according to the international 10/20 system of electrode placement [50] and includes 14 active electrodes at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 positions and two electrodes used as reference (CMS and DRL), corresponding to the position of the mastoids (see Fig. 1). Special attention was taken during our experiments in appropriately putting the headset on each subject's head.

EEG data were acquired with an internal sampling frequency of 2048 Hz. These data were properly bandpass filtered to avoid aliasing using hardware filters and down-sampled to 128 Hz with a precision of 16 bit.

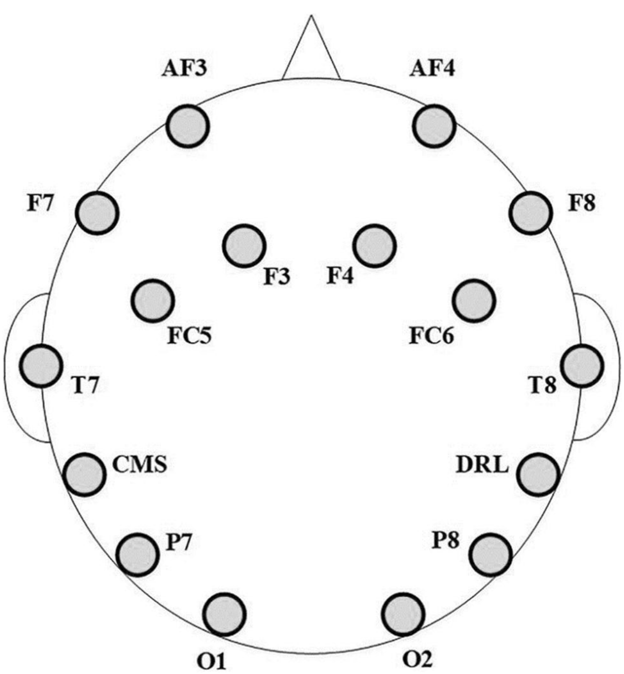

Fig. 1 Emotiv Epoc electrode scheme

2.5 EEG data analysis

Raw EEG data, directly registered from an EEG device, are significantly contaminated by several artefacts both physiological (blinks, eye movements, muscle activity, heartbeat) and non-biological (electrode impedance, noise, and interference from the electric line and other electric devices). This contamination is even more severe in case of the wearable devices such as the case of the headset adopted here and in uncontrolled environments. Thus, a pre-processing of the EEG data is needed before performing any kind of analysis.

2.6 EEG data pre-processing

The continuous EEG data recorded during the experiment were imported and initially pre-processed using EEGLab, an open-source environment for electrophysiological signal processing [18]. The pipeline of the processing we have adopted to clean the data is reported in Fig. 2.

We have chosen the mastoids as reference electrodes because they record fewer signals from the brain. However, the mastoid signal does contain some neural signals. Thus, as a preliminary step, we re-referenced the EEG data to average reference, assuming that the overall electric field on the whole scalp is zero. Then, the 14-channel raw data were filtered using a high pass FIR filter of 0.16 Hz to remove the DC component, and subsequently, a bandpass Notch filter was adopted to remove 50-Hz line noise.

To remove artefacts due to physiological and non-biological noise, we performed independent component analysis (ICA) that separated data in linearly independent components. The underlined assumption is that the multichannel EEG recordings are mixtures of brain activity and artefact signals that can be separated by ICA. Visual inspection and manual removal of the artefact components were then required to clean the data that was finally back-projected to the original time domain to get artefact-free EEG. To avoid loss of significant brain signals, we were conservative in component removal; thus, we also have added a further manual clean of the data, cutting time intervals where noise due to muscle activity, eye, and jaw movements were visually detected. An example of clean 14-channel EEG data is reported in Fig. 3, corresponding to a recording in PC condition and IS task of one of the participants involved.

