Master Thesis

Great Expectations: An Attempt to Clarify the Role of Theta Activity in Human Cognitive Control Processes

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ABSTRACT

The dual mechanisms of control (DMC) framework makes a distinction between proactive and reactive cognitive control processes. The results of a recent study suggest that the latter may be accompanied by a wider distribution of theta activity in the human brain than the former. The present study aimed to put that possibility to the test. The Add-n task, a digit transformation task, was used in an attempt to elicit proactive and reactive cognitive control processes in 37 individuals whilst their brain activity was being recorded by means of electroencephalography (EEG). Theta activity was found to be most pronounced at electrode FCz in all task conditions. Partial support was found for the notion that relatively challenging tasks and task conditions induce higher levels of frontal-midline theta activity than relatively unchallenging ones. Unlike expected, the results did not corroborate the idea that reactive cognitive control processes are accompanied by a wider distribution of theta activity in the human brain than proactive cognitive control processes. The attempted manipulation of the participants' cognitive control strategies may not have been effective, however, so no definitive conclusions can be drawn.

1. Introduction

Cognitive control can be defined as the ability to (consciously or subconsciously) optimise one's information processing strategy for a specific task or situation (Braver et al., 2008). Cognitive control processes are essential to our overall functioning (Miller & Wallis, 2008; Carter & Krug, 2012). Little is known about how cognitive control is realised in our brains, however. Arguably, this remains "one of the most fascinating mysteries of human cognition" (Braver, 2012, p. 106).

The influential working memory model of Baddeley and Hitch (1974) deserves credit for having drawn scholars' attention to the concept of cognitive control. However, its own account of that concept is controversial (Andrade & May, 2004; Braver et al., 2008; Conway et al., 2008). Little is known about the properties and specific interactions of the entity that the working memory model attributes all cognitive control processes to: the central executive (Eysenck & Keane, 1995; Jonides & Smith, 1997; Solso, 2000; Baddeley, 2002; Quinlan & Dyson, 2008; Logie, 2016; Chai et al., 2018). This is undesirable. More problematically, many scholars find it hard to unite the notion of a single central executive with empirical findings that suggest that cognitive control is an intrinsically variable phenomenon (Braver, 2012). They have felt inclined to resort to some sort of non-unitary "executive committee" instead (Baddeley, 1996, p. 8; Eysenck & Keane, 1995; Wagner et al., 2004). As Jonides and Smith already put it more than two decades ago, the term 'central executive' may actually be little more than "a convenient umbrella for a constellation of processes" (1997, p. 246). This line of thought has formed the basis for an alternative view on cognitive control: the dual mechanisms of control framework.

1.1. The dual mechanisms of control framework

The dual mechanisms of control (DMC) framework was first described in the literature in the early 2000s (Braver et al., 2008; Braver, 2012). It makes a distinction between two types of cognitive control processes (Braver et al., 2008; Braver, 2012; Bugg, 2014; Cooper et al., 2015; Chiew & Braver, 2017; Eschmann et al., 2018; Sauseng et al., 2019; Martins-Klein et al., 2020).

Proactive cognitive control processes involve an early selection process in which goal-relevant information is strongly focused on from the moment it is presented. Reactive cognitive control processes, on the other hand, involve a late adjustment process in which information that is initially focused on must subsequently make space for other (more relevant) information. It is not entirely clear yet how proactive and reactive cognitive control processes relate to each other (Chiew & Braver, 2017). Perhaps they should be treated as independent phenomena that can both be present simultaneously (to differing extents) at any given point in time (Fröber & Dreisbach, 2012). Alternatively, perhaps proactive and reactive control should be seen as two extremes on a single continuum (Braver et al, 2008; Braver, 2012). That would imply that, apart from proactive and reactive, cognitive control processes can also be hybrid in nature.

Reactive cognitive control processes are believed to involve activity in a much wider area of the human brain than proactive cognitive control processes (Braver et al., 2008; Braver, 2012; Chiew & Braver, 2017; Sauseng et al., 2019). Proactive cognitive control processes are believed to mostly involve activity in the lateral prefrontal cortex, whereas reactive cognitive control processes are believed to additionally involve activity in the anterior cingulate cortex, the (medial) temporal lobe and the parietal lobe. Empirical findings seem to support these views (Grandjean et al., 2012; Niendam et al., 2012; Chiew & Braver, 2017; Eschmann et al., 2018).

Proactive cognitive control processes have both advantages and disadvantages, which makes them more suitable for some tasks than for others (depending on the task goals). The same is true for reactive cognitive control processes. For many tasks, a mixed cognitive control strategy would be optimal (Braver et al., 2008; Braver, 2012; Chiew & Braver, 2017). Hence, humans rarely need to adopt a cognitive control strategy that is fully proactive or fully reactive in nature. The DMC framework posits that subtle task and situational differences can have a considerable impact on “the weighting between proactive and reactive control [processes]” (Braver et al., 2008, p. 86). There exists empirical support for this assumption (Braver et al., 2008). One factor that appears to be relevant in this context and that plays an important role in the present study, is the degree to which someone expects a task to be cognitively demanding. Research suggests that when people anticipate a low mental workload during a task, they will adopt a cognitive control strategy that is relatively proactive in nature (Speer et al., 2003; Braver et al., 2008; Braver, 2012). When people anticipate a high mental workload during a task, in contrast, they will adopt a cognitive control strategy that is relatively reactive in nature.

