Future Generation Computer Systems 113 (2020) 380–390

Contents lists available at ScienceDirect

Future Generation Computer Systems

journal homepage: www.elsevier.com/locate/fgcs

# Characterisation of mobile-device tasks by their associated cognitive load through EEG data processing

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ARTICLE INFO

*Article history:*
Received 7 February 2020
Received in revised form 22 June 2020
Accepted 6 July 2020
Available online 11 July 2020

*Keywords:*
Electroencephalography
Mobile computing
Cognitive load
Mental effort
Human–computer interaction

ABSTRACT

Interaction with mobile devices serves as a link to the cyber world and allows us to characterise user behaviours. The deep analysis of the interactions with the smartphone, aligned with the principles of the Internet of People, allow us to distinguish between normal and abnormal use. One of the multiple applications of this type of analysis will contribute to the early diagnosis of mild cognitive impairment, based on anomalies in the interaction. This work aims to take the first steps towards that ambitious goal: to determine the cognitive load required for different typical tasks with smartphones. By properly identifying which tasks require a higher cognitive load, we will be able to start studying metrics and indicators that contribute to the early diagnosis of cognitive pathologies. The analysis of cognitive load was carried out after an experiment with 26 users who performed 12 typical tasks with a mobile device while their brain activity was monitored through electroencephalography. The results identify that there are clearly tasks with a higher cognitive demand, with audio production and consumption being the most notable, which has been validated experimentally and statistically.


## 1. Introduction

Nowadays, many people have smartphones and other mobile devices. This widespread use makes it possible to provide applications and services to address various problems, such as those in healthcare. The large number of sensors in the smartphone provide data on location, movement, voice, battery, application use and more, which is a source of a great deal of information, especially in assessing the behavioural aspects of users' daily lives [1]. With regard to health, for example, the analysis of smartphone use allows us to track the locations and paths of the GPS followed by users, which can be used to measure things like anxiety levels to anticipate possible mental health problems [2]. Not only are sensor data relevant, but data from the interactions between users and their own mobile devices (e.g. the mistakes made while writing, the active/passive time in applications, the dual task of using the smartphone while walking) also provide valuable information related to human behaviour. Indeed, the smartphone can be a diagnostic ally [3], but it should play a complementary role in the doctor–patient relationship. In particular, in the case of dementia, Blanka Klimova [4] evidenced the potential of mobile apps for facilitating diagnostic support, minimising examiner bias, increasing patient independence, reducing hospitalisation costs and improving the overall quality of life for the elderly. All of this places analyses of interactions (explicit or implicit) with smartphones in an important position, as they can be very valuable both in the fields of human–computer interactions (HCI) and healthcare, whether for diagnostic purposes or even treatment.

This article is part of the project "Mobile computing-based Multitasking for Mild cognitive impairment Monitoring and early Screening (M4S)", which aims to contribute to the early diagnosis of mild cognitive impairment (MCI) by monitoring dual day-to-day tasks in terms of interactions with smartphones. MCI is highly related with dementia and Alzheimer's disease and its early diagnosis can contribute for the detection and intervention of them [5]. In fact, the World Health Organisation (WHO) determines the early diagnosis in order to promote early and optimal management as one of the main five goals for dementia care [6]. In the initial stage of this project, the aim is to determine the cognitive load required to carry out various typical tasks performed on a mobile device, which is the main objective of this work. The characterisation of smartphone typical tasks by their cognitive load will help in selecting which tasks should

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https://doi.org/10.1016/j.future.2020.07.013
0167-739X/

have their performance affected by MCI. Thus, this is a critical pre-requirement to face the next steps of the M4S project that aims to assess cognitive decline analysing the smartphone daily use. Anyhow, the conclusions and results of this document not only contribute to the above-mentioned project but also to the community of researchers in the field, leading to a better understanding of the cognitive processes associated with the use of mobile devices.

This paper is an extension of [7], and its main contribution is the improvement of the experiments in several aspects: (a) the number of participants, which was 26 compared to 6 in the previous paper; (b) the quality of the instrumentation, as the electroencephalography (EEG) headset is a scientific device with more accuracy, higher sample frequency and more channels; (c) the specification of the protocol, which was improved according to the application of the previous experiences; (d) a deeper analysis of the data obtained. In addition, we added extra information to the fundamentals and background, as well as a discussion section.

To study the cognitive load (i.e. the number of working memory resources or "mental effort" associated with a specific task, concepts explored in depth in Section 2.1), we analysed the EEG activity of users performing a set of typical tasks with a smartphone. The fundamentals of the EEG-based cognitive load analysis are also described in Section 2.1. To determine the set of tasks to study, this paper proposes a taxonomy of smartphone-based actions. We considered the related proposals in the literature (Section 2.2) and identified the significant characteristics of the tasks to classify them. As a result, this paper also proposes the HuSBIT-10 taxonomy: Human–Smartphone Basic Interactions Taxonomy for 10-s tasks (Section 3). An experiment with real users was conducted with the dual objective of (i) studying the cognitive load of different typical tasks with the smartphone and (ii) validating the classification made in the taxonomy in terms of the mental effort associated with the identified task categories. The protocol, material, and methods of the experiment, as well as the analysis and results of the data from the experiment, are developed in Section 4. Section 5 discusses the results, their meaning and the possible bias of the experiment. Finally, Section 6 concludes the paper, talking about the goals accomplished and future work.

## 2. Fundamentals and background

This section will talk about the background of this study, focusing on cognitive load fundamentals and smartphone–user interaction.

### 2.1. Cognitive load

Cognitive load is one of the main topics of this paper, hence it is necessary to go deeper into what it is and how it can be measured.

#### 2.1.1. Cognitive load fundamentals

Brain processes follow a pattern common to most people, even though each person usually responds in a specific way to external stimuli. A common link is cognitive load, a concept that refers to the number of working memory resources used to accomplish a task. Thus, the level of cognitive load depends on the characteristics of the task to be performed and the subject who performs it. Each task has a different load, that is, it may be more complex or simpler (depending on the steps or the level of precision required to perform the action), and each subject processes it differently according to his/her abilities and aptitudes [8]. It is common to refer to the cognitive resources that are used to perform a task as mental effort, which means that the terms "cognitive load" and "mental effort" are often used interchangeably, although they are not exactly the same.

