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REVIEW

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EEG power spectral measures of cognitive workload: A meta-analysis

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Abstract

Cognitive workload (CWL) is a fundamental concept in the assessment and monitoring of human performance during cognitive tasks. Numerous studies have attempted to objectively and continuously measure the CWL using neuroimaging techniques. Although the electroencephalogram (EEG) is a widely used technique, the impact of CWL on the spectral power of brain frequencies has shown inconsistent results. The present review aimed to synthesize the results of the literature and quantitatively assess which brain frequency is the most sensitive to CWL. A systematic literature search following PRISMA recommendations highlighted three main frequency bands used to measure CWL: theta (4–8 Hz), alpha (8–12 Hz), and beta (12–30 Hz). Three meta-analyses were conducted to quantitatively examine the effect of CWL on these frequencies. A total of 45 effect sizes from 24 studies involving 723 participants were computed. CWL was associated with significant effects on theta ($g = 0.68$, CI [0.41, 0.95]), alpha ($g = -0.25$, CI [−0.45, 0.04]), and beta ($g = 0.50$, CI [0.21, 0.79]) power. Our results suggests that theta, especially the frontal theta, is the best index of CWL. Alpha and beta power were also significantly impacted by CWL; however, their association seemed less straightforward. These results are critically analyzed considering the literature on cerebral oscillations. We conclude by emphasizing the need to investigate the interaction between CWL and other factors that may influence spectral power (e.g., emotional load), and to combine this measure with other methods of analysis of the central and peripheral nervous system (e.g., functional connectivity, heart rate).

KEYWORDS

beta, cognitive workload, EEG, spectral power, theta, alpha, meta-analysis

1 | INTRODUCTION

In our modern, highly connected societies, work environments impose increasingly high demands on our cognitive and cerebral resources that allow us to process information. Such a high demand on cognitive resources exposes individuals to situations of cognitive overload, which can be dangerous for their health (Klonowicz, 1995) and can lead to errors and accidents (Zoer et al., 2011). Electroencephalogram (EEG) is one of the main techniques for measuring the brain resources corresponding to *cognitive workload* (CWL). So far, several brain frequencies (mainly theta and alpha) have been candidates to reflect the mental state of an individual exposed to high CWL. Despite a growing number of studies, results do not always converge. One recent meta-analysis focused on the link between CWL and Event-Related Potential (ERP, Ghani et al., 2020), while two systematic reviews examined the main sensors usually used to measure CWL (Charles & Nixon, 2019; Tao et al., 2019). However, no meta-analysis specifically examined the relationships between CWL and EEG spectral power. The present quantitative review thus aims to synthesize the results of the literature, in order to evaluate whether brain frequency spectral power is a useful method for measuring CWL.

1.1 | Cognitive workload (CWL) concept

CWL is a fundamental concept in the study of human performance that emerged from the observation that our cognitive system has limited capacities to perform a cognitive task (Broadbent, 1971). This upper limit of our processing capacity led authors to postulate the existence of a finite quantity of *resources*, which must be used to perform a cognitive operation (Kahneman, 1973; Norman & Bobrow, 1975; Wickens, 2002). The limited amount of these resources implies that the more resources are needed for a processing operation, the less resources are available for other cognitive operations. Although the concept of mental resources has only a limited explanatory capacity (see Dehais et al., 2020, for a review on this issue with a neuroergonomic approach), it remains useful for studying and predicting human performance in cognitively demanding situations (e.g., multi-tasking). During a cognitive task, these attentional and neural resources are engaged, among other things, in processes of maintaining and manipulating relevant information, generally modeled by the concept of working memory (Baddeley, 2012; Cowan, 2016). Although it has been used and extensively studied since the 1960s, the concept of CWL has no single, consensual definition (Moray, 1979; Young et al., 2015). Nevertheless, it is commonly accepted that CWL is multidimensional in nature and can interact with many factors such as expertise, work environment, age, and other psychosocial factors (Hart & Wickens, 1990; Xie & Salvendy, 2000). In the present review, CWL will be defined as the amount of brain resources required for an individual to complete a task (i.e., cognitive activities requiring the achievement of a particular goal). Thus, CWL emerges from the interaction between the task to be performed and the individual, who has limited resources (Young et al., 2015). When the demand of the task leaves sufficient mental resources available to the individual, resource models consider that the individual should be able to maintain a high level of performance (e.g., in terms of speed or accuracy; Wickens, 2008). Cognitive overload occurs when the demand of the task exceeds the resources available to the individual, who is then no longer able to correctly process the relevant information or produce an adapted response. This state reduces efficiency and drastically increases the probability of making mistakes. Detecting and preventing situations of cognitive overload is crucial when applied to the study of operators whose errors can cause serious harm, as is the case in the industrial (nuclear), transportation (maritime, car, aviation), military and medical fields (McFadden et al., 2004; Senders & Moray, 2020). Valid and sensitive methods for measuring CWL continuously and in real time are thus indispensable.

1.2 | Measuring CWL

Historically, the first method used to infer an individual's mental state was to analyze their performance (e.g., response time, accuracy, error rates) on a task, which may be single or accompanied by a secondary task. This second task has generally no interest other than adding information to be processed in order to observe the effect of this additional task on the performance of the main task (Wickens, 1991). However, this method is not completely satisfactory. Indeed, the level of performance does not necessarily reflect the quantity of brain resources used by the individual: An increase in the demand of the task can lead to a strong increase in the cognitive resources invested to maintain an equivalent level of performance (Young et al., 2015). Having to wait for errors to appear makes the use of this method ineffective in operational environments where errors can be costly financially or humanly.

The second group of methods are subjective measures, which refer to the use of rating scales, self-reported by the individual after completing the task to be assessed. Two scales are usually used to assess subjective CWL: the National Aeronautics and Space Administration Task Load Index (NASA-TLX) scale (Hart & Staveland, 1988), and the Subjective Work-load Assessment Technique (SWAT) scale (Reid & Nygren, 1988). Besides the fact that the assessment cannot be done "online" (i.e., when the task is performed), many biases can also interfere with the validity of these measurements, such as the participant's understanding of the concept being assessed, the interaction between task performance and subjective assessment (e.g., poor performance will increase the subjective assessment of difficulty; Moray, 1982), social desirability, interindividual differences in the capacity for introspection and consciousness, memory bias (e.g., peak-end effects; Peterson & Kozhokar, 2017).

More recently, technical development has enabled the development of physiological measurements for assessing CWL. While the previous measures allow an indirect measurement of the individual's mental state, physiological sensors, by measuring certain characteristics of the central nervous system (e.g., brain) and peripheral nervous system (e.g., heart rate), give us physiological cues of the individual's mental state. Technological progress has enabled many laboratories to equip themselves with physiological sensors at lower prices, for increasingly precise measurements (Marini et al., 2019). Several studies have demonstrated the sensitivity of EEG as an index of CWL (e.g., Gevins et al., 1998; Lei & Roetting, 2011), particularly in the field of adaptive automation systems where brain activity is used as input to the system (Aricò et al., 2016; Parasuraman, 1990). Some studies suggest that EEG is more sensitive than other physiological measures (Brookings et al., 1996; Taylor et al., 2010), while others show that EEG can measure unique processes that are not detected by other physiological measures (Hankins & Wilson, 1998; Matthews et al., 2015). To select a relevant instrument for CWL measurement, it is necessary to consider the sensitivity of the measurement but also the conditions under which this technique can be used effectively. Brouwer et al. (2014) found that pupil size measurement was a more sensitive marker of cognitive effort than EEG. However, its use is limited to contexts where brightness is stable and flicker-free, which is very difficult to obtain in real-life situations. On the other hand, the use of EEG in real life is made possible by the refinement of algorithms for processing artifacts (Onikura et al., 2015). For instance, advances in algorithms have made it possible to effectively remove noise from the EEG signal, even when the signal is obtained during walking or running (Gwin et al., 2010).

1.3 | EEG technique and frequency power

The signal obtained by EEG comes from the post-synaptic excitatory (or inhibitory) potentials produced by the action potentials moving through the dendrites of pyramidal neurons in the outer layers of the cortex (Dickter & Kieffaber, 2013; Sanei & Chambers, 2013). The transition from the activity of dipole sources located in the brain (i.e., neurons) to a measurable electric field on the scalp is achieved by the geometry of the neurons (i.e., pyramidal) and the volume conduction properties of the different layers of the head (hair, scalp, skull, brain). These different layers attenuate and distort the electric field, making it impossible to measure small groups of neurons and making it difficult to locate the dipoles. However, the synchronized activity of several thousands of synapses and the summation of these electric fields via propagation through the tissues allows a weak, but measurable signal to be obtained at the surface on the scalp. This signal is measured by electrodes (less than 3 mm in diameter), whose surface is usually composed of silver and silver chloride (Ag/AgCl). The signal recorded by the sensors is then amplified and converted via an analog-to-digital converter. Due to the weakness of the measured signal, it is commonly accepted that the electrode impedance must be less than 5 kΩ to avoid increasing the noise level, which would result in a lower signal-to-noise ratio (Kappenman & Luck, 2010). Electrode placement is generally standardized according to the recommendations of the International Federation of Societies of Electroencephalography and Clinical Neurophysiology, known as 10–20 placement (Jasper, 1958). This technique is characterized by an excellent temporal resolution (milliseconds), making it possible to examine the temporal course of cognitive, perceptive, and sensory processes with great precision (Cohen, 2011). Compared to other neurophysiological recording techniques such as positron emission tomography and functional magnetic resonance imaging (fMRI), EEG recording device are small (e.g., possibly mobile), easier to set up (e.g., with dry electrodes), and less expensive to acquire and maintain. These advantages have made EEG an ideal tool for studying brain resource allocation in laboratories or in the field.