1.2. Theta activity and cognitive control

The DMC framework has grown quite influential in recent years (Martins-Klein et al., 2020) and has already inspired "a wealth of empirical research" (Chiew & Braver, 2017, p. 148). A second development that can be observed in the literature on cognitive control, concerns theta activity.

Neurons are often active in groups, so-called neuronal populations or assemblies (Hof et al., 2008; Cavanagh & Frank, 2014; Stankovski et al., 2017). The synchronised activity of such groups can give rise to brain oscillations (Kahana, 2006; McCormick, 2008; Frank, 2009; Fröhlich, 2016), which can be measured by means of electroencephalography (EEG) (Kutas & Dale, 1997). In the past, brain oscillations were mostly seen as by-products of neuronal activity with little functional value (Fröhlich, 2016). Today, in contrast, "rhythmic activity patterns" are seen by many scholars as "fundamental to how the brain works" (Fröhlich, 2016, p. 82; Fell & Axmacher, 2011; Hsieh & Ranganath, 2014). Brain oscillations may be able to affect neurons' electrical excitability and thereby enable selective communication between different groups of them (Fröhlich, 2016; Eschmann et al., 2018). It should be noted, however, that the "precise function of (…) brain rhythms remains mysterious" (Frank, 2009, p. 483).

Brain oscillations can occur at various frequencies, depending on the nature of the synchronised activity of the neurons that generate them. The frequencies in question can be categorised into various frequency bands (Miller & Buschman, 2012; Fröhlich, 2016), one of which – the theta band – plays a central role in the present study. The theta band can be defined as ranging from 4 Hz to 7 Hz (Cooper et al., 2015; Eschmann et al., 2018; Fuentes-García et al., 2019; Román-

López et al., 2019). Theta oscillations were already observed in the human brain more than seven decades ago (Arellano & Schwab, 1950; Ishihara & Yoshii, 1972; Hsieh & Ranganath, 2014). A "unifying framework of human theta oscillations that includes their appearance, functional roles, and underlying mechanisms [still seems to be] lacking," however (Fröhlich, 2016, p. 250; Hsieh & Ranganath, 2014). This is undesirable, of course, but fortunately it has not prevented scholars from developing a growing interest in theta activity in recent years (see Appendix A).

Many research findings point in the direction of an intricate relationship between theta activity and working memory. Consider a recent study by Pomper and Ansorge (2021), for example. They found that when people have to simultaneously hold two pieces of visual information in working memory, one of those two pieces is always a bit more readily available to them than the other. Which piece of information is prioritised in working memory constantly switches, and that switching appears to be reflected by changes in theta activity. A more established finding is that relatively difficult working memory tasks and task conditions tend to be accompanied by higher levels of theta activity (particularly frontal-midline theta activity) than relatively simple ones (Gevins et al., 1997; Gevins & Smith, 2000; Jensen & Tesche, 2002; Onton et al., 2005; Sauseng et al., 2007; Griesmayr et al., 2010; Roberts et al., 2013; Fuentes-García et al., 2019).

Encouraged by some of their findings, many scholars seem to have developed great expectations regarding the role of theta activity in human cognitive control in the course of the past decade or so (Griesmayr et al., 2010; Sauseng et al., 2010; Cavanagh et al., 2012; Cavanagh & Frank, 2014; Cooper et al., 2015; Fröhlich, 2016; Helfrich & Knight, 2016; Eschmann et al., 2018; Cooper et al., 2019; Eschmann et al., 2020). What could that role entail? If multiple parts of the human brain are together responsible for cognitive control (as the DMC framework posits), then their activity must somehow be synchronised (Duncan & Manly, 2012). Experts believe that brain oscillations might facilitate such synchronisation (Cavanagh et al., 2012; Miller & Buschman, 2012; Cooper et al., 2015; Brzezicka et al., 2019; Karakaş, 2020). The neurons of the involved brain areas might assemble in a single neuronal population and subsequently become more or less excitable as a function of that population's oscillation. It has been proposed that such "rhythmic excitability" could result in the instantiation of "transient functional networks between spatially distal sites" (Cavanagh & Frank, 2014, p. 416; Engel et al., 2001; Azouz & Gray, 2003; Fries, 2005; Nobre et al., 2012; Cooper et al., 2015). In other words, neuronal oscillations might explain how the various parts of the human brain that are together responsible for cognitive control operate in tandem with each other. Many scholars seem to believe that the oscillations in question fall within the theta band (Onton et al., 2005; Cavanagh et al., 2010; Griesmayr et al., 2010; Sauseng et al., 2010; Cohen, 2011; Fröhlich, 2016; Eschmann et al., 2018; Sauseng et al., 2019; Eschmann et al., 2020; Karakaş, 2020; Asanowicz et al., 2021). This could explain why past findings consistently point in the direction of an association between theta activity and cognitive control (Sauseng et al., 2010). Besides, because of their relatively long wavelengths, theta oscillations can easily travel across distances in the brain (Von Stein & Sarnthein, 2000; Buzsáki & Draguhn, 2004; Uhlhaas et al., 2010; Miller & Buschman, 2012; Cavanagh & Frank, 2014). This makes them seem more suitable for a synchronising role than the oscillations in most other frequency bands: only delta oscillations have longer wavelengths and are hence thought to be able to bridge larger distances. All in all, although much is still unknown in this area, theta activity might well be an essential "integrative brain mechanism" that underlies cognitive control (Sauseng et al., 2010, p. 1015).