With these basic concepts in mind, we can mention Sweller's [9] theory of cognitive load, which focuses on working memory and, specifically, on Mayer's [10] theory of multimedia learning. These theories are part of the cognitive sciences that seek to improve multimedia environments [11] within the information processing paradigm, taking it as a "natural information processing system" [12].

For this work, we assume that tasks with smartphones have different mental loads and are related to some external stimulus that may come from one or more channels, thus translating the tasks into cognitive information. Mostly auditory and visual channels activate working memory. Information processing in working memory is related to the activity that is consciously carried out [13]. Furthermore, recent research has shown that working memory is separated into three processors or channels [11]. When information passes through this memory, it is distributed between two partially independent processors, i.e. auditory and visual processors, which manipulate verbal and graphic information, respectively. In addition, there is a third processor known as the central-executive processor, which is responsible for coordinating the processing of information entering and leaving working memory.

Therefore, consideration should be given to how to present the information to avoid overloading these channels. Additionally, it is essential to consider whether the information is new, so that it can be acquired only if the subject's mental activity can relate it to mental schemes previously stored in long-term memory [10,14]. When a person has done a task repeatedly, his/her processing is different because he/she has response patterns associated with that task, and the execution is faster or easier to do. This is achieved with practice time and depends on the intuitiveness of the tasks, which was considered in the development of our work.

All the previous fundamentals are considered in this paper to define the taxonomy tasks with the smartphone and to define the experiment protocol, as we describe in the following sections.

#### 2.1.2. Cognitive load measures

There are lots of ways to estimate the cognitive load associated with a task, but, according to [15], there are three main approaches: (1) self-reports, (2) dual-tasks and (3) physiological measurements. The self-report method consists of asking the participants of a task about how difficult they perceived the task to be or about the mental effort required for it to be done. Estimating the cognitive load using this method has an important disadvantage, namely the high subjectivity involved in the responses of the participants. Through the second method, the dual-tasks, this subjectivity can be avoided. Dual-tasks consist of performing two tasks at the same time in such a way that, as the difficulty of the main task increases, the performance of the secondary task decreases, which can be objectively measured. An example of this could be trying to keep a constant beat with a foot as the secondary task while performing a typical cognitive load task, like the N-Back test [16]. The main problem with this technique is that the secondary task has its own load, so it complicates the estimation of the cognitive load associated only with the main task. Physiological measures avoid the problems of the other two methods, but they also have some disadvantages, notably, for many, the cost of the devices to acquire the physiological data and the difficulty to process said data. There are many physiological parameters that can be used to estimate cognitive load, like pupil dilation, heartbeat or neural activity. Eye tracking-based methods are really popular, and they have been proven to work as an index of mental workload, either through eye movement [17] or pupil dilation [18]. There are also other methods like electrocardiogram

(ECG) [19] or galvanic response [20] that are also used but are not as popular. EEG [21], a signal that is directly influenced by the cognitive load, is another very popular and frequently used method that can be used to measure neural activity.

Integrated cognitive load assessment in daily activities is still an unexplored field. As can be seen from the measurement mechanisms above, they all focus on testing in controlled environments. One of the few works that link cognitive load to mobile phone tasks is [22], which identified some examples of tasks that characteristically require working memory, namely typing information, deciding on a path and searching from display. To our knowledge, there are no works that attempt to quantitatively characterise cognitive load and its possible decline during the daily use of smartphones. Therefore, there is still no evidence about which specific tasks performed on the phone are suitable for this purpose, being this one of the challenges of this work.

#### 2.1.3. EEG-based cognitive load analysis

In relation to the electrical activity of the brain and its analysis through EEG, four main locations of the brain have been discussed in the literature to study neurological activity: parietal, occipital, temporal and frontal regions [4,23]. It has been observed that this neurological activity produces a range of electrical waves at different frequencies with a greater or lesser level of coverage depending on the task being performed.

A clear example of the differences that occur in the electrical response of the brain associated with neurological activity can be seen in the electrical oscillations emitted during sleep compared to those made when awake. The brain produces very low frequency (<1 Hz) electrical waves that are reflected in the EEG signals of sleep stages, between the 0.55–0.95 Hz range and with peaks at 0.7–0.8 Hz in the frequency band known as delta [24]. In contrast, higher frequencies and faster waves predominate in waking conditions, where the bands range from 0.5–40 Hz. The intervals corresponding to each band are as follows: 0.5–4 Hz (delta band), 4–8 Hz (theta band), 8–13 Hz (alpha band), 13–30 Hz (beta band) and, finally, 30–40 Hz (gamma band), although there is no consensus on the exact limits of each band, and it is common to find different ranges for each one in the literature. As mentioned above, the composition of the electrical response largely depends on the cognitive task.

EEG allows the capture the electrical response of the brain by means of electrodes placed on the scalp. These electrical signals are generated by ionic movements in and around neurons during the activation and deactivation of neurons involved in a cognitive task. EEG measures the fluctuating voltages in these electrical signals. While there is no straightforward way to estimate cognitive load from EEG electrical signals, some approaches can be found in the literature. The three most commonly used analysis techniques are: (i) Event-Related Desynchronisation (ERD), (ii) Theta–Alpha Ratio (TAR) and (iii) techniques based on machine learning. In relation to detecting changes in cognitive load using the ERD technique, Klismech found that the spectral power in the theta band increases, while the spectral power in the alpha band decreases [21]. Further relevant contributions have studied the use of ERD from alpha and theta bands to measure cognitive load. For example, Antonenko et al. have applied the ERD technique to two different case studies related to the learning context [25].