The EEG signal can be decomposed into several frequency ranges (usually by a Fourier transform), whose power is determined by power spectral analysis. Although there are no standardized frequency ranges and the boundaries may change slightly depending on the author, the frequency ranges are classically defined as follows: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–50 Hz). Alpha and beta frequencies are sometimes decomposed into subbands whose functional differences have been observed (Klimesch, 1999; Staufenbiel et al., 2014): low alpha (8–10 Hz), high alpha (10–12 Hz), or beta1 (12–20 Hz) and beta2 (20–30 Hz). Numerous studies have focused on theta and alpha frequencies, which have long been associated with cognitive processes (Gevins et al., 1997; Klimesch, 1999, 2012; Onton et al., 2005; Roux & Uhlhaas, 2014). Roughly speaking, the theta frequency in the frontal cortex is positively correlated with increasing CWL, while conversely, the alpha frequency of the parietal cortex decreases as CWL increases (Gevins et al., 1997; Lei & Roetting, 2011). This dissociation has not always been demonstrated in the literature (e.g., Borghini et al., 2014). An increase in theta, particularly frontal theta, is often associated with an increase in working memory load (Deiber et al., 2007; Jensen & Tesche, 2002; Onton et al., 2005), but some studies show a decrease in theta power associated with a high load (e.g., Brzezicka et al., 2019). Alpha, on the other hand, yielded much more inconsistent results, with some studies showing an increase in alpha in association with increased workload (Jensen et al., 2002; Klimesch, 2012), while other studies showed the opposite (Michels et al., 2010; Palva & Palva, 2007). The studies examining the beta band also show diverging results, with increases in load leading to a power increase (Chen & Huang, 2016; Kornblith et al., 2016) or decrease (Proskovec et al., 2019).

The primary aim of this quantitative review is, therefore to synthesize and combine the results of the literature, in order to clarify the relationship between the different brain oscillations spectral power and an increase in CWL. Indeed, extant reviews that focused on the major physiological measures of CWL (Charles & Nixon, 2019; Lean & Shan, 2012; Tao et al., 2019) did not quantitatively address this issue.

To deepen the analysis, several *moderators* were selected a priori based on the literature. Concerning brain oscillations, we were interested in the specific *frequency* bands measured across the different EEG component when they contain several sub-bands that may have different functional roles (i.e., low & high alpha, beta1 & beta2, Fink et al., 2005; Klimesch, 1999). In order to study the spatial specificities of the measured oscillations, the brain *region* of interest was also used as a moderator variable. Regarding individual characteristics, we controlled for the *gender* of the individuals involved in the studies, as several studies have shown that gender can have an impact on CWL (de Moura et al., 2017; Hancock et al., 1992) as well as on brain oscillations (Güntekin & Başar, 2007). We also examined the effect of *expertise*, which may generate variability in the measurement of CWL, since with equal task load, experts process information more efficiently than novices (Ward et al., 2019). This processing efficiency is accompanied by changes in brain activity, with a reduction in the activity of the prefrontal and parietal cortex (Bilalić & Campitelli, 2018). Moreover, the recent development of low-cost mobile EEG systems (Ayaz & Dehais, 2018) that accompanied the emergence of neuroergonomics, has made the study of brain activity in ecological conditions (i.e., similar to a real-world setting) easier. As this type of system naturally attracts researchers looking to evaluate CWL online and will certainly be increasingly developed in the future, we additionally wanted to compare the EEG measurements obtained according to the *type of system* used (i.e., mobile EEG or not). We also coded for the number of tasks to be performed by the participant (i.e., single or multiple), in order to examine the impact of a *multitasking* situation on brain oscillations. Performing several tasks "at the same time" implies managing the prioritization of these tasks according to different criteria (e.g., priority, interest, difficulty; Wickens & Gutzwiller, 2017). This task management thus induces an additional demand on cognitive resources compared to the execution of a single task (i.e., management load; Xie & Salvendy, 2000), and can, therefore generate a greater CWL. Finally, we considered mental fatigue, which is an intrinsically related concept to CWL and is also associated with decreased performance (Bendak & Rashid, 2020) and can cause impairment in theta and alpha spectral power (Borghini et al., 2014). To investigate this factor, we estimated the *time-on-task* (i.e., duration of required mental effort) during which participants' EEG activity was recorded. When the total duration was not explicitly given in the article, an estimate was computed.

2 | Method

2.1 | Inclusion and exclusion criteria

Only studies that were published in a peer-reviewed journal were eligible. Moreover, they had to meet the following criteria: (a) contain at least one quantitative EEG measure of the usual frequency bands (i.e., delta, theta, alpha, beta, and gamma) with spectral power analysis; (b) introduce a manipulation of the CWL in order to oppose low and high load; (c) use a within-subject design or compare independent groups; (d) present sufficient statistical information to calculate an effect size (e.g., mean, standard deviation, and sample size); (e) focus on healthy young adults; (f) present original data; (g) be written in English. Reviews, conference papers, book chapters, and studies using overlapping data were excluded. To restrict the scope of this study and to allow comparison between the effect sizes, we did not included studies that uses alternative types of EEG analyses (e.g., time-frequency analysis, ERP, brain networks connectivity) nor those that compared classification algorithms (Lotte et al., 2007).

2.2 | Information sources

We conducted a systematic search of the literature, in accordance with the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (Moher et al., 2009). The search covered a period up to September 2019 in the following databases: arXiv (19), Cochrane Library (48), Embase (925), IEEE Xplore (425), PsycINFO (643), PubPsych (190), PubMed (684), Science Direct (3759), SpringerLink (4302), Taylor & Francis Online (783), Web of Science (1220). A combination of the following keywords was used: "EEG or electroencephalogra*" and "cognitive load"; "EEG or electroencephalogra*" and "cognitive workload"; "EEG or electroencephalogra*" and "mental load", "EEG or electroencephalogra*" and "mental workload". Moreover, we manually performed a search in the major reviews of the field (Borghini et al., 2014; Charles & Nixon, 2019; Kramer, 1991; Lean & Shan, 2012; Tao et al., 2019; Young et al., 2015) and in the reference lists of included articles ($K = 23$). For studies that met the inclusion criteria but in which information was missing, we contacted the corresponding author of the paper ($K = 7$, only one author responded, for whom the data were no longer accessible). References were managed using Excel spreadsheets.

2.3 | Study selection

Eligibility assessment was performed by two authors. After having removed the duplicates, studies were screened by their title, following the flowchart sequence (Figure 1). Then, abstracts were screened and studies that did not meet the inclusion criteria were excluded. When the abstract did not provide enough information (e.g., type of EEG analysis), the study was eligible for full-text screening. Finally, full texts were screened and studies meeting all inclusion criteria were included for the meta-analysis ($K = 24$).

2.4 | Data collection

When reported, we extracted the following information from each study: (1) sample size, (2) mean age (and standard deviation) and gender of participants, (3) research domain, (4) study design (within- or between-participants), (5) frequency band(s), (6) electrode position, (7) number of tasks and method used to increase the CWL, (8) time on task, (9) method used to estimate spectral power, and (10) statistical data used to calculate effect sizes. Datafiles and the R script for the meta-analysis can be found on the Open Science Framework (OSF) through the following link: https://osf.io/xrb4z/.