1.3. Theta activity and the DMC framework

In what appears to have been a first-of-its-kind EEG study, Eschmann et al. (2018) recently examined theta activity in the context of the dual mechanisms of control framework. To elicit proactive and reactive cognitive control processes in their participants, they used two different tasks. An implementation of the delayed match-to-sample (DMTS) task was used to elicit proactive cognitive control processes. At the start of each trial, participants were presented with a pattern of small squares. They were instructed to remember that pattern over a delay period and subsequently compare it (or a mirrored version of it, depending on the condition that they were in) with another pattern. Eschmann et al. (2018) assumed that this task would mostly induce proactive cognitive control processes to support “the sustained and anticipatory maintenance of goal-relevant information” (p. 58). To elicit reactive cognitive control processes, they used an implementation of the well-known Stroop task. During each trial, participants were presented with a single word (usually a colour name, e.g. “red”) printed in randomly coloured ink. They were instructed to name the colour of the ink. Eschmann et al. (2018) assumed that this task would mostly induce reactive cognitive control processes to support a late adjustment process in which the information that is typically focused on first (the lexical meaning of the word) makes space for the information that is needed (the colour of the ink).

During the DMTS task, Eschmann et al. (2018) mostly recorded theta oscillations at the most frontal electrode sites (Fp1, Fp2 and Fz). During the Stroop task, they observed theta activity at many other electrode sites (including posterior ones) as well. The researchers concluded that reactive cognitive control processes involve a wider distribution of theta activity in the human brain than proactive cognitive control processes. Since the DMC framework posits that the set of brain areas that are together responsible for reactive cognitive control processes is larger than the set of brain areas that are together responsible for proactive cognitive control processes, this conclusion appears to offer some support for the notion that theta oscillations play an important synchronising role in human cognitive control. The researchers themselves indeed argued that they had found evidence for “large scale theta synchronization” (Eschmann et al., 2018, p. 62). Other scholars have interpreted their findings in a similar manner since (Sauseng et al., 2019).

Eschmann et al. (2018) seem to have been the first researchers to observe “scalp topographical differences of theta activity between tasks differing in their cognitive control demands” (p. 63). There has never been a follow-up to their study so far. This is undesirable, especially since Eschmann et al. (2018) made use of two different tasks to elicit proactive and reactive cognitive control processes in their participants (Andrade & May, 2004). Task differences unrelated to cognitive control may have confounded their results (Sauseng et al., 2019). Eschmann et al. (2018) already admitted this themselves and indicated that they had a different research question in mind when they designed their study. They called upon the academic community to conduct more research on theta activity and cognitive control. The present study can be seen as a response to that call. The aim of this study was to put the conclusion of Eschmann et al. (2018) to another test. To ensure that it would not suffer from the same weakness, a single task was used to elicit both proactive and reactive cognitive control processes: the Add-n task.

1.4. The Add-n task

The Add-n task is a digit transformation task. It was first described in the literature by Nobel laureate Daniel Kahneman and his colleague Jackson Beatty in 1966 (Beatty & Kahneman, 1966; Kahneman & Beatty,1966). Inspired by earlier research (Hess & Polt, 1960; Hess & Polt, 1964; Hess, 1965), Kahneman and Beatty wanted to investigate whether the size of one's pupils alters as a function of one's mental workload. They devised several tasks to manipulate their subjects' mental workload, including an elegant "transformation task" (Kahneman & Beatty, 1966, p. 1584). Following Röber (2019), the task in question shall be referred to as the Add-n task here. In the Add-n task, a participant is first briefly shown a sequence of four digits (Kahneman, 2011). This is followed by an interval during which the participant is expected to add *n* (a non-negative integer) to each of those four digits. Finally, the participant is asked to disclose their solution by saying it out loud, writing it down or entering it on a keyboard. As an illustration, consider the sequence '2 8 3 7'. If *n* were to equal 0, the correct solution would likewise be '2 8 3 7'. The correct solution would be '3 9 4 8' if *n* were to equal 1 and '4 0 5 9' if *n* were to equal 2.