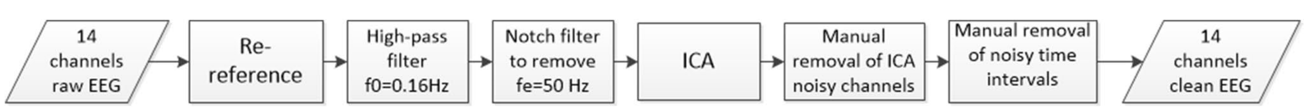

Fig. 2 Pre-processing on the raw EEG data for each of the fourteen channels

2.7 Spectral analysis of EEG data

We performed spectral analysis of EEG data to correlate variations in frequency band power due to the different cognitive tasks and workload of our experiment. Previous works [46, 51] suggested that different frequency brain waves are associated with different classes of cognitive processes. In particular, several studies have investigated cognitive load measurements, showing that alpha and theta waves play a great role in measuring cognitive load [41].

The brain waves and frequency bands here considered, together with the main brain activities they are related to, are reported in Table 1.

Our signal analysis, reported in Fig. 4, has been performed on a clean dataset composed of 14-channel EEG signals, for each device condition: mobile and PC, d = MB, PC, for each of the eleven subjects sb_j, $j = 1, 2, \ldots 11$, for baseline (BL), and for the two tasks, comprehension (CO), and information-seeking (IS), t = BL, CO, IS. The time duration of each EEG recording varies between 2 and 5 min.

The first step of our procedure (frame segmentation) divided each record into frames of 5 s. On each of these frames, the power spectrum density (PSD) has been estimated using the Welch method [53].

Then the band power for each of the brain waves considered was estimated for each frame, obtaining a distribution of values. To further clean the data, and assuming the EEG signal to be stationary over each record, we applied an outlier removal strategy. For each brain wave, the band power values, and thus the corresponding frames, that exceed the mean value of 2 standard deviations were discarded. Starting from the survived frames, the power spectrum density has

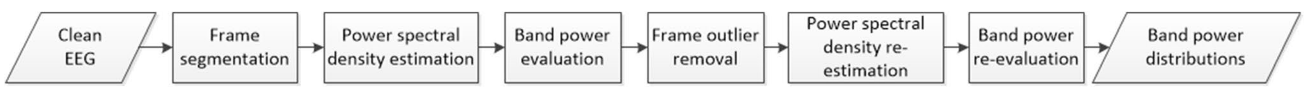

Fig. 3 Band power estimation for each channel, each subject, each task: $t = \{CO, IS\}$, each experimental condition: $d = \{MB, PC\}$

Table 1 Brain waves considered and their frequency band. Note that for Gamma waves, the upper limit of 60 Hz is related to the sampling frequency of 128 Hz of the EEG headset

Brain waves	Frequency band (Hz)	Brain activities
Theta	4–8	They are related to working memory tasks [52]
Alpha	8–12	They are mainly related to relaxed mental states
Beta	12–30	They are involved in conscious thought and logical thinking and are associated with high levels of arousal
Gamma	30–60	They are involved in learning, memory, and information processing