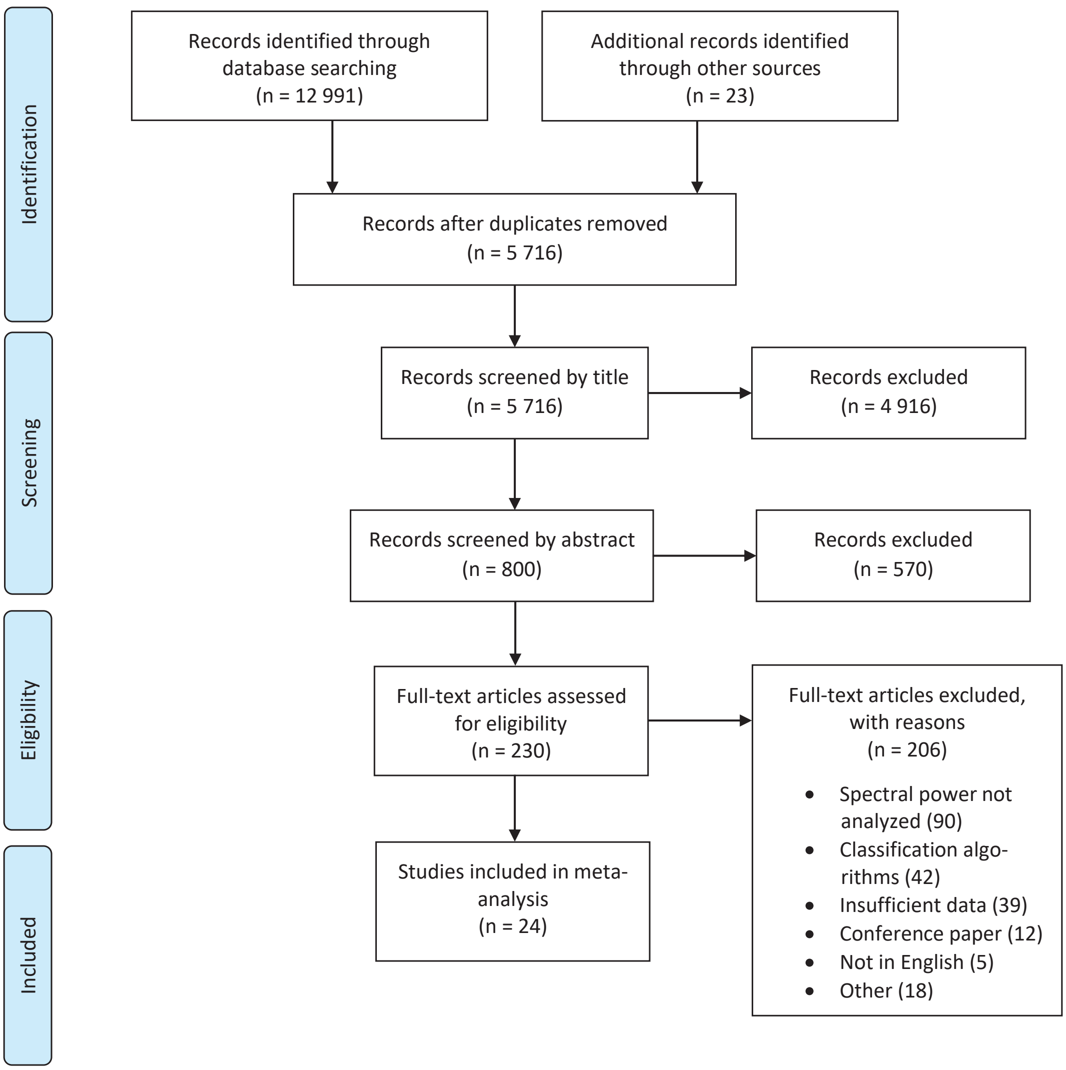

FIGURE 1 PRISMA flow diagram of the systematic search

2.5 | Summary measures

Statistical analyses were conducted in RStudio (RStudio Team, 2020, version 1.3.1093) using R (R Core Team, 2013, version 4.0.1). We used the *esc* package in order to compute the effect sizes (Lüdecke, 2018), and the *meta* (Schwarzer, 2007), *metafor* (Viechtbauer, 2010), and *dmetar* (Harrer et al., 2019) packages to conduct the meta-analyses and meta-regression.

We computed a Hedges's *g* statistic for the standardized mean difference in bandwidth power between high and low workload conditions. If the experimental comparison involved more than two load levels, the standardized mean difference was between the harder and the easier condition. Since most studies evaluated this difference in the same individual (within-subject design), we calculated repeated-measures effect sizes. Hedges's *g* statistic was preferred to Cohen's *d* because it adjusts for the small sample bias (Hedges, 1981). A positive effect size indicates an increase in average bandwidth power in the high workload condition.

Effect sizes were calculated based on the means and standard deviations, following Morris and DeShon's correction for within-subject designs (Morris & DeShon, 2002). As none of the studies reported the correlation values between the low and high load measure, we used a correlation value of $r = 0.50$ (which is considered as relatively conservative; Balk et al., 2012). Studies that reported *F*, *t* or Cohen's *d* values were converted to *g* (Lakens, 2013).

Knowing that all effect sizes should be independent in a meta-analysis—to avoid under-estimated standard errors of the average effects—we conducted three separate meta-analyses on the three main frequency bands measured in the included studies (i.e., theta, alpha, and beta). Studies measuring other bands were too few to be meta-analyzed (e.g., delta, gamma, theta/alpha ratio). When a study provided different measurements of the same frequency within the same participant (e.g., one measure of theta per electrode), data were averaged together to compute one effect size (Cooper et al., 2019). An exception was made for alpha and beta spectral power analyses, for which some studies (alpha: $K = 3$; beta: $K = 2$) reported low and high alpha and beta1 and beta2 measurements, respectively. Although this lack of independence may lead to an underestimation of the standard error, the small number of studies concerned precludes the use of multivariate or three-level meta-analyses (Cheung, 2019). On the other hand, this small number of studies reduces the risk of obtaining Type I error rates (Song et al., 2020).

2.6 | Synthesis of results

Given the diversity of protocols included, we expected high heterogeneity between the studies, and therefore applied a random effects model to combine and weight effect sizes across studies using inverse variance methods. We also included an analysis of the data by a fixed effects model (see Supplementary data), since there is a risk of overestimating effect sizes when a random effects model is used in the presence of strong publication bias (Cooper et al., 2019). We quantified heterogeneity using the effect sizes' percentage of variability (i.e., the I^2 statistic). A value of 75% and above indicates high heterogeneity, a value of 50% indicates moderate heterogeneity, a value of 25% indicates low heterogeneity and a value of 0% indicates no heterogeneity (Higgins et al., 2019). Despite its ease of interpretation, the I^2 statistic depends on the sampling error and number of studies included. To have an indicator independent of the number of studies, we also calculated the between-study-variance estimator τ^2, using the Hartung–Knapp–Sidik–Jonkman method (IntHout et al., 2014). Although the DerSimonian and Laird method is widely used for random effects meta-analysis, this method has been shown to be biased toward type 1 error, producing false positives (IntHout et al., 2014). It has been recently established that this method is outperformed by the Hartung–Knapp–Sidik–Jonkman method, especially when the number of studies is small (IntHout et al., 2014). Heterogeneity was also statistically assessed by the Chi-square test (Cochran's *Q*-statistic). Since Cochran's *Q* test may be under-powered when few studies have been included (West et al., 2010), it is recommended to choose a *p* value higher than the classical threshold of significance (i.e., $p < .05$). We, therefore set the significance threshold at $p < .10$.

A sensitivity analysis was performed when heterogeneity was significant and greater than 50%. We used the "leave-one-out" function to assess the influence of each study on the results and heterogeneity. This method consists in removing one study at a time from the meta-analysis and repeating the operation until each study had been removed once to verify that our conclusions were not influenced by a single study (Viechtbauer, 2010). Influence analyses were then carried out by visual inspection of Baujat et al. (2002) and Viechtbauer and Cheung graphs (Viechtbauer & Cheung, 2010). Lastly, studies for which the 95% confidence interval was outside the 95% confidence interval of the pooled studies were considered outliers (Viechtbauer & Cheung, 2010) and were excluded from the meta-analysis and meta-regression.

Sensitivity analyses were pre-specified to assess the impact of our subgroups on the overall effect size. Subgroup analyses were performed on categorical moderator variables using a mixed-effects model (i.e., random effects within and fixed effects between, Borenstein & Higgins, 2013). The purpose of the subgroup analyses was twofold: to conduct sensitivity analyses to explain the presence of heterogeneity, and to investigate relevant theoretical points related to the coded categorical moderator variables, following the recommendations of Richardson et al. (2019). Subgroups with less than three studies were not reported (Higgins et al., 2019). Meta-regression was used for continuous moderator variables to test whether those variables had a significant impact on the average effect size (*time-on-task*, year of publication, and sample size).

Potential publication bias was investigated by visual inspection of contour-enhanced funnel plots and tested statistically by Egger's linear regression (Egger et al., 1997). The contour-enhanced funnel plot is an improved version of the funnel plot, which has often been criticized because of its subjective interpretation (Peters et al., 2008). Contour lines that are superimposed on the funnel correspond to perceived "milestones" of statistical significance (p = .01, .025, .05). These different contours help to distinguish an asymmetry caused by the nonreporting of nonsignificant studies (publication bias) from an asymmetry caused by other factors (e.g., poor methodological quality, linguistic bias, chance; Egger et al., 1997). An asymmetry caused by the absence of studies with a statistically non-significant effect size is an indication of publication bias. Conversely, if the asymmetry is caused by studies that should have had statistically significant effect sizes, factors other than publication bias should be considered (Higgins et al., 2019). When the distribution was significantly asymmetrical according to Egger's regression, suggesting a publication bias, we used the trim-and-fill method (Duval & Tweedie, 2000) to compute a bias-corrected estimate of the average effect.

3 | Results

3.1 | Study selection

After duplicates had been removed, 5 716 unique records were identified in searches through the database and reference list. 4 916 records were then excluded from the preliminary screening of titles. Among the remaining 800 records, 570 were excluded after screening of abstracts because they did not manipulate CWL (69), they did not include any EEG measure with spectral power analysis (74), they were a book chapter (89), conference paper (205), review article (39), dissertation (7), inaccessible (4), technical report or article using classification algorithms (67), not in English (10) or focused on a clinical population (6). Two hundred and thirty reports were retrieved for detailed evaluation of the full-text and a total of 24 records met the inclusion criteria and were included in the quantitative review (see Figure 1).

3.2 | Study characteristics

The included studies, published between 1984 and 2019 (mean: 2014, median: 2017), involved a total of 723 participants (mean age of 24.4 ± 3.42, 33.3% female) for which 45 effect sizes were computed. Of these effect sizes, 16 were from a difference in the mean power of the theta band, 17 from the alpha band and 12 from the beta band. Four studies examined expertise (k = 7, Fallahi et al., 2016; Jaquess et al., 2017; Morales et al., 2019; Orlandi & Brooks, 2018), five studies used a portable EEG system (k = 9, Castro-Meneses et al., 2020; Fallahi et al., 2016; Matthews et al., 2015; Morales et al., 2019; Orlandi & Brooks, 2018). Four studies used multiple tasks to induce CWL (k = 9, Fallahi et al., 2016; Gong et al., 2019; Matthews et al., 2015; Puma et al., 2018) and the *N-Back* task was the most frequently used method for increasing CWL (k = 12, Brouwer et al., 2014; Grissmann et al., 2017; Hsu et al., 2015; Murata, 2005; Pergher et al., 2019; Rietschel et al., 2012). Twelve studies used Fast-Fourier Transformation (k = 26, Fallahi et al., 2016; Gentili et al., 2018; Hsu et al., 2015; Jaquess et al., 2017; Kakizaki, 1984; Matthews et al., 2015; Morales et al., 2019; Murata et al. 2005; Pavlov & Kotchoubey, 2017; Pergher et al., 2019; Puma et al., 2018; Sammer et al., 2007), two studies used Short-Time Fourier Transformation (k = 3, Dasari et al., 2017; Zhang et al., 2016), one study used Continuous-Fourier Transformation (k = 1, Hsu et al., 2017), three studies used Welch's method (k = 5, Gong et al., 2019; Grissmann et al., 2017; Zakrzewska & Brzezicka, 2014), and six studies did not report the method used to estimate the EEG spectral power (k = 10, Brouwer et al., 2014; Castro-Meneses et al., 2020; Lee, 2014; Orlandi & Brooks, 2018; Rietschel et al., 2012; Shaw et al., 2018). The individual studies, sample characteristics, encoded moderator variables, and effect sizes with standard errors are presented in Table 1. Method used to manipulate CWL, estimate spectral power, electrode placement, and the estimation of time-on-task are presented in Table S1.