Kahneman and his colleagues made use of the Add-n task on several occasions in the late 1960s (Kahneman et al., 1967; Kahneman et al., 1968; Kahneman et al., 1969). Since then, the Add-n task (which should not be confused with the serial addition task) has not been used very often (Steinhauer et al., 2000). It only seems to have popped up in works of student research every now and then (Kimchi, 1982; Stone et al., 2004; Bishop, 2014; Röber, 2019), although similar tasks can sporadically be encountered in the literature without any reference to Kahneman and Beatty (consider subtests 5 and 8 of the 1972 study by Ishihara & Yoshii, for example).

Research suggests that the Add-n task can be used to effectively manipulate people's mental workload (Kahneman & Beatty, 1966; Kahneman et al., 1969; May et al., 1990). Kahneman once wrote that he thinks finding the solution to a sequence can be an "exceptionally effortful" challenge if n does not equal 0 (2011, p. 34). The larger the value of n, the more demanding the Add-n task appears to become (Kahneman et al., 1969; Steinhauer et al., 2000; Röber, 2019). It seems fair to assume that most people would also naturally expect this to be the case. If so, this would provide reason to believe that as n grows larger, the cognitive control processes that are elicited by the Add-n task become more reactive (and less proactive) in nature. As was discussed in section 1.1, after all, past research suggests that when people anticipate a relatively low mental workload during a task, their cognitive control processes will become relatively proactive in nature. When people anticipate a relatively high mental workload during a task, on the other hand, their cognitive control processes will become relatively reactive in nature.

1.5. The present study

In the present study, participants were subjected to three conditions of the Add-n task: the Add-0 condition, the Add-1 condition and the Add-2 condition. In line with the discussion at the end of section 1.4 above, it was theorised that the Add-2 condition would elicit more reactive cognitive control processes than the Add-1 condition, and that the Add-1 condition would elicit more reactive cognitive control processes than the Add-0 condition. Eschmann et al. (2018) concluded from their findings that reactive cognitive control processes involve a wider distribution of theta activity in the human brain than proactive cognitive control processes. The aim of this study was to put that conclusion to another test by answering the following question: if $x, y \in \{0, 1, 2\}$ and $x > y$, does the Add-x condition of the Add-n task involve a wider scalp topographical distribution of theta activity in the human brain than the Add-y condition of the Add-n task? In other words, is the scalp topographical distribution of theta activity most focal in the Add-0 condition, more extended in the Add-1 condition, and most extended in the Add-2 condition?

It should be noted that the Add-0 condition is fundamentally different from the Add-1 condition and the Add-2 condition: the former only involves remembering a sequence of digits, whereas the latter involve mentally transforming those digits as well. There is a difference between maintaining information and manipulating it (Veltman et al., 2003; Jablonska et al., 2020). In the present study, any observed differences between the Add-0 condition and the other two conditions could be caused by that confounding factor, rather than by differences related (more directly) to cognitive control (Wagner et al., 2004; Itthipuripat et al., 2013; Lamp et al., 2016). Hence, the focus was primarily on the Add-1 condition and the Add-2 condition in this study.

2. Methodology

2.1. Participants

In total, 37 individuals (14 males and 23 females) took part in this study (age 23.7 ± 9.1 years). Most of them were German (n=17) or Dutch (n=14). The remaining participants were Bulgarian (n=3), Latvian (n=1), Swiss (n=1) and French (n=1). The first 20 participants took part in the experiment in the spring of 2019. The remaining 17 participants took part in the experiment in the spring of 2021. The same methodology was used on both occasions, apart from some minor differences. The 2019 procedure involved darkening the laboratory during the experiment, for instance, whereas the 2021 procedure did not. To find out whether there were major differences between the data that was collected in 2019 and the data that was collected in 2021, 'Year of measurement' was included as a between-subjects factor in all relevant statistical analyses. Interested readers could consult Röber (2019) for a comprehensive description of the 2019 procedure. In this text, the procedure that was followed in the spring of 2021 shall be described.

All participants were either related to or socially acquainted with at least one member of the research team. Participation was voluntary. The participants did not receive any remuneration in exchange for their help. During the experiment, all participants had normal or corrected-to-normal vision. None of the participants had ever undergone any head or brain surgery. Likewise, none of the participants had drunk any alcohol during the last 24 hours before the experiment. The participants were informed about the nature of the experiment when they were invited to take part in it. They were also provided with a detailed information sheet shortly in advance of the experiment. All participants provided their informed consent directly before the start of the experiment. The experimental procedure was approved by the Ethics Committee of the Faculty of Behavioural, Management and Social Sciences at the University of Twente (request 210176).