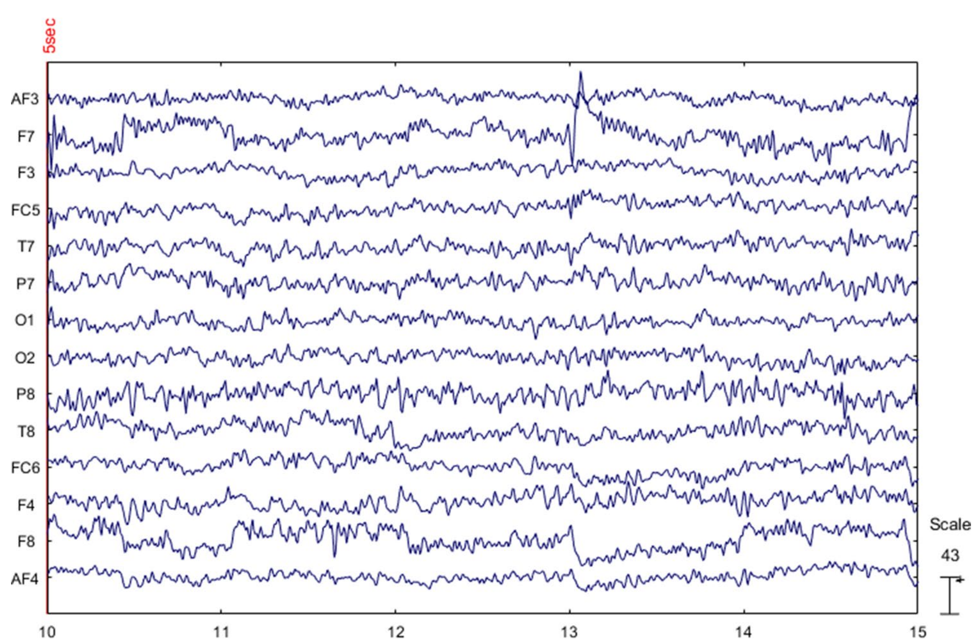

Fig. 4 14 EEG channels after the pre-processing, corresponding to one subject, IS task, PC condition

been thus re-estimated, producing the new distributions of band power values.

3 Results

After the pre-processing applied to filter the EEG raw data and the processing described in the previous section, we obtained 2464 power distributions: 2464 = 11 subjects × 2 conditions (PC, MB) × 3 tasks (BL, CO, IS) × 4 brain waves (Theta, Alpha, Beta, Gamma) × 14 electrodes.

Following the results obtained in the literature [41], that report an increase in theta power and a decrease in alpha power while the cognitive load increases, we first considered the ratio of theta and alpha power over all the electrodes, and we averaged these values concerning the subjects, to compare the two tasks of IS and CO and the two conditions (PC and MB).

In Fig. 5, the ratios between Theta and Alpha average power are reported for the different tasks (left image, comprehension (CO); right image, information-seeking (IS)), comparing the two different devices.

For all the electrodes, tasks, and conditions, the ratios are greater than one, always indicating a higher activation in the theta rhythm than in the alpha one.

From Fig. 5, we observe that:

1. In the case of IS, for all the electrodes, the ratio is higher than in the case of PC, even if differences remain contained, suggesting a higher cognitive load using a PC-based device than using a mobile phone.
2. In the case of CO, the PC condition still shows the highest contributions, confirming that the cognitive load seems to be higher while adopting a PC-based device instead of adopting a mobile phone.
3. In the case of CO, differences in the ratio are in general higher than in the case of IS and appear significantly lateralized.

Several studies in the literature have shown that a lateralized brain activity can be related to cognitive-emotional interactions. In particular, higher activity of the right prefrontal cortex compared to the left one has been referred to negative affective states [54, 55].

The lateralization of the responses, evident in Fig. 5 on the left, could be related to the negative emotions that the reading of the flood in Florence in 1966 (CO task) could have induced as it was a dramatic event that caused the death of 35 persons.

To further analyse the results shown in Fig. 5, we recall that several works have underlined that theta waves at Fz (frontal lobe) and alpha waves at Pz (parietal lobe) position are mostly modulated by different level of cognitive load. However, since these positions are not provided by the Emotiv headset, we have estimated their theta and alpha power values, linearly combining the theta and alpha power values of F3 and F4 and P7 and P8, respectively.