3.3 | Meta-analysis of outcome measures

3.3.1 | Theta

Individual study (k = 16) and aggregate effect size for studies measuring the theta band are presented in Figure 2 (see Figure S1 for the fixed effects model). Overall, CWL had

TABLE 1 Characteristics of studies assessing the impact of cognitive workload on theta, alpha, and beta power included in the meta-analysis

Study author	Year	*N*	Age, mean (*SD*) [range]	Gender	Frequency	Region	Expert.	EEG port.	S/M	Hedges g	SE
Brouwer et al.	2014	35	27	Mixed (19 F)	Theta (4–8 Hz)	Frontal	None	NP	S	0.15	0.24
	–	–	–	–	Alpha (8–13 Hz)	Parietal	–	–	–	−0.11	0.24
Castro-Meneses et al.	2020	35	25.11 (2.33)	Mixed (27 F)	Theta (4–7 Hz)	Frontal	None	P	S	0.27	0.24
Dasari et al.	2017	8	25 (4.3)	Male	Theta (4–8 Hz)	Frontal	None	NP	S	1.01	0.40
	–	–	–	–	Alpha (8–12 Hz)	Multiple	–	–	–	−1.26	0.49
Fallahi et al.	2016	40	32.63 (0.57)	Male	Theta (4–8 Hz)	Central	Expert	P	M	0.40	0.26
	–	–	–	–	Alpha (8–12 Hz)	Central	–	–	–	−0.70	0.23
Gentili et al.	2018	17	24.9 (4.4)	Mixed (17 F)	Theta (3–8 Hz)	Multiple	None	NP	S	0.99	0.34
	–	–	–	–	High alpha (10–13 Hz)	Multiple	–	–	–	−0.45	0.15
Gong et al.	2019	15	19.5 (1.1)	Male	Theta (4–7 Hz)	Frontal	None	NP	M	0.50	0.37
	–	–	–	–	Beta (14–30 Hz)	Frontal	–	–	–	0.99	0.88
Grissmann et al.	2017	24	23	Female	Theta (4–7 Hz)	Frontal	None	NP	S	1.18	0.44
Grissmann et al.	2017	24	23	Female	Alpha (8–12 Hz)	Parietal	None	NP	S	−0.81	0.43
Hsu et al.	2015	30	21.8 (1.1)	Male	Theta (4–7 Hz)	Frontal	None	NP	S	0.18	0.26
	–	–	–	–	Alpha (8–13 Hz)	Frontal	–	–	–	−0.04	0.26
	–	–	–	–	Beta (13–30 Hz)	Frontal	–	–	–	0.19	0.26
Hsu et al.	2017	16	22.9	Mixed (12 F)	Beta (16–32 Hz)	Multiple	None	NP	S	0.32	0.36
Jaquess et al.	2017	27	[19–26]	Male	Low alpha (8–10 Hz)	Parietal	Expert	NP	S	−0.21	0.07
	–	–	–	–	High alpha (10–13 Hz)	Parietal	–	–	–	−0.38	0.11
Kakizaki	1984	24	21 (2)	Male	Theta (4–8 Hz)	Occipital	None	NP	S	1.01	0.30
	–	–	–	–	Alpha (8–13 Hz)	Occipital	–	–	–	0.58	0.29
	–	–	–	–	Beta1 (13–20 Hz)	Occipital	–	–	–	0.88	0.30
	–	–	–	–	Beta2 (20–30 Hz)	Occipital	–	–	–	0.79	0.30
Lee	2014	43	Students	Mixed (21 F)	Beta (13–30 Hz)	Frontal	None	NP	S	0.22	0.08
Matthews et al.	2015	150	19.57 (3.46)	Mixed (65 F)	Theta (4–8 Hz)	Multiple	None	P	M	0.15	0.12
	–	–	–	–	Alpha (9–13 Hz)	Multiple	–	–	–	−0.01	0.11
	–	–	–	–	Beta (14–30 Hz)	Multiple	–	–	–	−0.01	0.11

TABLE 1 (Continued)

Study author	Year	*N*	Age, mean (*SD*) [range]	Gender	Frequency	Region	Expert.	EEG port.	S/M	Hedges *g*	SE
Morales et al.	2019	8	31.37 (2.2)	Mixed (6 F)	Beta (13–30 Hz)	Frontal	Expert	P	S	1.78	0.87
Murata	2005	8	[21–24]	Male	Theta (4–6.32 Hz)	Multiple	None	NP	S	0.88	0.53
	–	–	–	–	Alpha (8–12.4 Hz)	Multiple	–	–	–	0.68	0.52
	–	–	–	–	Beta (16–32 Hz)	Multiple	–	–	–	0.27	0.50
Orlandi & Brooks	2018	10	–	Female	Beta1 (13–20 Hz)	Multiple	Expert	P	S	1.15	0.69
	–	–	–	–	Beta2 (20–36 Hz)	Multiple	–	–	–	1.50	0.73
Pavlov & Kotchoubey	2017	65	20.92 (2.96)	Female	Beta2 (20–30 Hz)	Multiple	None	NP	S	0.54	0.21
Pergher et al.	2019	20	25.16	Mixed (12 F)	Theta (4–8 Hz)	Frontal	None	NP	S	0.88	0.33
Pergher et al.	2019	20	25.16	Mixed (12 F)	Alpha (8–12 Hz)	Parietal	None	NP	S	−0.31	0.32
Puma et al.	2018	20	27.25 (3.88)	Mixed (6 F)	Theta (4–8 Hz)	Frontal	None	NP	M	0.51	0.32
	–	–	–	–	Alpha (8–12 Hz)	Parietal	–	–	–	−0.32	0.32
Rietschel et al.	2012	11	27.1 (3.7)	Mixed (5 F)	Low alpha (8–10 Hz)	Multiple	None	NP	S	−0.27	0.41
	–	–	–	–	High alpha (10–13 Hz)	Multiple	–	–	–	−0.28	0.42
Sammer et al.	2007	20	25.4	Mixed (10 F)	Theta (3.5–7.5 Hz)	Frontal	None	NP	S	1.09	0.47
Shaw et al.	2018	12	[21–35]	Mixed (1 F)	Low alpha (8–10 Hz)	Multiple	None	NP	S	−0.22	0.71
	–	–	–	–	High alpha (11–13 Hz)	Multiple	–	–	–	−0.25	0.86
Zakrzewska & Brzezicka	2014	69	23 (3.46)	Mixed (40 F)	Theta (4–6 Hz)	Frontal	None	NP	S	0.70	0.25
Zhang et al.	2016	16	23.88 (2.70)	Male	Theta (4–8 Hz)	Frontal	None	NP	S	2.28	0.46

Note: Abbreviations: Expert.: Expertise of participants (None or Expert); EEG port.: Portability of the EEG system (Not portable or Portable); S/M = Single or Multiple tasks; SE = Standard error.

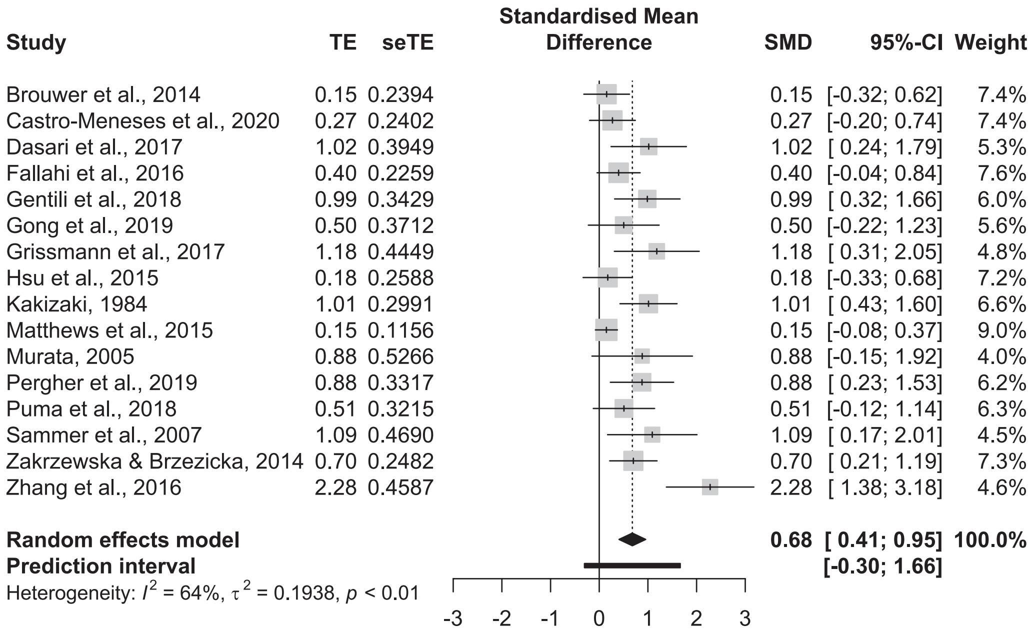

FIGURE 2 Forest plot of standardized effect sizes (*g*) of theta power in high versus low workload conditions. Total standardized mean difference with 95% confidence and prediction interval, weight, and heterogeneity are reported

a large effect on the theta band, $g = 0.68$, 95% CI [0.41–0.95], $p < .01$, indicating that theta power during high workload tasks was significantly greater than theta power in low workload conditions. Nevertheless, heterogeneity was pronounced and highly significant, $Q = 42$, $df = 15$, $p < .01$, tau$^2 = 0.19$, $I^2 = 64.3\%$.