In addition, some recent studies have explored the use of the TAR technique as a measure of cognitive load [26–28]. In particular, Trammell et al. [24] have found associations between age and estimated cognitive load by using this technique. TAR is obtained by dividing the spectral power of the theta band of an electrode placed in the middle frontal area, which is known as Fz, by the spectral power of the alpha band of an electrode placed in the central parietal area, which is known as Pz.

Other novel and powerful approaches to estimate cognitive load are based on machine learning. Many research studies have used these techniques for this particular purpose, for example, [29], which uses Naïve-Bayes, and [30], which uses deep convolutional neural networks. Through machine learning models, robust and useful metrics can be extracted from EEG signals, although some problems have been reported in regard to the sample size and data gathered from the acquisition trials. Specifically, (i) it takes a large number of participants to adequately train a classifier or fit a regression model to work properly on EEG data from anyone; (ii) the studies found are mostly based on supervised learning; therefore, a big labelled dataset is required to train the model; (iii) the trained models are usually not available, so they cannot be reutilised in other experiments. Such considerations forced us to discard machine learning techniques as a method for this work.

### 2.2. Mobile-device interaction background

There is a large area of literature on HCI focusing on mobile devices. Nowadays, many projects and research studies utilise user-centred design and development, emphasising the role of usability and user experience in terms of interactions with mobile devices. According to Hoober [31], users interact with their mobile devices in three different ways: (1) using only one hand, (2) using both hands, and (3) passively. This same paper also indicated other types of considerations when studying human–device interactions: whether use is active or passive; whether the device is being used for speaking; and how users express their body posture when interacting with their smartphones, namely walking, standing or sitting.

Karam and Shraefel carried out an extensive study in 2005 that led to the creation of a general taxonomy of gestures in HCI [32]. In this work, the authors also presented a review of possible interactions with any device, not only mobile ones. Focusing on smartphones, the most common inputs were the camera, the touch surface and the sensors-on-body (e.g. accelerometer, GPS). The last input is considered as a pervasive or implicit way of interacting with the mobile device. In the case of interaction with touch screens, Wroblewski [33] proposed a popular reference as a standardised guide about gestures in these kind of displays.

Moreover, numerous works have focused on the analysis of user–smartphone interactions in different domains, using a variety of measurement mechanisms and pursuing multiple objectives. Today, works such as the one presented by Hinckley et al. [34] show new ways to detect interaction with smartphone screens before it occurs, which is referred to as "pre-touch sensing". Cameras and vision-based systems are also useful to analyse interactions with mobile applications. Authors such as Souza [35] and Chang [36] have highlighted the importance of eye-tracking data for usability studies, comparing them with traditional techniques.

It is possible to study behaviour by analysing the interactions between users and their smartphones. In this regard, new patterns of use and behaviour can be found [37], as well as different types of smartphone users [38]. Smartphone use is an important observational tool in psychological science. Taking into account all the data provided by these mobile devices, as determined by Harari et al. [1], it is also possible to measure and analyse patterns of smartphone addiction by interacting with them [39,40].

Interactions with smartphones occur at different levels. These interactions can be studied through information provided by the operating system, built-in sensors and buttons on physical devices, as well as with installed applications. Considering the objectives of this article, and taking into account the related work, in which no research on the classification of smartphone tasks at the cognitive level has been found, this paper proposes a specific taxonomy of the basic tasks related to the most common types of interactions with smartphones in the following section.

## 3. Proposed taxonomy: HuSBIT-10

According to the objectives of our study, we needed to define a set of usual tasks focused on user–smartphone interaction. These tasks are quick, simple and require less than 10 s. The name of the taxonomy is HuSBIT-10: Human–Smartphone Basic Interactions Taxonomy for 10-second tasks.

First, four types of interactions that a user could carry out with their smartphone were identified: ($\tau$) touch, ($\iota$) look, ($\varsigma$) talk, and ($\eta$) listen. All of them are closely related to the human senses, which are critical for analysing cognitive load and information processing [8]. Additionally, considering some of the approaches in the literature mentioned in Section 2.2, the types of interactions can be classified into two categories: ($\alpha$) active and ($\rho$) passive, depending on whether the user explicitly interacts with the device. This enables us to determine whether a specific type of interaction of the first four types mentioned above is active or passive.

Furthermore, any smartphone interaction task could employ one or more of the above types of interaction. Therefore, we have defined the AMPEC-10 as a term to group the five types of tasks that a user can perform with the smartphone in a maximum time of 10 s (limit obtained experimentally), making use of the four types of interaction. The acronym AMPEC-10 corresponds to the following grouping of tasks according to their type:

- (A) Automated. This represents tasks without a significant cognitive effort that is typically performed automatically or unconsciously.
- (M) Psychomotor. This kind of task requires a quick or direct interaction with the smartphone, where the main difficulty is to perform a touching interaction carefully or with proper accuracy.
- (P) Production. This includes tasks that require basic content creation, requiring creative skills to produce new content.
- (E) Exploration. This kind of tasks requires the analysis of a set of data to obtain specific information.
- (C) Consumption. This defines tasks that involve content consumption.

It is important to consider the prevalence of the types of interactions (touch, look, speak and hear) in these types of tasks. A first exploration reveals that touch and look interaction types are the most common interactions between the user and the smartphone. Also, as discussed in Section 2.2, talking and hearing occur less frequently. This confirms what other studies in the literature have found [41,42].

Based on these assumptions, the HuSBIT-10 taxonomy has been modelled to classify any task with a duration of less than 10 s that users perform with their smartphones. In Table 1, there is an overview of the identified tasks (classified by task type) and some examples. The aim of the HusBIT-10 approach is to provide support for classifying AMPEC-10 tasks in terms of planning and cognitive load from a two-dimensional perspective, as well as to promote replicability in other trials and experiments.

## 4. Experiment: Cognitive load in smartphone interactions

This section will explain how the experiment was performed, including the protocol followed, information about participants and materials used. The analysis process followed will also be described, as well as the results of the analysis.