In Fig. 6, the power of the theta waves, estimated in the Fz position divided by the power of the alpha waves estimated in the Pz position, is reported, comparing the two devices and the three types of tasks: BL, CO, and IS. From Fig. 6, we observe that:

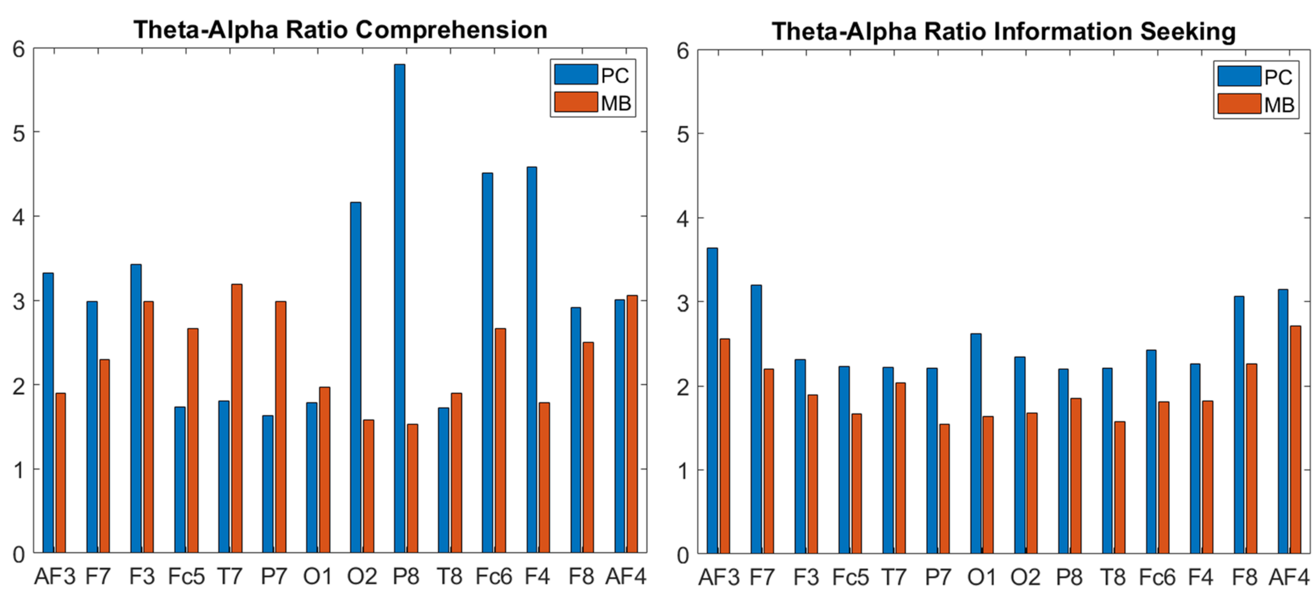

Fig. 5 Ratio between theta and alpha average power. On the left the CO task, while on the right the IS task

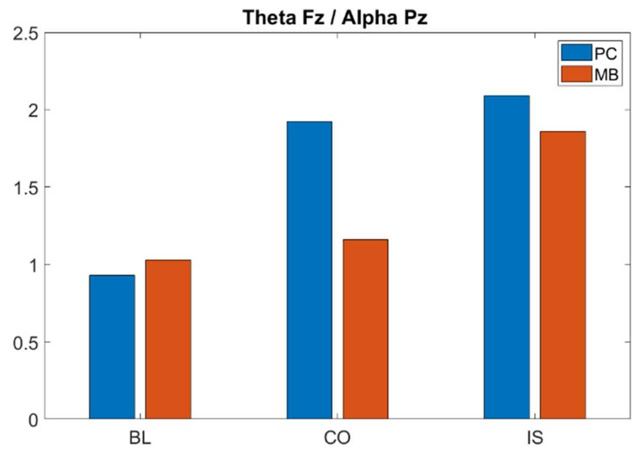

Fig. 6 Ratio between theta power on the estimated Fz and alpha power on the estimated Pz

1. In the baseline (BL) as expected, the considered ratio is about one in both the conditions.
2. In both CO and IS tasks, it seems that the PC-based device requires a higher cognitive load.
3. The IS task seems to require more cognitive load than the CO task, especially using a mobile phone.