2.2. COVID-19 measures

In the spring of 2021, the Netherlands was in lockdown as a result of the COVID-19 pandemic. Strict measures were taken to minimise the risk of spreading the COVID-19 virus in the EEG laboratory. The researchers wore N95 respirators and gloves at all times, ensured that the room was properly ventilated, and regularly disinfected their (gloved) hands with alcohol. They also tried to maintain distance between themselves and the participants whenever possible, and they disinfected all possible fomites (such as desk surfaces, keyboards and pens) before each session. The participants were asked to disinfect their hands and put on an N95 respirator before entering the laboratory. They were only allowed to take off their respirator during the experiment. The participants were explicitly asked not to come to the laboratory if they had any COVID-19 symptoms or if they had recently been in touch with an infected individual. Nobody appears to have been infected with SARS-CoV-2 as a consequence of participating in this study.

2.3. Experimental procedure

The experiment took place in the EEG laboratory on the campus of the University of Twente. Each session took approximately 2 to 2.5 hours and involved two tasks: the Add-n task and the Sternberg task. Since the latter task was not part of this study, it will not be reported on here.

A single experimental session (with a single participant) looked as follows. After the participant had read the information sheet and signed the informed consent form, standard procedures were followed to prepare them for the EEG recording (see, for example: Hörsting & Titsing, 2021).

Once prepared, the participant was given a form with a detailed explanation of the Add-n task. The participant was informed that they would be subjected to three conditions of the Add-n task: the Add-0 condition, the Add-1 condition and the Add-2 condition. The participant was then asked to indicate which of those conditions they expected to involve the lowest mental workload and which of those conditions they expected to involve the highest mental workload. Next, the room was silenced and the Add-n task was presented on a computer screen that was positioned at a distance of approximately 60 cm from the participant's eyes. The participant was asked to try to avoid making any unnecessary (eye) movements during the experiment.

As Figure 1 shows, each participant faced six blocks of the Add-n task (with two blocks per condition). The order of the conditions was counterbalanced across the participants. The three conditions were first gone through once, and then a second time (with different trials) in the same order. Each block consisted of twenty randomly ordered trials. A schematic overview of a single trial in an Add-2 block can be found in Figure 2. At the beginning of every trial, a brief instruction was displayed for 2000 ms: "ADD ZERO", "ADD ONE" or "ADD TWO". Next, a sequence of four digits was presented for 1000 ms. A green square was subsequently displayed at the centre of the screen for 3000 ms. The participant was expected to come up with their solution during this interval. Finally, a question mark popped up on the screen. The participant was expected to first say their solution out loud (digit by digit) and then enter that solution on a keyboard. It was made clear to the participant that there was no need to hurry: the

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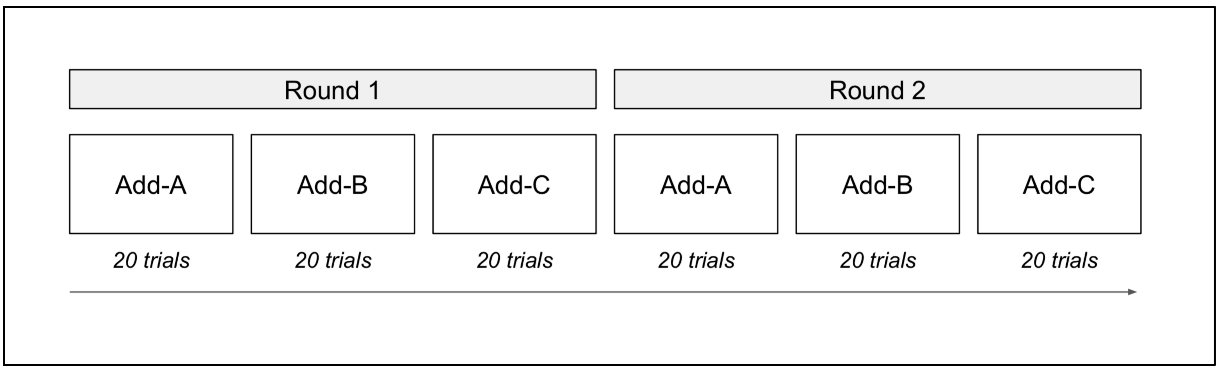

Figure 1. An overview of the experiment. Each participant was subjected to 120 trials of the Add-n task.

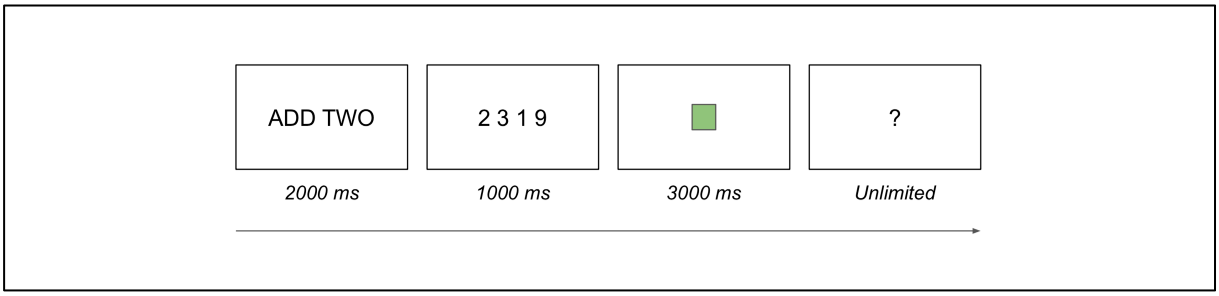

Figure 2. A schematic representation of a single trial in an Add-2 block. The correct solution is '4531'.