3.3.1.1 | *Sensitivity analyses*

An influence analysis by the leave-one-out method and identification of the studies whose 95% confidence interval was outside the 95% confidence interval of the pooled studies revealed that two studies could be considered as outliers (Matthews et al., 2015; Zhang et al., 2016). After removing these studies ($k = 14$), the overall effect size remained stable and heterogeneity was no longer significant, $g = 0.62$, 95% CI [0.41–0.83], $p < .01$, $Q = 17.14$, $df = 13$, $p > .10$, tau$^2 = 0.07$, $I^2 = 24.2\%$.

3.3.1.2 | *Subgroup analysis of categorical moderator variables (Table S2)*

The test for subgroup differences between *EEG systems* suggested that there was a statistically significant subgroup effect ($p < .001$), meaning that the effect of CWL on the theta band was significantly different depending on the EEG system used. The effect of CWL on the theta band was greater for the non-portable EEG system subgroup ($g = 0.81$, $p < .01$) than for the portable EEG system subgroup ($g = 0.22$, $p < .01$). However, there is an insufficient number of studies in the portable EEG subgroup ($k = 3$) and a substantial unexplained heterogeneity between the studies within the non-portable subgroup ($I^2 = 55\%$), thus the validity of the CWL effect estimates for each subgroup is uncertain. The test for subgroup differences between *single* and *multiple tasks* indicated that there was a statistically significant subgroup effect ($p < .05$), suggesting that the theta band was more impacted by CWL during single task ($g = 0.81$, $p < .01$) than during multiple tasks ($g = 0.28$, $p < .01$). However, a smaller number of studies and participants contributed to the multi-task subgroup ($k = 4$, $N = 225$) than to the single-task subgroup ($k = 12$, $N = 306$), meaning that the covariate distribution is problematic for this subgroup analysis. There is substantial unexplained heterogeneity between the trials within the single-task subgroup ($I^2 = 62\%$). Therefore, the validity of the CWL effect estimates for each subgroup is uncertain. The test for subgroup differences between brain *regions* indicated that there was a statistically significant subgroup effect ($p = .04$), suggesting that the brain regions measured were affected differently by the effect of CWL on the theta band. The pooled effect estimate for the frontal region was large and significant ($g = 0.66$, $p < .01$). Central, occipital, and multiple region subgroups were not reported because of an insufficient number of studies ($k < 3$). Subgroup meta-analyses using *gender* and *expertise* as predictor variables were not done because of the insufficient number of studies per subgroup ($k = 1$ within expert and female subgroup).

3.3.1.3 | *Meta-regression of continuous moderator variables*

Meta-regression analysis did not reveal any effect of year of publication, sample size, nor time-on-task.

3.3.1.4 | *Publication bias*

Visual inspection of the funnel plot asymmetry (Figure 3) and Egger's linear regression revealed a publication bias, $B = 3.13$, 95% CI [1.87–4.39], $p < .05$. The trim-and-fill procedure suggested that seven studies could be added ($k = 23$), resulting in a decrease in the effect size ($g = 0.35$, 95% CI [0.01–0.69], $p < .05$) and an increase in heterogeneity ($Q = 87.45$, $df = 22$, $p < .01$, $\text{tau}^2 = 0.52$, $I^2 = 74.8\%$).

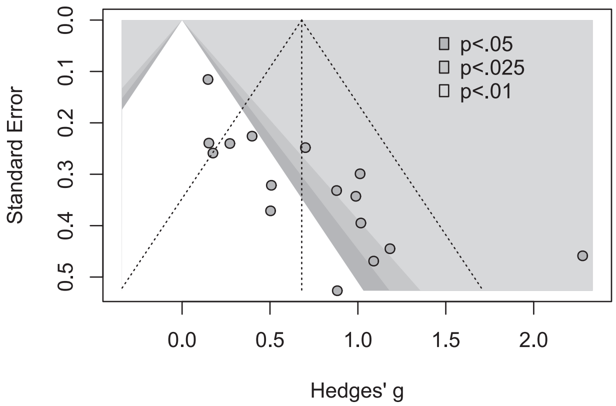

FIGURE 3 Contour-enhanced funnel plot of studies measuring theta band activity. Some studies are missing on the left-hand side of the plot, where results would be in the area of non-significance (i.e., the white area where $p > .05$) and for which non-reporting bias is a plausible explanation

3.3.2 | Alpha

A random effects model applied to the studies which measured the alpha band ($k = 17$) resulted in a significant effect size with moderate heterogeneity, $g = -0.25$, 95% CI [−0.45 – −0.04], $p < .05$, $Q = 29.76$, $df = 16$, $p < .01$, $\text{tau}^2 = 0.11$, $I^2 = 46.2\%$, indicating that alpha power during high workload tasks was significantly lower than alpha power during low workload conditions (Figure 4, see Figure S2 for the fixed effects model).

3.3.2.1 | *Sensitivity analyses*

An influence analysis by the leave-one-out method and identification of the studies whose 95% confidence interval was outside the 95% confidence interval of the pooled studies revealed that one study could be considered as an outlier (Kakizaki, 1984). Withdrawing this study resulted in an increase in the mean effect size and a decrease in heterogeneity, $g = -0.30$, 95% CI [−0.47 – −0.12], $p < .01$, $Q = 22.11$, $df = 15$, $p > .10$, $\text{tau}^2 = 0.08$, $I^2 = 32.1\%$.

3.3.3.2 | *Subgroup analysis of categorical moderator variables (Table S2)*

The test for subgroup differences between alpha *frequency bands* indicated a statistically significant subgroup effect ($p < .01$), suggesting that alpha frequency sub-bands were influenced differently by CWL. The effect of CWL on the alpha power was significantly larger for the high alpha (10–12 Hz) subgroup ($g = -0.39$, $p < .01$), while the effect

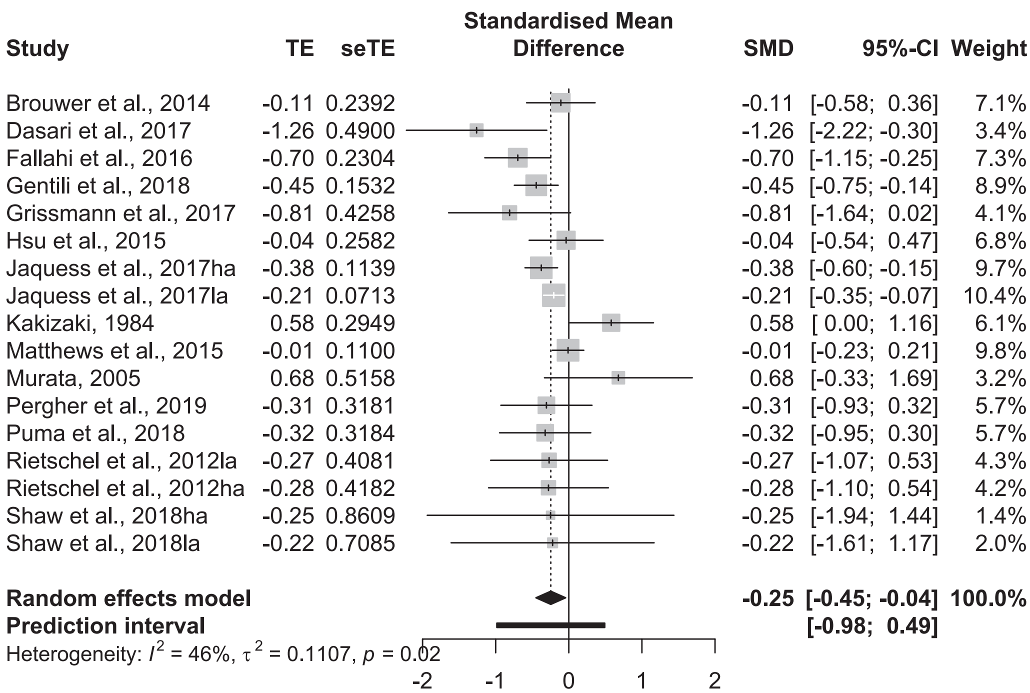

FIGURE 4 Forest plot of standardized effect sizes (g) of alpha power in high versus low workload conditions. Total standardized mean difference with 95% confidence and prediction interval, weight, and heterogeneity are reported

was smaller for the low alpha (8–10 Hz) subgroup ($g = -0.21$, $p < .01$) and no longer significant for the broad-band subgroup ($g = -0.21$, $p = .22$). However, a smaller number of trials and participants contributed to the high and low alpha subgroups (high alpha: $k = 4$, $N = 67$; low alpha: $k = 3$, $N = 50$) than to the broad-band subgroup ($k = 10$, $N = 359$), meaning that the uneven covariate distribution may not be able to produce valid results.

The test for subgroup differences between brain *region* suggested that there was a statistically significant subgroup effect ($p < .01$), meaning that the effect of CWL on the alpha band was significantly different depending on the brain region measured. The effect of CWL on the alpha band was larger for the parietal region ($g = -0.29$, $p < .01$) than for the multiple region subgroup ($g = -0.23$, $p = .12$). A sufficient number of studies and participants (parietal: $k = 6$, $N = 153$; multiple: $k = 6$, $N = 79$) were included in each subgroup, so the covariate distribution was not problematic for this subgroup analysis. Frontal, central, and occipital electrode location groups were not reported because of the insufficient number of studies ($k < 3$). Results of subgroup meta-analyses for the *gender* and *multi-tasking* moderators did not show any significant effects. Subgroup meta-analyses using *expertise* and type of *EEG system* as predictor variables were not reported because of the insufficient number of studies ($k < 3$).

3.3.2.3 | *Meta-regression of continuous moderator variables*

Meta-regression analysis revealed a significant effect of publication year ($B = -0.03$, $p < .01$) and no effect of sample size and time-on-task.