### 4.1. Experiment protocol and method

The experiment gathered evidence in terms of EEG data in an empirical manner, with the data quantitatively analysed. The question that guides this experiment is: "Do the different tasks that are typical with mobile devices have characteristic and different levels of cognitive load?" This question made us propose two hypotheses to be tested through this experiment:

**Hypothesis 1.** There are tasks with the smartphone that present a characteristically higher or lower cognitive demand than the rest.

**Hypothesis 2.** The tasks or interactions with mobile devices identified in the HuSBIT-10 taxonomy have similar cognitive burdens within each category.

The experiment was conducted in the MAmI research lab at the University of Castilla–La Mancha, a group focused on health informatics and HCI (http://mami.uclm.es). The participants were informed about the scope and goals of this research and the collected data. The work was conducted with 26 participants, from 19 to 36 years old (31% females and 69% males) who received and signed the information sheet and consent form, which provided detailed information about the study's objective, procedures, and types of data to be collected. All participants had the opportunity to consider their participation before making a final decision. Thereby, the preservation of the dignity and autonomy of the participants was ensured by their voluntary participation and the fact that they could leave the study at any time without any consequences. The age range selected serves to ensure that participants are adults who are in a life stage prior to the onset of cognitive impairment, or at least to reduce the risk of suffering from any type of cognitive impairment that could bias the data. We based this decision on the studies that determine that deterioration begins to occur naturally after the age of 45 [43].

This study followed the empirical method for gathering evidence regarding EEG data while participants interact with a smartphone. The protocol employed within the experiment can be summarised as follows: (1) all participants were wearing the EEG headset (Fig. 1a) and sat at a desk with the smartphone (Fig. 1c); (2) participants were required to perform the EEG calibration with the software provided by the manufacturers of the headset (Fig. 1b); (3) all participants were told about the general procedure that consisted of performing 12 tasks with a duration of around 10 s, which were randomly sorted for each participant to avoid any bias related to the order of activities; (4) all participants received instructions for the actions to perform with the smartphone to ensure they fully understood them before each task; (5) the participants, without receiving any additional instruction, performed all the tasks planned. This entire process for each participant took approximately 30 min.

### 4.2. Material

The cognitive load was studied using a device for capturing EEG signals for scientific purposes, the Bitbrain Versatile EEG 16. This device has 16 EEG channels and two references for positioning and accurate spatial resolution. The EEG headset includes a flexible cap that allows the customisation of the position of the water-based electrodes. The configuration used for the experiments, according to the International 10–20 System [44], is shown in Fig. 2 and consists of five frontal electrodes (F3 and F7 on the left hemisphere, F4 and F8 on the right hemisphere, and Fz in the midline), four temporal electrodes (T3 and T5 on the left hemisphere and T4 and T6 on the right hemisphere), three central electrodes (C3 on the left hemisphere, C4 on the right

**Table 1**
AMPEC-10 tasks classification according to HuSBIT-10 approach.

| Task category | Id | Task type | Characteristics | Examples |
|---|---|---|---|---|
| Automated | A1 | Query an item | $(\alpha)$ $(\tau, \iota)$ | Check time/Check if there are notifications/Check if I have Wi-Fi |
| | A2 | Action on any physical button | $(\alpha)$ $(\tau)$ | Turn on–off device/Turn up–down volume |
| Psychomotor | M1 | Pattern | $(\alpha)$ $(\tau, \iota)$ | Device unlock (with unlock pattern) |
| | M2 | Move | $(\alpha)$ $(\tau, \iota)$ | Add and move a shortcut |
| | M3 | Dismiss | $(\alpha)$ $(\tau, \iota)$ | Close opened apps, Close notification preview |
| | M4 | Copy & Paste | $(\alpha)$ $(\tau, \iota)$ | Share information among applications |
| | M5 | Select | $(\alpha)$ $(\tau, \iota)$ | Select a part of a text |
| Production | P1 | Text Production | $(\alpha)$ $(\tau, \iota)$ | Add a new contact/Set an alarm/Write a message/reminder |
| | P2 | Voice Production | $(\alpha)$ $(\tau, \varsigma)$ | Make a call/Make a voice command/Create voice message |
| | P3 | Visual Production | $(\alpha)$ $(\tau, \iota)$ | Take a photo |
| Exploration | E1 | Search on a textual set | $(\alpha)$ $(\tau, \iota)$ | Search for a contact/Search for a song/Search for date in the calendar/Last call made to someone |
| | E2 | Search on a visual set | $(\alpha)$ $(\tau, \iota)$ | Search for a specific application/Browse images/Change direct-access settings (e.g. airplane mode) |
| | E3 | Analysis of textual contents | $(\alpha)$ $(\tau, \iota)$ | Change setting details (e.g. data roaming)/Do a search in an Internet browser |
| | E4 | Analysis of visual contents | $(\alpha)$ $(\tau, \iota)$ | Search for a route/site on a map |
| Consumption | C1 | Text Consumption | $(\rho)$ $(\iota)$ | View/Read notifications, Read a text message |
| | C2 | Audio Consumption | $(\rho)$ $(\eta)$ | Listen to an audio message/Listen to a podcast |
| | C3 | Media Consumption | $(\rho)$ $(\iota, \eta)$ | Watch a video |

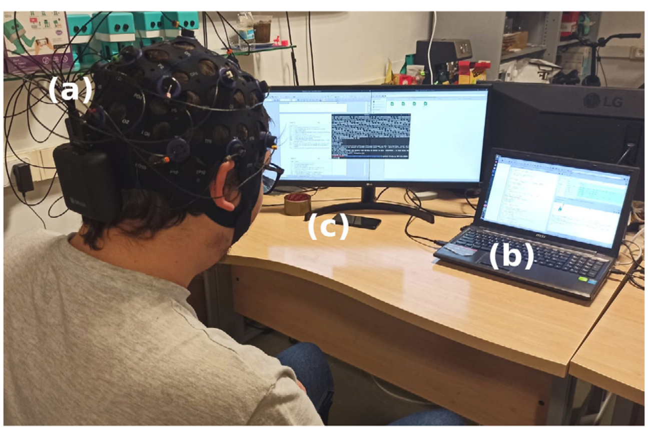


**Fig. 1.** Experiment setup with the following materials: (**a**) Bitbrain Versatile EEG 16 EEG headset; (**b**) Laptop with the required software to collect raw data and eeglib to process and analyse; (**c**) Smartphone Samsung J6 with Android 9.0 Pie;.