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question mark would stay on the screen until all four digits had been entered, after which a new trial would start. The participant was explicitly instructed to calculate their solutions for the Add-1 trials and the Add-2 trials in their mind, and not to use a trick that involves remembering the original digits and then looking at the keyboard to arrive at the correct outcome. Once the participant had gone through all six blocks of the Add-n task, the EEG cap was removed from their head and they were kindly thanked for their participation. The participant was offered a snack and a beverage, and they were given the opportunity to wash their hair in the laboratory. The participant was then thanked once more and escorted out of the building.

2.4. Equipment

The experiment was administered on a desktop computer that ran Windows 7 in lean mode. A standard QWERTY keyboard and a 22'' LED monitor with a refresh rate of 60 Hz were connected to that computer. To implement the Add-n task, a popular stimulus delivery and experimental control program called Presentation was used (Neurobehavioral Systems, Inc.). The participants' EEG activity was recorded with 32 active electrodes (not including the ground) that were positioned according to the standard 10-20 system (see Appendix B). The actiCAP snap EEG system with slide-in electrode holders was used (Brain Products, GmbH). Electrodes TP8 and Fpz served as the online reference electrode and the ground, respectively. The EEG signals were sampled at a rate of 500 Hz and amplified with an actiCHAMP amplifier (Brain Products). The signals were registered on a separate desktop computer that ran Windows 10. A software package called BrainVision Recorder was used for this purpose (Brain Products).

2.5. Data analysis

The collected behavioural data and the collected EEG data were subjected to a number of statistical analyses, as will be described in the following subsections. IBM SPSS Statistics 26 was used for this purpose (IBM, Inc.). A level of significance of α=0.05 was adopted.

2.5.1. Workload expectations

Pearson's chi-squared test was used to analyse the participants' workload expectations for the three conditions of the Add-n task. A significant *p*-value would imply that the sample did not have random expectations about which condition would involve the lowest mental workload and which condition would involve the highest mental workload. In other words, it would imply an association between the factors 'Condition' and 'Workload expectation'. To determine the strength of any such association, Cramér's V was calculated (Lomax & Hahs-Vaughn, 2012).

2.5.2. Task performance

For each subject, it was calculated how many of the digits that had been typed in at the end of each trial were correct. If the correct response at the end of a trial was '2 9 3 8' but '3 8 3 8' had been entered, for example, a participant was deemed to have made two mistakes during that trial. For each condition, each participant's total number of correct entries was calculated. The calculated numbers were then converted into percentage scores by dividing them by the maximum number of correct entries per condition (160). Finally, the percentage scores were arcsine transformed (to give them a normal distribution) and subjected to a one-way repeated measures analysis of variance (ANOVA) with 'Condition' (3: Add-0, Add-1, Add-2) as the within-subjects factor. 'Year of measurement' (2: 2019, 2021) was included in the ANOVA as a between-subjects factor. Simple planned contrasts were conducted to compare the three conditions with each other one by one. A few trials were accidentally not recorded for two subjects. Since it was impossible to retrieve how many mistakes those subjects had made during the missing trials, it was decided to exclude their data from the performance analysis.

2.5.3. EEG data

2.5.3.1. Processing pipeline

A Python script was written to process the collected EEG data (see Appendix C). The code has been published online under an open-source license.[1] A global outline of the code, which made extensive use of the MNE-Python package (version 0.22.0), will be provided in this subsection.

The EEG data files were processed one by one (i.e., participant by participant) in the following manner. First, an average reference was computed. Electrode TP8, which served as the online reference electrode in the laboratory, was granted a normal electrode status. Next, the raw EEG data was subjected to a visual inspection. All channels that appeared to contain a large amount of noise during at least 40% of the recording were marked as 'bad'. On average, 0.66 of the 32 channels (2.05%, SD=0.80) were marked as 'bad' for each participant. Independent component analysis (ICA) was subsequently used to clean the EEG data. This involved various steps. A copy was made of the data first, and a finite impulse response (FIR) filter with a lower passband edge frequency of 0.1 Hz and an upper passband edge frequency of 30 Hz was applied to that copy. Next, an ICA solution was generated with the FastICA algorithm (Oja & Yuan, 2006). The extracted independent components were then inspected one by one. All components that were unrelated to cortical activity, such as components that had mostly captured ocular movements, were removed (see Appendix D). On average, 30.34 components (SD=0.80) were extracted for each participant, of which 9.37 components (30.95%, SD=2.18) were discarded. The final step of the ICA involved applying the generated ICA solution to the original data. All major frequency drifts were subsequently removed from the cleaned data by applying a FIR filter to it. The filter in question was identical to the filter that was used during the ICA. Next, the data was split up into small time-windows that were centred around the on-screen appearances of the trials' (original) four-digit sequences. Each epoch ran from 500 ms before to 4.000 ms after such an appearance, the time-window in which most of the mental