Finally, we analysed the variations in brain wave activities comparing respectively the baseline (BL) with the two task conditions (BL-CO and BL-IS) and the CO with IS (CO-IS). To this end, for each device and electrodes and each subject, we studied the power distributions in the three comparisons: BL-CO, BL-IS, and CO-IS, applying an F-test statistical analysis to reject the null hypothesis that two considered distributions belong to the same population. In our investigation, we adopted a p-value of < 0.05.

In Fig. 7, the results of this analysis are reported in tables that can be interpreted underlying that:

- Tables on the left column are referred to the mobile condition, while tables on the right to the PC-based one.
- Each table refers to a brain wave, and each table row refers to an electrode.
- Within each table, the three comparisons BL-CO, BL-IS, and CO-IS are considered, reporting two values, labelled as positive (pos) and negative (neg).

  Pos means that the mean power of the considered power distribution (subject, electrode, brain wave, and device) is higher for the task on the left in the comparison (for instance, BL in case of BL-CO or BL-IS and CO in CO-IS) implying a positive difference in mean powers. *Neg* means that the mean power is higher for the task on the right, implying a negative difference in powers. The reported values are the number of subjects (out of 11) that show a positive (pos) or negative (neg) difference which is statistically significant ($p < .05$).
- Within the tables, we have adopted a colour-coding that goes from dark blue, for the lowest values, to dark red for the highest ones. White corresponds to values in the middle of the range for that table.
- Analysing for instance the table at the bottom of the first column, that is referred to the mobile device and gamma waves, we can observe that in the comparison between baseline and comprehension (BL-CO), all the subjects (11 out of 11) show an increment (that is statistically significant) in the gamma power for the parietal, occipital, and temporal electrodes of the left hemisphere. For all the electrodes, we can then affirm that the majority of the subjects showed a positive increment. It is worth noting that the reported values indicate the accordance among subjects in terms of coherent variations in power, but not absolute values of this power.

Thus, keeping in mind these notes, analysing Fig. 7, we observe that:

- There are significant variations in all the bands and for both devices, comparing each of the two tasks for the baseline (BL-CO and BL-IS), indicating that CO and IS required higher cognitive load than BL did. Power generally increases during the tasks for all the bands except for alpha, which is coherent with the expectation, as alpha rhythm is related to a state of relaxation. In particular, there is higher accordance in the response of the brain activity among subjects in the mobile condition.
- From the comparison of CO and IS, it emerges for both the conditions (MB and PC) that there is a high coherence of the subjects in showing an increase of power in IS with respect to CO, for theta, beta, and gamma rhythms and a decrease of alpha power, suggesting that IS requires a higher cognitive load than CO.

These analyses are in line with similar studies in the literature [12]. As already reported, theta waves are refereed to be related to the processing of new information and increase as mental workload increases [56]. Alpha waves are mainly related to relaxed and reflecting state, and literature in the state of the art underlines the inverse correlation between the EEG power in the alpha frequency band and mental workload [57]. Beta waves are associated with states of alertness, engagement, and working. In particular, changes in complexity and mental loads have been reported to cause an increase in beta band powers [57, 58]. Finally, gamma waves are associated with high mental activity [46].

Fig. 7 Comparison of the mean power of the four brain waves: theta, alpha, beta, and gamma in the two conditions, MB and PC. The reported values compare respectively baseline (BL) with the two tasks: comprehension (CO) and information seek (IS)): BL-CO, BL-IS, and CO with IS: CO-IS. The first column of tables reports the analysis for each of the 14 channels in case of the mobile condition, while the second column of tables reports the same analysis in the case of PC. These comparisons are reported as the number of subjects that shows a positive (pos) or negative (neg) difference of power within each band, which is statistically significant ($p < 0.05$)