3.3.2.4 | *Publication bias*

Visual inspection of the funnel plot asymmetry (Figure 5) and Egger's linear regression test revealed a potential publication bias, $B = -1.42$, 95% CI [−2.06 – −0.24], $p < .05$. The trim-and-fill procedure suggested that four studies could be added ($k = 20$), resulting in a decrease in the effect size ($g = -0.15$, 95% CI [−0.69–0.38], $p = .55$), and high heterogeneity ($Q = 104.28$, $df = 19$, $p < .01$, $tau^2 = 1.19$, $I^2 = 81.8\%$).

3.3.3 | Beta

3.3.3.1 | *Sensitivity analyses*

The aggregated effect sizes for the 12 studies measuring beta band activity are presented in Figure 6 (see Figure S1 for the fixed effects model). Overall, CWL had a moderate effect on the beta band, $g = 0.50$, 95% CI [0.21–0.79], $p < .01$, indicating that beta power during a high workload task was significantly greater than beta power in the low workload condition. However, heterogeneity was

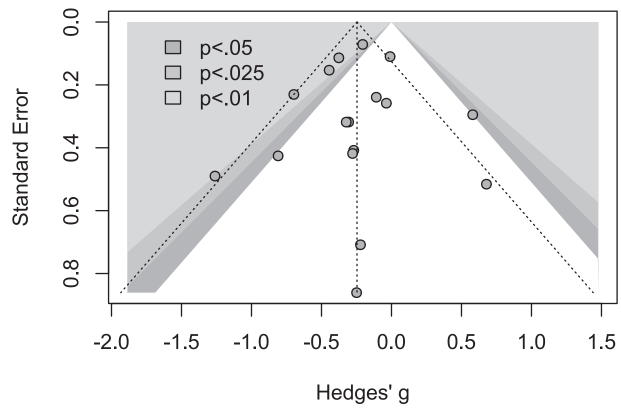

FIGURE 5 Contour-enhanced funnel plot of studies measuring the alpha band. Some studies are missing on the right-hand side of the plot, where results would be in the area of non-significance (i.e., the white area where $p > .05$) and for which non-reporting bias is a plausible explanation

substantial and significant, $Q = 23.23$, $df = 11$, $p < .01$, $tau^2 = 0.15$, $I^2 = 52.6\%$. Sensitivity analyses did not identify any potential outlier.

3.3.3.2 | *Subgroup analysis of categorical moderator variables (Table S2)*

The test for subgroup differences between beta *frequency bands* suggested that was a statistically significant subgroup effect ($p < .01$), meaning that the effect of CWL on the beta band was significantly different depending on the beta sub-band measured. The effect of CWL was significant and large for the beta1 (13–20 Hz, $g = 0.93$, $p < .01$) and beta2 band (20–30 Hz, $g = 0.74$, $p < .01$), while the effect was no longer significant when the broad-band frequency (13–30 Hz) was used ($g = 0.28$, $p = .07$). However, there is an insufficient number of studies in the beta1 ($k = 2$, $N = 34$) and beta2 subgroups ($k = 3$, $N = 99$), so the covariate distribution is problematic. Therefore, the validity of the CWL effect estimates for each subgroup is uncertain. The test for subgroup differences between beta *region* suggested that there was a statistically significant subgroup effect ($p < .10$), meaning that the effect of CWL on the beta band was significantly different depending on the brain region measured. The effect of CWL on the beta band was higher for the multiple region ($g = 0.59$, $p < .05$) than for the frontal region ($g = 0.33$, $p > .05$). There is a substantial unexplained heterogeneity between the studies within the frontal region subgroup ($I^2 = 43\%$). Therefore, the validity of the CWL effect estimates for each subgroup is uncertain. The occipital electrode location subgroup was not reported because of the insufficient number of studies ($k < 3$). The test for subgroup differences for *expertise* highlighted a statistically significant subgroup effect ($p < .01$), meaning that the effect of CWL on beta band activity was significantly different

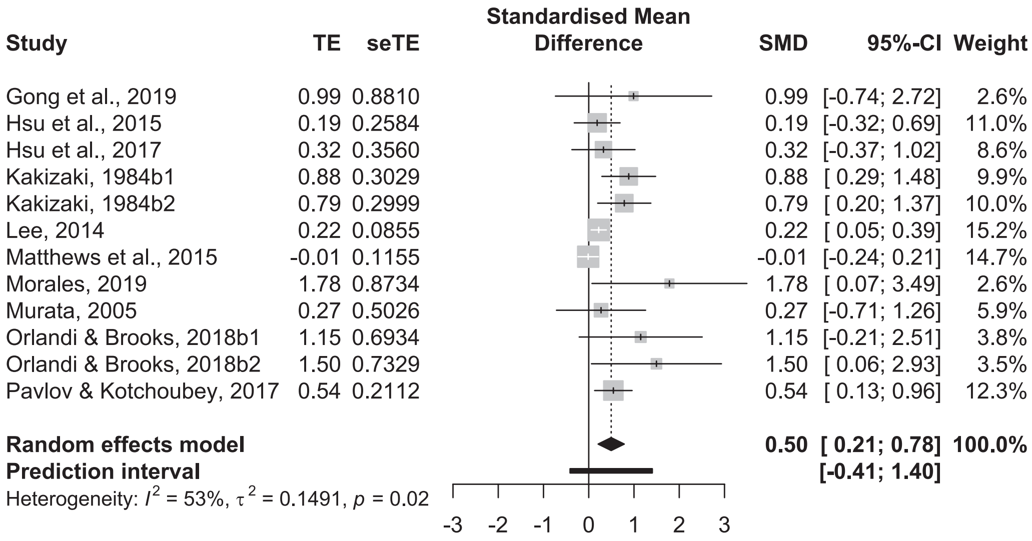

FIGURE 6 Forest plot of standardized effect sizes (g) of beta power in high versus low workload conditions. Total standardized mean difference (SMD) with 95% confidence and prediction interval, weight, and heterogeneity are reported

depending on the participant's expertise. The effect of CWL on the beta band was larger for the expert subgroup ($g = 1.43$, $p < .01$) than for the non-expert subgroup ($g = 0.36$, $p < .01$). The smaller number of studies and participants in the expert subgroup ($k = 3$, $N = 28$) and the substantial unexplained heterogeneity between the studies within the non-expert subgroup ($I^2 = 49\%$) may reduce the validity of this effect. The results of subgroup meta-analyses for *gender* and *EEG portability* did not show any significant result. Subgroup meta-analysis using *multitasking* as predictor variable was not reported because of the insufficient number of studies per subgroup ($k < 3$).

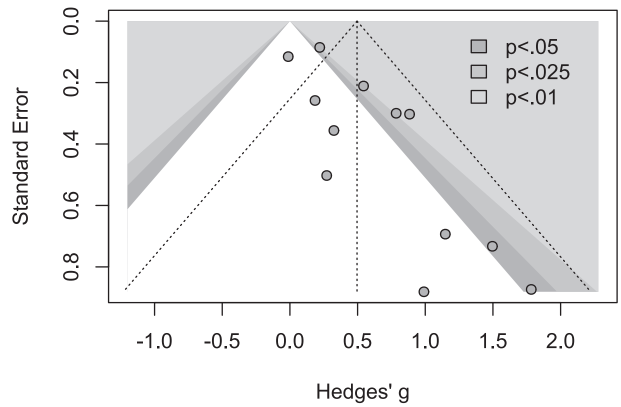

FIGURE 7 Contour-enhanced funnel plot of studies measuring the beta band. Some studies are missing on the left-hand side of the plot, where results would be in the area of non-significance (i.e., the white area where $p > .05$) and for which non-reporting bias is a plausible explanation

3.3.3.3 | Meta-regression of continuous moderator variables

Meta-regression analysis revealed a significant effect of time-on-task ($p < .05$, $R^2 = 45.54\%$) and sample size ($B = -0.01$, $p < .05$) and no effect of publication year.

3.3.3.4 | Publication bias

The funnel plot asymmetry (Figure 7) could have been caused by publication bias. Egger's linear regression test revealed a publication bias, $B = 1.61$, 95% CI [0.7–2.53], $p < .01$. The trim-and-fill procedure suggested that six studies could be added, resulting in a decrease in the effect size ($g = 0.21$, 95% CI [−0.17–0.59], $p > .05$) and an increase in heterogeneity ($Q = 43.61$, $df = 17$, $p < .01$, $tau^2 = 0.47$, $I^2 = 61\%$).

4 | Discussion

CWL is an important concept in many fields (e.g., system design, adaptive automation). Although it has been the focus of research for more than fifty years, the methods used to evaluate it are still of interest. EEG, as one of the most accessible brain imaging methods, has often been a favorite candidate.

In the current study, we reviewed articles that investigated EEG spectral band power differences during low and high workload tasks. Our meta-analysis is the first to quantitatively examined the impact of CWL on the three bands most often used in the literature: theta ($k = 16$), alpha ($k = 17$), and beta ($k = 12$). We found significant evidence for the influence of CWL on the three power bands. The standardized mean difference of band power between high and low workload was 0.68 with a 95% confidence interval of 0.41 to 0.95 for theta, −0.25 with a 95% confidence interval of −0.45 to −0.04 for alpha, and 0.50 with a 95% confidence interval of 0.21 to 0.79 for beta. We will begin by discussing these results and the accompanying subgroup analyses to investigate the effect of our selected moderators, then we will consider the limitations of this review as well as future perspectives for the measurement of CWL by EEG.