[1] Please see the repository called 'Alexander-Haas-Thesis-2021/Code' on GitHub (www.github.com).

computations were expected to have taken place in the Add-1 condition and the Add-2 condition. Baseline correction was applied to the data when the epochs were created (mode: mean; interval: -500 ms to 0 ms). All epochs that still contained major artefacts after this step were dropped. Two criteria were used here: a minimum amplitude difference criterion of 0.1 μV and a maximum amplitude difference criterion of 150 μV. For two participants, more than 30% of all epochs had to be dropped. It was decided to exclude those two participants' data from the remainder of the EEG analysis. (Their data also was not used to calculate any of the statistics reported earlier in this section.) For the other participants, 6.51% of all epochs had to be dropped on average. After this was done, all channels that were previously marked as 'bad' were interpolated on the basis of the signals that had been recorded by their neighbouring channels. This was done for all epochs. For each condition-electrode combination, average power scores were subsequently calculated (looking at all epochs) for various frequencies by means of the multitaper method. Those scores were then normalised by dividing all of them by their collective sum. (All of the participant's power scores were used to compute that collective sum: the normalisation was not performed at the condition-level, but at the participant-level.)

Applying the above procedure to all EEG files ultimately resulted in a single data structure that contained thousands of normalised power scores for each participant. All power scores that were obtained at sampling frequencies in the range of 4.0 Hz to 7.0 Hz were subsequently used to calculate an average theta power score for each participant-condition-electrode combination. The calculated average theta power scores were then extracted for further processing in SPSS.

2.5.3.2. Scalp topographical theta distributions

To find out whether there were any differences between the conditions' theta distributions, three topoplots were generated. In addition, a two-way repeated measures ANOVA was performed on the extracted data with 'Condition' (3: Add-0, Add-1, Add-2) and 'Electrode' (32: Fp1, Fp2, F7, F3, F1, Fz, F2, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4, P8, PO7, PO8, Oz) as the two within-subjects factors. 'Year of measurement' (2: 2019, 2021) was also included in the analysis as a between-subjects factor.

2.5.3.3. Frontal-midline theta activity and task difficulty

To get an impression of the reliability of the output of the EEG processing pipeline, it was examined to what extent that output was aligned with a comparatively well-established fact about theta activity that was already briefly discussed in section 1.2: the fact that relatively challenging tasks and task conditions tend to be accompanied by higher levels of frontal-midline theta activity than relatively unchallenging ones. On the basis of the literature, one would expect that the Add-n task tends to induce higher levels of frontal-midline theta activity as *n* increases. Four electrodes were selected to compute a single mean frontal-midline theta power score for each participant-condition combination: F1, F2, Fz and FCz. Those scores were subsequently subjected to a one-way repeated measures ANOVA with 'Condition' (3: Add-0, Add-1, Add-2) as the within-subjects factor. 'Year of measurement' (2: 2019, 2021) was also included in the analysis as a between-subjects factor. Polynomial planned contrasts were conducted to examine whether a significant linear trend could be observed in the EEG data, and simple planned contrasts were conducted to compare the three conditions with each other one by one.

3. Results

3.1. Workload expectations

In total, 17 participants were asked to indicate which condition of the Add-n task they expected to involve the lowest mental workload and which condition of the Add-n task they expected to involve the highest mental workload. A significant association was found between the factors 'Condition' and 'Workload expectation', χ^2=90.71, p<0.001. That association was found to be very strong, ϕ_c=0.94 (Field, 2013). Almost all of the surveyed participants (n=16, 94.12%) expected the Add-0 condition to involve the lowest mental workload and the Add-2 condition to involve the highest mental workload. The remaining participant also expected the Add-0 condition to be the least demanding one. Unlike the other participants, however, he expected the Add-1 condition to involve a higher mental workload than the Add-2 condition.