MOBILE	BL-CO		BL-IS		CO-IS	
theta	pos	neg	pos	neg	pos	neg
'AF3'	6	4	4	6	3	5
'F7'	1	6	1	6	3	1
'F3'	6	4	2	5	3	4
' Fc5'	3	5	2	6	5	3
'T7'	3	6	4	6	6	1
'P7'	2	6	4	5	5	5
'O1'	3	6	3	7	4	6
'O2'	4	4	5	5	5	4
'P8'	3	6	7	2	5	3
'T8'	3	6	4	5	5	3
'Fc6'	2	7	3	7	7	2
'F4'	5	4	5	2	5	4
'F8'	3	7	2	5	6	2
'AF4'	5	4	6	4	5	4

PC	BL-CO		BL-IS		CO-IS	
theta	pos	neg	pos	neg	pos	neg
'AF3'	6	4	3	6	4	6
'F7'	7	3	5	3	2	8
'F3'	1	6	2	8	4	4
' Fc5'	5	4	3	5	0	6
'T7'	4	6	1	6	1	8
'P7'	3	3	1	6	0	5
'O1'	4	2	4	5	3	2
'O2'	4	5	1	6	2	7
'P8'	4	4	2	8	3	7
'T8'	3	4	1	7	1	5
'Fc6'	1	6	1	6	4	5
'F4'	4	6	2	5	2	7
'F8'	3	6	2	7	4	5
'AF4'	4	2	3	3	2	7

MOBILE	BL-CO		BL-IS		CO-IS	
alpha	pos	neg	pos	neg	pos	neg
'AF3'	8	3	6	1	6	3
'F7'	6	4	5	3	5	2
'F3'	7	4	7	3	6	3
' Fc5'	6	4	6	4	6	3
'T7'	6	5	6	2	6	2
'P7'	6	5	7	3	6	1
'O1'	5	2	7	4	6	4
'O2'	7	3	8	2	9	2
'P8'	6	4	6	3	9	1
'T8'	5	4	4	2	6	2
'Fc6'	4	3	6	2	9	2
'F4'	7	3	9	1	6	3
'F8'	6	4	5	4	7	1
'AF4'	6	3	6	3	6	3

PC	BL-CO		BL-IS		CO-IS	
alpha	pos	neg	pos	neg	pos	neg
'AF3'	6	3	4	5	5	5
'F7'	7	3	5	4	2	7
'F3'	5	5	4	4	5	3
' Fc5'	5	3	6	3	3	3
'T7'	6	3	5	3	2	7
'P7'	4	1	5	1	4	3
'O1'	6	2	8	2	5	2
'O2'	5	2	4	4	2	3
'P8'	5	1	4	5	3	6
'T8'	6	5	4	5	2	4
'Fc6'	2	5	3	4	4	3
'F4'	5	5	5	4	4	4
'F8'	4	5	4	4	4	4
'AF4'	5	3	6	4	3	5

MOBILE	BL-CO		BL-IS		CO-IS	
beta	pos	neg	pos	neg	pos	neg
'AF3'	6	3	4	6	4	7
'F7'	3	6	4	7	6	3
'F3'	5	6	6	5	3	3
' Fc5'	4	5	4	6	4	3
'T7'	1	9	2	7	5	4
'P7'	1	9	0	9	4	6
'O1'	3	7	3	6	5	5
'O2'	3	7	1	6	3	5
'P8'	2	8	3	8	4	6
'T8'	2	8	1	9	2	6
'Fc6'	2	8	3	4	5	1
'F4'	4	6	8	3	6	4
'F8'	2	9	3	7	5	2
'AF4'	5	6	4	7	6	4

PC	BL-CO		BL-IS		CO-IS	
beta	pos	neg	pos	neg	pos	neg
'AF3'	5	5	5	5	3	8
'F7'	9	2	5	5	2	8
'F3'	5	5	4	5	2	6
' Fc5'	5	4	4	5	2	7
'T7'	6	2	2	7	1	7
'P7'	3	6	1	9	0	7
'O1'	3	4	5	5	3	5
'O2'	5	4	3	7	2	9
'P8'	4	5	3	7	2	7
'T8'	5	4	3	7	3	8
'Fc6'	3	6	1	7	4	7
'F4'	7	4	4	6	4	7
'F8'	4	6	5	5	3	8
'AF4'	4	6	6	5	2	7