4.1 | Theta

The theta frequency power is the most sensitive to the increase in CWL due to an increase in the task demands: theta power was greater in high versus low cognitive load conditions. Moreover, this effect is specifically observed for the frontal region, as indicated by our subgroup analysis. The theta of the frontal cortex is a frequency that has been associated with the processes of working memory and executive functions. The increase in theta power has often been related, in a proportional way, to the amount of information to be retained in memory (Gärtner et al., 2015; Howard et al., 2003; Jensen & Tesche, 2002; Maurer et al., 2015; Onton et al., 2005; Roux & Uhlhaas, 2014; Wisniewski et al., 2015) as well as information manipulation (Griesmayr et al., 2010; Griesmayr et al., 2014). Studies showing that an increase in theta power predicted performance in working memory tasks have suggested the functional role of this frequency in this type of process (Womelsdorf et al., 2010; Zakrzewska & Brzezicka, 2014). At the neuroanatomical level, studies coupling EEG and fMRI (Meltzer et al., 2007; Michels et al., 2010; Scheeringa et al., 2009; Tsujimoto et al., 2010) as well as studies by magnetoencephalography (Gevins et al., 1997; Meltzer et al., 2007; Onton et al., 2005) have associated this frequency with the activation of two regions: the anterior cingulate cortex (ACC) and the medial prefrontal cortex (mPFC). The activation of these two regions has been associated with executive control and working memory processes (Bush et al., 2000; Niendam et al., 2012; Shenhav et al., 2013). More than simply being involved in memory processes, the theta could allow the allocation of different cortical resources according to the task (Onton et al., 2005; Sauseng et al., 2007; Shenhav et al., 2013). Thus, theta may underpin cognitive control and the distribution, efficient or not, of cognitive resources (Cavanagh & Frank, 2014).

Surprisingly, our subgroup analysis results showed a smaller average effect size in multi-tasking situations compared to single-tasking situations. This result, inconsistent with what is generally observed in the literature (Borghini et al., 2014), is also in contradiction with the hypothetical role of theta power in cognitive control, which should be strongly solicited during multitasking. For example, a study that trained elderly people via video games showed an increase in frontal-midline theta power associated with the training gains of the multi-task training (Anguera et al., 2013). This inconsistent result may be due to the insufficient number of studies ($K = 4$) that used multi-tasking. Three of these 4 studies had a relatively high standardized effect size (Fallahi et al., 2016: $g = 0.40$; Gong et al., 2019: $g = 0.50$; Puma et al., 2018: $g = 0.51$), compared to the study by Matthews et al. (2015); $g = 0.15$). In the latter study, which was detected as an outlier in our analyses, the comparison between low and high CWL was operationalized by asking participants to perform two separate tasks at the same time: a threat detection task, in which participants were instructed to identify potentially dangerous individuals in a 3D visual scene, and a change detection task, where participants were instructed to detect the simultaneous appearance, disappearance or movement of two icons on a map. These tasks, which are specific to military operations, are cognitively demanding and may, therefore, require significant neural recruitment even when performed alone. Performing these two tasks concurrently might not be associated to an increase in theta power because the theta power may already be high in the "low load," single-task condition and may not have increased considerably in the dual-task condition (i.e., ceiling effect). However, the unequal distribution of studies between subgroups prevents any categorical conclusions and further work is needed to investigate the impact of multi-tasking on theta power. The second outlier detected by our analyses (Zhang et al., 2016) had a very large effect size ($g = 2.28$). The authors studied the impact of a single visual working memory task with parametric variation of load (1 to 6) on the theta power in the frontal midline region (Fz). Moreover, the authors extracted the theta power during stimulus retention times, the periods in which the most resources are committed (Jensen & Tesche, 2002). Focusing on the critical period undoubtedly enabled such a large effect size to be obtained.

Some studies have shown that theta power was modulated by the increase in task demand only for individuals having higher working memory capacities (Zakrzewska & Brzezicka, 2014) or presenting higher performance in multitasking situations (Puma et al., 2018). In these studies, groups with low performances showed high theta power throughout the experiment, regardless of the level of difficulty. The neural efficiency hypothesis—that is, at equal performance, a higher neural activation is a sign of less efficient neural processing (Neubauer & Fink, 2009)—could explain this phenomenon. The hypothesis surmises that a high theta power for low performers in a low-demand condition reflects a greater recruitment in neural resources and therefore, less efficient neural processing. High performers, on the other hand, demonstrate neural efficiency to meet the demands of the simplest tasks with fewer neural resources (i.e., lower theta power). Increased difficulty then requires greater neural resources, matching the increase in theta power. This increase then reaches a plateau when the demands of the task require all the available neural resources (Puma et al., 2018; Zakrzewska & Brzezicka, 2014; Zhang et al., 2016). By indexing the level of effort required for a certain type of task, the theta could be an indicator of the level of neural efficiency of the participants. This hypothesis, although speculative, could partly explain the inconsistency of the results evaluating theta and CWL (e.g., Brouwer et al., 2014; Hsu et al., 2015).

4.2 | Alpha

Alpha spectral power appears to be negatively impacted by the increase in CWL: an increase in CWL leads to a decrease in alpha power. The presence of the alpha frequency has long been considered as indexing a "wakefulness" state of the brain, due to its desynchronization during cognitive tasks (the "cortical idling hypothesis," Pfurtscheller et al., 1996). Several studies have indeed observed a decrease in alpha power associated with an increase in task demands (Fairclough & Venables, 2006; Fallahi et al., 2016; Fink et al., 2005; Klimesch, 1999; Pergher et al., 2019; Sterman et al., 1994). Klimesch et al. (2007) hypothesized that alpha synchronization may correspond to an active process of inhibiting information that is not relevant to the task (the "inhibition-timing hypothesis"): The hypothesis postulates that when faced with a cognitive demand, the cortical areas involved in the processing of the task experience a desynchronization of alpha power (i.e., uninhibited), while the areas that are not necessary to the task or that could interfere with it are inhibited by alpha synchronization, particularly in the occipito-parietal areas (Jensen et al., 2002; Klimesch et al., 2007; Rihs et al., 2007). This may explain why an increase in alpha power has also been observed during the processing of cognitive tasks (Jensen et al., 2002; Palva et al., 2005; Tuladhar et al., 2007). The alpha rhythm could thus act as an information inhibiter which optimizes the signal-to-noise ratio for the benefit of the neurons involved in the processing of relevant information (Klimesch, 2012). This functional role of alpha has been supported in numerous studies of visual attention that have shown that the allocation of attention in one direction is accompanied by a suppression of alpha in the contralateral visual cortex and an increase in alpha in the ipsilateral visual cortex (Clayton et al., 2019; Wildegger et al., 2017). In a recent study that used rhythmic transcranial magnetic stimulation (rTMS) during a visuospatial working memory task (Riddle et al., 2020), 10 Hz magnetic pulses at the posterior parietal cortex contralateral to the non-cued hemifield (where distractors are presented), increased visual working memory performance compared to arrhythmic TMS. This study suggests the involvement of parietal alpha in the inhibition processes. Our subgroup analyses are consistent with those results, showing a greater decrease in alpha power in the parietal area following an increase in CWL.

However, a controversy remains because some studies observed an increase in alpha power in areas involved in cognitive processing (e.g., Jensen et al., 2002). An explanation for this discrepancy has been advanced by van Ede (2018), who argue that the posterior alpha power increases during the encoding of verbal material (even when the stimuli are encoded visually), whereas it decreases during the encoding of visual material (van Ede et al., 2017). However, this explanation based on the nature of the stimuli (i.e., visual or verbal) does not account for some of our results. Kakizaki's study (Kakizaki, 1984, considered as an outlier by our analyses), measured the cerebral activity of the occipital cortex (Oz) during an increase in CWL imposed by mental arithmetic tasks. Results revealed an increase in the spectral power of all frequencies, including alpha, with the increase in CWL. Calculation involves many cortical networks (e.g., prefrontal, premotor, parietal; Zago et al., 2001), including the occipital cortex. Indeed, it has been shown that injury of the occipital cortex impairs the calculation process when the digits to be manipulated are presented visually (Dehaene & Cohen, 1997). The involvement of this region during the task should, therefore have resulted in a decrease in alpha power. Moreover, in Murata's study (Murata, 2005), participants were asked to determine whether the stimulus (letter) presented on the screen matched the stimulus presented one, two or three trials previously, in terms of letter and location. Alpha power measured in Fz, Cz, and Pz also increased with the difficulty of the task. Further studies evaluating the modulation of alpha according to the type of stimuli must be conducted in order to test the hypothesis of alpha specificity. Concerning the power of alpha sub-bands, results from the literature showed that high alpha interacts with visual cognitive tasks and semantic memory demands, while low alpha reflects a general attentional demand, not specific to the task (Klimesch, 1999). The results of our subgroup analyses, although based on a small number of studies, provides support to the literature. Among the studies that measured both sub-bands, the difference in sensitivity to CWL between lower and upper alpha was minor when measured during an N-back (Rietschel et al., 2012) or stimulus detection task (Shaw et al., 2018), but larger in the case of a more visually rich flight simulator environment (Jaquess et al., 2017). The difference between these two sub-bands thus appears to be quantitative rather than qualitative, with the upper alpha slightly more sensitive to CWL than the lower alpha. Overall, the inverse relationship between alpha and CWL seems well established, as indicated by the very similar estimated effect sizes from the random and fixed effects models used in the present meta-analysis.