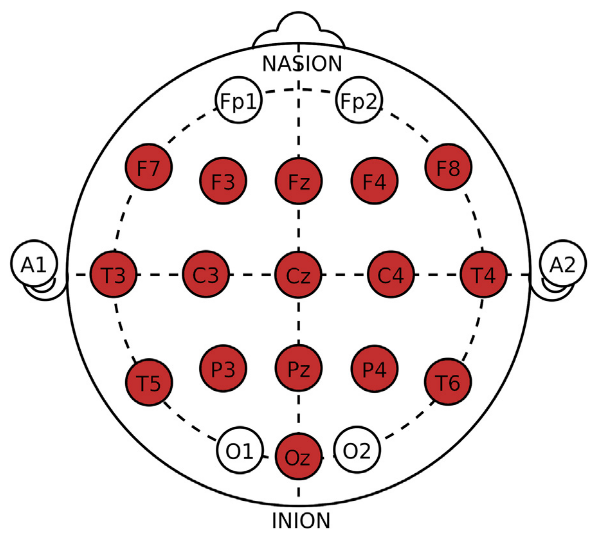


**Fig. 2.** Positions of the electrodes used during the EEG recording for the experiments.

hemisphere and Cz in the midline), three parietal electrodes (P3 on the left hemisphere, P4 on the right hemisphere and Pz in the midline) and one occipital electrode (Oz). The headset uses a sequential sampling method at a rate of 256 samples per second with a resolution of 24 bits. To collect the EEG raw data, we used the Bitbrain viewer software, which was provided by the headset manufacturer.

For the EEG data processing, we used specialised software developed to process EEG data called eeglib [45,46], which is a Python-based library for EEG processing that provides data structures for that purpose. This library can load CSV and EDF files that are typical formats in which EEG is stored and also allows the user to import the data from Python and NumPy data structures. It can apply three different pre-processing techniques to the signals: bandpass filtering, z-scores normalisation and Independent Component Analysis. It also includes a set of processing techniques to extract features from data: FFT, Higuchi Fractal Dimension, Petrosian Fractal Dimension, Hjorth parameters, Detrended Fluctuation Analysis, Lempel–Ziv Complexity, Multiscale Sample Entropy, Synchronisation Likelihood and Pearson Cross Correlation Coefficient. The library includes a tool to generate datasets (in pandas DataFrame format) that can be easily used to apply to machine learning techniques or to perform statistical analysis.

The smartphone used in the experiment was a Samsung J6 with the operating system Android 9.0. The list of specific tasks to perform is shown in Table 2. The selection of the specific tasks to be performed in the experiment is arbitrary, since there is no literature background on how to make such a decision based on scientific evidence. The selection followed a series of basic criteria: (a) the tasks are consistent with the HuSBiT-10 taxonomy, (b) they are consistent with the neuropsychological theories set out in Section 2, (c) they avoid tasks that are heavily dependent on previous knowledge or experience and (d) they require at least 10 s to be completed to have enough data for analysis. In relation to the second requirement, we included tasks associated with working memory in accordance with the findings of [22]; the set was completed with tasks that clearly require controlled and conscious processing. For example, task E2 was chosen as a visual exploration that requires selective attention in a context with distractors. Regarding the latter requirement, some tasks are made up of several sub-tasks, such as M2 or M5, because all the tasks were required to take 10 s, and some had to be lengthened that way.

As we show in Table 2, there are three tasks per category to keep the same number of tasks in each category, so they can be analysed more consistently. Therefore, the following tasks from the taxonomy were excluded: M1, M4 and E1. M1 was discarded because it implies knowing a pattern beforehand, which complicates carrying it out within the experiment. To perform the M4 task, it is usually necessary to also do M5, so M5 was selected instead of M4 to facilitate execution. Within the Exploration tasks, all were suitable for the experiment, so E1 was arbitrarily discarded. Thus, the total number of evaluated tasks was 12. The design of the list of tasks follows the considerations and fundamentals about cognitive load in Section 2.1, trying not to overload any channels or include too much new information for participants.

The category Automated was omitted due to the extremely low cognitive load associated with unconscious or mechanical tasks. The information processing can be either controlled or automatic [47,48], considering whether it occurs when the information at hand is consciously being addressed. Moreover, a characteristic alteration of controlled processes has been demonstrated in people with dementia [49]. This is the reason why Automated tasks were not considered.

### 4.3. EEG data processing

Participants performed all the tasks described in Table 2, specifically, three defined tasks per category considered in the HuSBIT-10 proposed taxonomy. EEG activity was recorded during each task for a 10-s interval (EEG segment). The recorded EEG data can be found in the link in the Supplementary Material section.

The data processing is graphically described in Fig. 3. The left side of the figure shows the structure of folders. It is composed of three levels, the first one being made up by a folder for each participant. Each of those folders contains another folder for each task. The task folders contain the files created during the EEG recording, which include not only the raw EEG data but also other data like the Inertial Measurement Unit (IMU) data or the EEG impedances. There are 26 (participants) × 12 (tasks) = 312 EEG files in total.

Each of those files was loaded and pre-processed by applying a 2–15 Hz bandpass filter to reject artefacts and noise included in the frequencies that are not necessary for this analysis. Once filtered, the signal was segmented into 6-second windows, with an overlap of half a second. For each of these windows, the TAR was computed as indicated below and then averaged for all windows.

$$TAR = \frac{Theta_{Fz}}{Alpha_{Pz}}$$

Theta $_{Fz}$ is the spectral power of the theta band (4–8 Hz) in the electrode Fz (frontal midline), and Alpha $_{Pz}$ is the spectral power of the alpha band (8–13 Hz) in the electrode Pz (parietal midline). The TAR used for estimating the cognitive load of each task was an average of all the windows. In the previous paper, the TAR index was computed using four electrodes instead of only two due to the limitations of the previous headset, which does not have the electrodes Fz or Pz.