MOBILE	BL-CO		BL-IS		CO-IS	
gamma	pos	neg	pos	neg	pos	neg
'AF3'	3	6	3	8	3	7
'F7'	3	7	4	6	6	3
'F3'	2	6	3	7	3	7
' Fc5'	2	7	3	8	4	3
'T7'	0	11	0	9	6	3
'P7'	0	11	0	11	4	6
'O1'	0	11	1	10	3	4
'O2'	1	10	0	9	2	7
'P8'	1	9	3	8	4	7
'T8'	2	7	1	9	2	7
'Fc6'	0	6	4	5	3	3
'F4'	3	7	3	6	5	6
'F8'	2	6	2	7	4	3
'AF4'	3	7	4	7	6	5

PC	BL-CO		BL-IS		CO-IS	
gamma	pos	neg	pos	neg	pos	neg
'AF3'	5	4	5	5	3	8
'F7'	7	3	4	6	1	10
'F3'	3	5	1	9	2	9
' Fc5'	5	4	4	6	1	10
'T7'	5	2	1	9	1	10
'P7'	2	7	0	9	0	10
'O1'	5	5	3	8	3	6
'O2'	3	6	1	9	0	11
'P8'	3	7	2	9	1	10
'T8'	5	6	2	7	2	8
'Fc6'	4	6	1	9	2	8
'F4'	4	5	3	6	4	7
'F8'	4	5	4	6	3	8
'AF4'	5	4	3	8	0	9

4 Conclusions

This study investigated how different online activities can affect the cognitive load experienced by the users and if tasks and devices can influence this cognitive process. To this end, the power of EEG brain waves, collected with a wearable device, has been studied.

The results obtained analysing the ratio of theta and alpha power, a well-known indicator in the literature of the presence of cognitive load, show that the baseline (BL), as expected, requires the lower cognitive load in both the conditions, while IS task seems to require more cognitive load than the CO task, in both conditions and especially using a mobile phone.

In general, the power of all the brain wave bands increases in all conditions (MB and PC) during the two tasks (CO and IS), except for alpha, which is usually high in a state of relaxation and low cognitive load.

One interesting observation comes from the lateralization of the brain wave responses in the case of the CO task. This can be attributed to the emotional state, as already reported by the literature, recalling that the text read was about a dramatic event.

This observation deserves a deeper analysis in future work, together with further comparisons between different devices considering different levels in terms of cognitive load required by the same task (either CO and IS).

As underlined before, people include website navigation into their daily routines, and for this, it is important to create an interaction that is as easy as possible. As the web continues to evolve, more and more website designs depend upon a complex, flexible structure [59–61]. However, the lack of understanding of the major impediments for the user within that structure presents a substantial problem to both designers and users. The designers lack a clear view of what areas to focus on to improve the interaction, and users experience higher frustration levels and inability to find information. One method of determining critical aspects within a website is to measure the user's cognitive load level. The designer can then take the results of the cognitive load measurements and work to redesign the problematic areas [59–61].

In conclusion, an effective design allows users to focus on the information of interest. While this statement sounds obvious, many website architectures are an obstacle to be overcome. They impose a high cognitive load with poor navigation or forcing the user to figure out cryptic categories or link names, drawing cognitive resources away from the user's primary task of finding and comprehending the site's information [59–62]. Having information about how the cognitive load varies for the device adopted and the considered task can provide useful indicators in this direction. This work suggests that using a low-cost EEG wearable device, it is possible to effectively quantify the induced cognitive load, allowing the development of new experiments to deeply analyse these dependencies and provide suggestions for an ideal web user experience.

Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval Approval from the human research ethics committee (*Commissione Etica per la Ricerca in Psicologia* CERPS, Department of Psychology, Catholic University of the Sacred Heart, Milan) has been obtained.

Conflict of interest The authors declare no competing interests.

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