4.3 | Beta

The results regarding the beta frequency range revealed a moderate positive effect of CWL on this frequency. Numerous studies have established the involvement of the beta frequency in a variety of cognitive processes such as working memory (Chen & Huang, 2016; Deiber et al., 2007), language processing (Weiss & Mueller, 2012), long-term memory (Hanslmayr et al., 2014), and decision making and reward processing (Marco-Pallarés et al., 2015). However, the functional role of this frequency is debated. Some researchers consider that the beta frequency plays a role in maintaining cognitive representations and motor commands (the "status quo hypothesis," Engel & Fries, 2010), while others argue that this frequency allows network-level communication and endogenous (re)activation of information (Spitzer & Haegens, 2017). Moreover, some authors suggest that there are functional distinctions between beta1 and beta2, and that these sub-bands have functional roles similar to their neighboring frequencies (i.e., alpha and gamma). Thus, beta1 is thought to have an inhibitory role and could contribute to the protection of WM representations (Hanslmayr et al., 2009; Kornblith et al., 2016; Pereira & Wang, 2015), while beta2 is thought to be more involved in top-down information processing processes (Kornblith et al., 2016; Marco-Pallarés et al., 2015). Our meta-analysis by subgroup analyses indicate that beta1 ($g = 0.93$, $k = 2$; Kakizaki, 1984; Orlandi & Brooks, 2018) and beta2 ($g = 0.74$, $k = 3$; Kakizaki, 1984; Orlandi & Brooks, 2018; Pavlov & Kotchoubey, 2017) were much more sensitive to CWL than broad-band beta ($g = 0.28$, $k = 7$). The insufficient number of studies in these subgroups and a redundancy of these studies across subgroups could explain these unexpected results. Another subgroup analysis revealed that expert participants ($g = 1.43$, $k = 3$; Morales et al., 2019; Orlandi & Brooks, 2018) showed a greater increase in beta power with an increase in CWL than non-expert participants ($g = 0.36$, $k = 9$). Here, we must note that some of the studies had characteristics that could explain the aforementioned subgroup analysis results. Orlandi and Brooks' study (Orlandi & Brooks, 2018) took place in the Maritime Safety Queensland Simulator, in which participants were asked to complete several berthing tasks that lasted one to two hours depending on the difficulty. Morales et al. (2019) measured the activity of four pairs of surgeons during a surgical exercise on domestic pigs. The surgeons performed eight surgical exercises, with an average duration of approximately 20 minutes. The first study had a total time-on-task comprised between 360 and 480 min, while the second had a time-on-task of about 172 min, which is much larger than the average time-on-task of the other studies ($M = 42.73$ min). Such heavy and time-consuming protocols might explain the very large increase in beta power observed by the estimated effect sizes.

Our results seem to indicate that the beta frequency is positively associated with CWL. However, the numerous mechanisms that underlie this frequency and their specificities still need to be specifically investigated for a better understanding. Studies specifically aimed at distinguishing the functional roles of beta according to its location (e.g., prefrontal, parietal) and frequency (i.e., beta1 & beta2) under high CWL are thus still needed.

Taken together, our results support the use of the theta power spectral as a neurophysiological index of CWL. The theta frequency of the frontal cortex, although it cannot be associated with a unique cognitive process, appears to be most strongly associated with CWL. While the alpha and beta frequencies are believed to reflect inhibition and engagement processes of brain resources, the frontal cortex theta frequency seems to have a more straightforward relationship with cognitive engagement.

4.4 | Limitations

At the methodological level, several factors limit the results of this quantitative review.

First, our meta-analyses did not include all studies that are relevant to the topic and cannot claim to be exhaustive. Inclusion is determined by the statistical indices provided by the studies and estimating a mean effect size, therefore requires being more restrictive in including studies than in a systematic review. Also, several publications that matched the inclusion criteria were not included, because the authors did not answer and we, therefore lacked the necessary information to calculate an effect size. In addition, by restricting the studies included in the analysis to those published in peer-reviewed journals, it is possible that some data available in the literature (e.g., gray literature, non-English sources) were not included. Restricting our selection to studies published in peer-reviewed journals could in part explain the asymmetry observed on the different funnel plots; an asymmetry that shows a bias in favor of studies with large standard errors and large positive ES, symptomatic of the "file drawer problem" (Rosenthal, 1979). The trim-and-fill method aims to identify asymmetries caused by publication bias and to correct them, by virtually integrating missing studies. After estimating and integrating the number of missing studies, this method makes it possible to recalculate a meta-analysis considering the newly integrated studies. This resulted, for each of the three frequencies investigated, in a decrease in the estimated effect sizes. It is, therefore, possible that the effects initially observed in our analyses were overestimated due to publication bias. However, the "trim-and-fill" method does not consider other factors that can influence a funnel plot asymmetry (e.g., Egger et al., 1997). Moreover, in the presence of strong intergroup heterogeneity, this method is known to produce biased estimates (Terrin et al., 2003). The intergroup heterogeneity observed in our meta-analyses can be explained by the methodological diversity of the included studies, such as the tasks used to generate CWL, the type of EEG system used (e.g., headset, wireless EEG) and the location of the electrodes (e.g., one at Fz, two at F3, F4). This heterogeneity was expected due to the wide variety of protocols that have attempted to measure CWL and reflects the interest of CWL measurement in many areas. This review, which is not intended to be limited to a specific field, therefore reflects this diversity. As discussed above, it is important to keep in mind that different tasks were used to modulate cognitive load (see Table S1). Some of the included studies compared EEG spectral power between a 0-back and a 1-back condition on the N-Back test, while other studies compare 1-back and 3-back conditions. This difference in mental effort is expected to be an important moderator of the computed effect size but is difficult to assess quantitatively due to the diversity of protocols.

4.5 | Future work

Before EEG can be proposed as a functional CWL measurement system in cognitively demanding professional situations such as those experienced by military, medical, transport, or nuclear operators, many factors need to be studied in greater depth. Several studies comparing three levels of CWL (low, moderate, and high) have observed no difference between moderate and high loading conditions (e.g., Castro-Meneses et al., 2020; Gevins et al., 1998). This quantitative review was restricted to comparing relatively distinct loads (low vs. high load). More studies might be interested in investigating intermediate levels of difficulty, which could then be analyzed by meta-regression.

With regard to the safety domain, the study of the emotional load also seems to be of crucial importance, considering that unforeseen and/or extremely dangerous unexpected events can greatly affect operators, despite their training. For example, Grissmann et al. (2017) observed a decrease in the activity of the frontal theta under negative affective valence. The authors considered that the negative stimuli interfered with the processing of the task through the reduction in activity of the frontal cognitive control network.

The combined study of attentional reserve and CWL also seems to be a promising avenue for both applied and fundamental research. To our knowledge, only two studies have jointly studied CWL (by spectral power) and attentional reserve (by ERP; Jaquess et al., 2017; Shaw et al., 2018). These two constructs appeared indeed to be strongly linked, considering that CWL represents what is used and attentional reserve what remains available from our limited resources. The study of these two constructs could lead to a finer understanding of our cognitive capacities and their limits.

Our meta-analysis was limited to the comparison of spectral power difference in the frequency bands of interest. However, this method of analysis of the brain electrical signal is embedded in a simplifying localizationist framework and does not allow to take account of the interconnected neural networks that enable cognitive functions (Herbet & Duffau, 2020). For example, one model that is gaining influence in the understanding of the human brain is the "communication through coherence" model (Fries, 2005, 2015), which suggests that neural synchronization is the functional mechanism by which information transmission and perceptual binding occurs in the brain (Chapeton et al., 2019; de Vries et al., 2020). We suggest that the systematic study of the effect of CWL on the interareal coherence and functional connectivity of the brain could be of interest to complete our understanding of the effect of CWL on our brain activity (e.g., Kamzanova et al., 2020; Muthukrishnan et al., 2020).

For field application purposes, it is likely that frequency spectral power will not be able to measure all of the constituent dimensions of CWL (Matthews et al., 2015). Indeed, it is illusory to expect an increase in cognitive demand to be treated in the same way for each individual, especially in real-world settings where several tasks must generally be performed in parallel. Responding to this demand implies a cascade of processes (from the commitment of cognitive resources to self-regulation processes) that can vary inter and intraindividually across tasks, goals, and time. It is unrealistic to search for a measure that would index all these phenomena at once. However, the increase in the activity of the central nervous system that can be measured by EEG, and particularly the frontal theta spectral power, allows us to have a reflection of the neural resources engaged to complete the task. This index can serve as a basis for the systematized study of other processes involved in the resolution of a cognitive task, such as effort allocation (Hockey, 1997) or stress regulation (Matthews et al., 2002). A better estimate of CWL could be made by coupling EEG with another technique, for example with heart rate variability measures which seems sensitive for other dimensions of CWL (Matthews et al., 2015) with a certain robustness, as shown by a recent meta-analysis (Hughes et al., 2019).

5 | CONCLUSION

Overall, our results argue in favor of a sensitiveness of EEG for CWL. Among the three main frequencies used in the literature, the theta power spectral is the most sensitive to an increase in task demand. The beta band was also sensitive to CWL, while the alpha band was inversely correlated with it. The EEG technique, even with few electrodes, appears to be an inexpensive and valid way to measure some aspects of CWL in real time. However, the presence of heterogeneity and potential publication bias means that our results should be taken with caution. Several studies still need to be carried out in order to test the different hypotheses concerning the functional role of these frequencies and their interaction with interindividual differences.

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AUTHOR CONTRIBUTIONS

Samy Chikhi: Conceptualization; data curation; formal analysis; investigation; methodology; software; writing – original draft; writing – review and editing. **Nadine Matton:** Conceptualization; funding acquisition; supervision; writing – review and editing. **Sophie Blanchet:** Conceptualization; project administration; supervision; writing – review and editing.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

TABLE S1 Additional characteristics of studies assessing the impact of cognitive workload on theta, alpha and beta power included in the meta-analysis

TABLE S2 Results of subgroup differences analyses

FIGURE S1 Forest plot of standardized effect sizes (*g*) of theta power in high versus low workload conditions using fixed-effect model. Total standardized mean difference (SMD) with 95% confidence and prediction interval, weight, and heterogeneity are reported

FIGURE S2 Forest plot of standardized effect sizes (*g*) of alpha power in high versus low workload conditions using fixed-effect model. Total standardized mean difference (SMD) with 95% confidence and prediction interval, weight, and heterogeneity are reported

FIGURE S3 Forest plot of standardized effect sizes (*g*) of beta power in high versus low workload conditions using fixed-effect model. Total standardized mean difference with 95% confidence and prediction interval, weight, and heterogeneity are reported

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