The next step was to build a table including the TAR for each participant and task. One of the problems of comparing the TAR between each participant is the high variability depending of the particularities of each person. To solve this, the cognitive load estimator was normalised for every participant using a min–max scale, which is described below:

$$Normalized\,(X_i) = \frac{X_i - \min(X)}{\max(X) - \min(X)}$$

where $X$ is a numerical signal, $X_i$ is the element from X in the position $i$, min($X$) is the smallest element in $X$ and max($X$) is the biggest element in $X$. This type of normalisation has the main advantage of easy interpretability because all the numbers are between 0 and 1. It should be noted that this type of normalisation significantly changes the distribution of the data, going from a Gaussian to a bimodal one, since there are a lot of extreme values (0 and 1).

The last step averaged the whole table with the normalised values from each task to obtain a cognitive load index associated with each task.

### 4.4. Results

The experiment results show differences among the cognitive load associated with some of the tasks. Table 3 summarises the average cognitive load value for each task, considering all the participants, while Fig. 4 shows the boxplot representing the same information. It can be observed that the task with the highest cognitive load is P2, which consists of audio production, followed by C2, in which the participants were listening to an audio recording. From this, we can observe that both tasks are related to audio. The tasks with the lowest cognitive load are E2, which consisted of counting elements in a picture, followed by C1, in which the participant reads a text. Analysing each task group, relevant facts from each group can be observed. One general idea that can be extracted is that all the groups contain one element that notably differs from the other two. The Production group (P) has the highest cognitive load, and P2 has a considerably higher value than P1 and P3. The Consumption group (C) appears to have the least cognitive load as it contains the second and third elements with the lowest cognitive loads, but C2 has a significantly high value. In the Psychomotor group (M), M3 and M5 have close values, while M2 is marginally higher. M2 involves dragging an icon from the apps menu to the smartphone main screen, which presented some problems for the participants because this is done in different ways depending of the version of the phone's software; some of the participants were used to other ways of executing this task, which could have increased the cognitive load. Lastly, the Exploration group also contains two types of tasks with a similar cognitive load (E3 and E4) and one that was notably different (E2).

To check if H1 can be accepted, a one-way ANOVA was carried out, the results of which are shown in Table 4. They show a rather low $p$-value, thus rejecting that the average of all groups is the same at a significance level of 0.05, which confirms H1.

To explore this more in depth, we decided to perform a pairwise Student t-test between every task. Student t-test was chosen because the size of the sample is small (n = 26). Table 5 shows

**Table 2**
List of tasks performed in the experiment according to HuSBIT-10 taxonomy.

| Task category | Task type | Specific task in the experiment |
|---|---|---|
| Psychomotor | M2 | Add and move an app shortcut (2 times). |
| | M3 | Close all apps in the background. |
| | M5 | Select one word, then two, then two and a half words in a Wikipedia article. |
| Production | P1 | Write down an excuse or justification for not attending a meeting with someone. |
| | P2 | Create a voice message answering a friend who has just written about cancelling a meeting. |
| | P3 | Take an artistic photo of nearby objects considered to be the most expensive. |
| Exploration | E2 | Count the number of beach umbrellas in a picture from *"Where's Wally"*? |
| | E3 | Switch off data roaming in the device settings. |
| | E4 | Search how to reach a given place (about 500 m away) with a map of the current location. |
| Consumption | C1 | Read a synopsis of the book Portico on Wikipedia. |
| | C2 | Listen to a voice recording. |
| | C3 | Watch a video about soap cutting. |

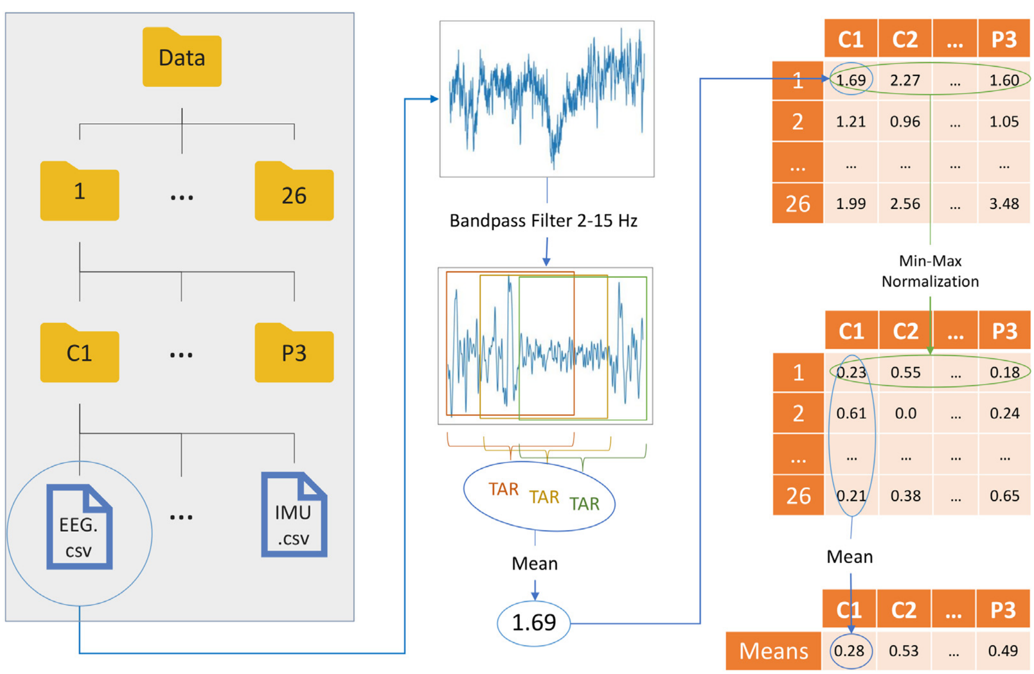


**Fig. 3.** Graphical representation of the processing applied to the data.

**Table 3**
Results of cognitive load in each task performed in the experiment according to HuSBIT-10 taxonomy. The colour of each cell is a gradient going from dark red, which represents the minimum in the row, to bright green, which represents the maximum in the row.

| Task | M2 | M3 | M5 | P1 | P2 | P3 | E2 | E3 | E4 | C1 | C2 | C3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.45 | 0.38 | 0.36 | 0.51 | 0.72 | 0.49 | 0.27 | 0.48 | 0.45 | 0.28 | 0.53 | 0.35 |
| Standard Deviation | 0.25 | 0.25 | 0.27 | 0.3 | 0.32 | 0.33 | 0.23 | 0.25 | 0.28 | 0.24 | 0.36 | 0.24 |

the matrix with the p-values of the application of the t-test to each pair of tasks; the cases in which $p => 0.05$ are shown in green, and the cases in which $p < 0.05$ are shown in red. To avoid type I errors for the whole experiment, we also applied the Holm–Bonferroni correction, which is indicated using asterisks. Extreme cases, like P2 or E2, have different means than most of the other tasks, while the means of central cases are too similar between them. As the distribution of the data cannot be ensured to be normal, both t-tests could be affected by that, although they are

**Table 4**
Results of a one-way ANOVA analysis performed with the data.

| | Df | Sum of squares | Mean sum of squares | F | p-value |
|---|---|---|---|---|---|
| Task | 11 | 4.255313 | 0.386847 | 4.951202 | 4.52E−07 |
| Residual | 300 | 23.43956 | 0.078132 | | |

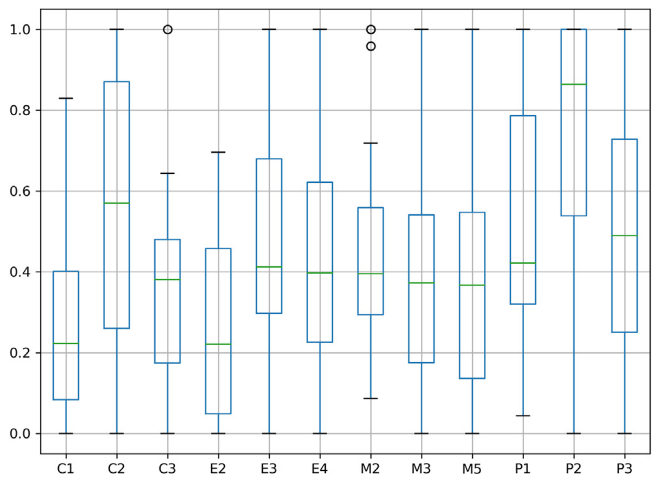


**Fig. 4.** Boxplot representing the cognitive load for the 12 evaluated tasks.

robust to non-normal distribution whenever the sample statistic follows a normal distribution.

We also grouped the tasks by the type of interactions (($\tau$) touch, ($\iota$) look, ($\varsigma$) speak and ($\eta$) hear) involved and averaged them. The results are shown in Table 6. It is important to note that some tasks belong to more than one group, and that the groups speak and hear consist of only one task. With regard to the passive ($\rho$) and active ($\alpha$) components of each type of task, they were averaged, as well, showing a mean value of 0.39 for passive tasks and 0.46 for active tasks.

## 5. Discussion

This section discusses the scope of the obtained results. It is necessary to note that the EEG signal has certain limitations due to its nature. EEG signals can be very sensitive to noise and pick up unwanted artefacts [50] caused by many factors, such as facial movements like blinking or mouth movements [51]. For this reason, EEG data are not directly analysed as a whole; they must be filtered, processed, validated with metrics or characteristics (as is the case with TAR) and, finally, analysed in detail. For these reasons, the diversity in the data obtained, such as non-uniformity between subjects and intra-subjects, as well as the standard deviation in the results obtained for cognitive loads, is reasonable.

Considering this, the results obtained show that the main categories identified in the taxonomy do not carry a clearly higher or lower cognitive load in a categorical way. It is observed that Production activities usually carry a higher cognitive load possibly because of their creative component, requiring the user to plan and devise content. In general, Consumption and Psychomotor activities require less cognitive load, with Exploration activities being in the middle. There are some tasks that are significantly outside the norm. On the one hand, task E2, which consists of counting umbrellas in an image, has a low cognitive load possibly because it only requires visual acuity and concentration, without the need for higher level cognitive tasks such as executive function. On the other hand, the C2 task about consumption of an audio content, in addition to having a higher cognitive load than the rest of the Consumption tasks, has the highest standard deviation. C2 together with P2, both with the highest cognitive loads, have in common, unlike the rest, the use of the auditory channel, which also requires language processing. Passive tasks show, in general, a smaller cognitive load than active tasks, which could imply that active tasks are more demanding. This finding is consistent with Mayer's [10] cognitive theories of multimedia learning and has its roots in Paivio's [52] theory of dual coding. It focuses on how we acquire new information through dual channels and then process it with short-term memory and integrate it into long-term memory. Dual channels have limited capacity and require active processing (organising information and integrating it into mental models). For this reason, information from dual channels generally carries a greater cognitive load.

It can be noted that there are important differences in the results from the previous paper to this one, in which the Exploration tasks had the highest cognitive load. In the present paper, the Production tasks showed the highest cognitive load, and the high cognitive load of listening to an audio recording was observed. There are many possible reasons for these changes. Possibly this is because of the usage of a different headset where we considered the exact electrodes for TAR calculation (in previous experiments we used a less precise headset with an approximation in the TAR metric). Other reasons are the different computation of the TAR index and the incorporation of more people into the experiment. We assume that both aspects, headset and experiment set-up, is much more reliable in the current work. Anyhow, there are consistencies between both experiments: The Consumption and Psychomotor tasks had the lowest cognitive load, and Exploration tasks showed a higher cognitive load than these two groups.

How movement during activity affects the results should be considered, as it could affect the EEG signal. The participants in the experiment were asked to try to move as little as possible, and they complied quite well. However, the P3 task involves more movement by the participants, as they have to turn their bodies to look for items to photograph, so the value of the TAR for that task cannot be ruled out.

Finally, it should be noted that, although attempts have been made to identify characteristic tasks of each type, there is a high degree of dependence on the task itself. Likewise, the previous knowledge, experience and skills of the users condition the cognitive load required by each task. To mitigate this limitation, a population uniform in age and with high knowledge and experience in the use of new technologies was chosen. In any case, and in future work, it would be interesting to define multiple tasks of the same type and categorise the previous experience of users to measure the correlation (if any) among these aspects.

## 6. Conclusions

With this work, we are aiming to take the first step towards a new research line that aims to contribute to the early diagnosis of MCI through the analysis of everyday interactions with smartphones. One contribution of this paper is HuSBIT-10, the taxonomy of typical tasks with smartphones. The taxonomy is based on similar classifications focused on other devices found in the literature, as well as on the cognitive components related to each of the tasks. Researchers in HCI can use this taxonomy as a model that classifies the types of interactions with smartphones. However, the main contribution is the characterisation of the cognitive load associated with each of these tasks. From these results, we can confirm Hypothesis 1, which states that there are tasks that present a characteristically higher or lower cognitive demand than the rest, by looking, for example, to tasks E2 and

**Table 5**
Matrix with the p-values of the application of Student t-test for each pair of tasks. The cells in a red colour contain p-values under the significance value and the ones in green colour contain p-values over the significance level. The cells with an asterisk correspond to the comparisons that are considered different after applying the Holm–Bonferroni correction.

| | C1 | C2 | C3 | E2 | E3 | E4 | M2 | M3 | M5 | P1 | P2 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **C2** | 0.005 | | | | | | | | | | |
| **C3** | 0.290 | 0.038 | | | | | | | | | |
| **E2** | 0.847 | 0.003 | 0.203 | | | | | | | | |
| **E3** | 0.007 | 0.508 | 0.076 | *0.004** | | | | | | | |
| **E4** | 0.027 | 0.353 | 0.189 | 0.016 | 0.722 | | | | | | |
| **M2** | 0.017 | 0.355 | 0.148 | 0.009 | 0.744 | 0.962 | | | | | |
| **M3** | 0.175 | 0.077 | 0.727 | 0.118 | 0.167 | 0.338 | 0.287 | | | | |
| **M5** | 0.256 | 0.060 | 0.881 | 0.181 | 0.127 | 0.268 | 0.223 | 0.854 | | | |
| **P1** | 0.004 | 0.791 | 0.043 | 0.002 | 0.671 | 0.465 | 0.470 | 0.094 | 0.072 | | |
| **P2** | *0.000** | 0.057 | *0.000** | *0.000** | 0.004 | 0.002 | 0.002 | 0.000 | 0.000 | 0.019 | |
| **P3** | 0.014 | 0.656 | 0.096 | 0.008 | 0.864 | 0.638 | 0.654 | 0.178 | 0.140 | 0.833 | 0.016 |

**Table 6**
Cognitive load of tasks grouped by the type of interaction involved and averaged.

| Touch | Look | Speak | Hear |
|---|---|---|---|
| 0.446 | 0.403 | 0.715 | 0.533 |

P2. However, we cannot fully support Hypothesis 2 because every category of the taxonomy has one task with notoriously different cognitive burdens than the others. These results guide the next steps of our research on early diagnosis of MCI. We will focus on analysing the performance of the tasks with higher cognitive load where mental decline should be clearly reflected. This is precisely the hypothesis to be validated in the immediate future work.

This paper has shown an important advance from previous research, mainly due to the effort to improve the quality of the experiment. The previous work stated the importance of using a better EEG device in future work, as well as increasing the sample size to obtain a higher statistical significance, which has been the course of action followed in this work. Future work will also focus on studying the cognitive load during dual-tasking, including other types of sensors like pressurised insoles. Moreover, future work will involve analysing cognitive load when interacting with specific mobile applications for people with special needs. Examples of this are augmented reality for guiding people with dementia [53,54], mobile-based biomedical signal measurement [55] and avatar-based apps for emotion management [56]. Research will also continue to apply smartphones to the early detection of cognitive impairment, relying on HuSBIT-10 taxonomy. The future work in these terms would be to meet a consensus about the taxonomy with relevant communities in HCI and publish it into open-source repositories.

## Ethical standards

The authors assert that all procedures contributing to this work accomplish with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008. The project of which this work is a part obtained the approval to carry out this research (c-290-Proc. num 11/2019) by the "Committee on Ethics in Research with Medicines" of the Integrated Care Management Unit at Castilla-La Mancha Health Service.

## CRediT authorship contribution statement

**Luis Cabañero:** Software, Formal analysis, Data curation, Writing - original draft, Investigation, Visualization. **Ramón Hervás:** Conceptualization, Validation, Investigation, Supervision, Writing - review & editing, Project administration, Funding acquisition. **Iván González:** Conceptualization, Validation, Writing - review & editing, Supervision. **Jesús Fontecha:** Conceptualization, Methodology, Writing - review & editing. **Tania Mondéjar:** Validation, Writing - review & editing. **José Bravo:** Resources, Supervision, Funding acquisition.

## 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.

## Acknowledgements

This research was funded by the MINISTERIO DE CIENCIA, INNOVACIÓN Y UNIVERSIDADES, Spain, grant number RTI2018-098780-B-I00 (national research project) and the S1911001D predoctoral contract by JUNTA DE COMUNIDADES DE CASTILLA-LA MANCHA, Spain. The EEG headset was purchased with funding from the UNIVERSITY OF CASTILLA–LA MANCHA, Spain, grant number 2019-AYUDA-27430.

## Supplementary Materials

The EEG dataset generated and analysed for this study can be found in https://www.esi.uclm.es/www/mami/web/index.php/datasets.

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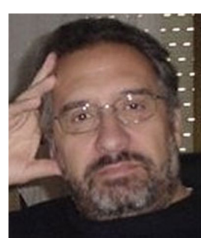

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