3.2. Task performance

On average, as Figure 3 shows, the participants made fewer mistakes in the Add-0 condition than in the Add-1 condition. Likewise, on average, the participants made fewer mistakes in the Add-1 condition than in the Add-2 condition. These findings are in line with the workload expectations described in section 3.1. (Interestingly, the participant who expected the Add-1 condition to be the most cognitively demanding one also scored worse in that condition than in the other two conditions.) Mauchly's test showed that the sphericity criterion was satisfied for 'Condition', $\chi^2(2)=0.96$, $p=0.620$, so no correction had to be applied to the degrees of freedom for the repeated measures ANOVA. Results of the ANOVA revealed a significant main effect of the factor 'Condition' on the participants' performance, $F(2, 66)=39.02$, $p<0.001$, $\eta_p^2=0.54$. Simple planned contrasts revealed that the difference between the participants' performance in the Add-0 condition and their performance in the Add-1 condition was statistically significant, $F(1, 33)=46.84$, $p<0.001$, $\eta_p^2=0.59$. The difference between the participants' performance in the Add-0 condition and their performance in the Add-2 condition was significant as well, $F(1, 33)=60.75$, $p<0.001$, $\eta_p^2=0.65$. The relatively small difference between the participants'

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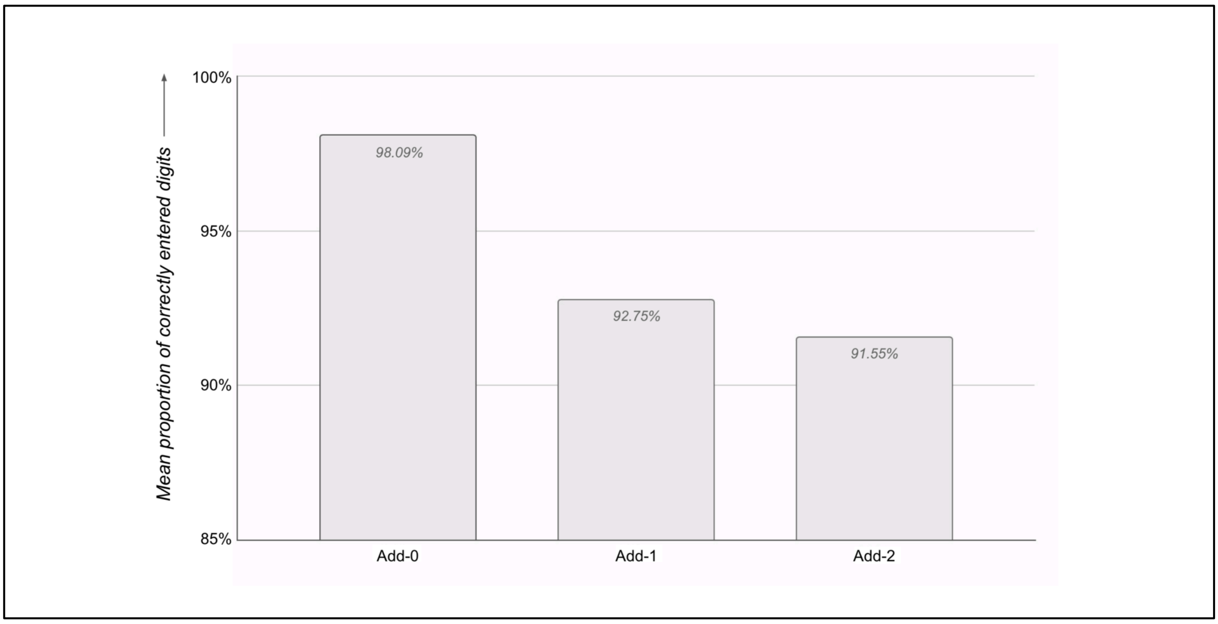

Figure 3. On average, the subjects scored best in the Add-0 condition and worst in the Add-2 condition.

performance in the Add-1 condition and their performance in the Add-2 condition, on the other hand, was not found to be statistically significant, $F(1, 33)=0.82$, $p=0.372$, $\eta_p^2=0.02$. The between-subjects factor 'Year of measurement' did not have a significant main effect, $F(1, 33)=0.26$, $p=0.617$, $\eta_p^2=0.01$. The interaction between 'Year of measurement' and 'Condition' was not significant either, $F(2, 66)=0.45$, $p=0.642$, $\eta_p^2=0.01$. Estimated marginal means and their corresponding confidence intervals and standard errors can be found in Table 1.

3.3. Scalp topographical theta distributions

The sample's average scalp topographical distribution of theta activity was plotted for each condition of the Add-n task (see Figure 4). In each condition, more theta activity was recorded at electrode FCz than at any other electrode. Some variation can be observed between the three distributions. The differences are not very pronounced, however. Mauchly's test showed that the sphericity criterion was violated for the factor 'Condition', $\chi^2(2)=11.68$, $p=0.003$. The Greenhouse-Geisser estimate of sphericity was greater than 0.75, $\varepsilon=0.77$, so Huynh-Feldt correction was applied (Field, 2013). The results of the two-way ANOVA revealed that the main effect of 'Condition' was not significant, $F(1.64, 54.12)=1.51$, $p=0.232$, $\eta_p^2=0.04$, which implies that the overall theta power scores did not significantly vary across the three conditions. Mauchly's test showed that the sphericity criterion was also violated for the factor 'Electrode', $\chi^2(495)=855.25$, $p<0.001$. The Greenhouse-Geisser estimate of sphericity was smaller than

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Table 1

Estimated marginal means (and their corresponding confidence intervals and standard errors) for the main effect of 'Condition' on the subjects' task performance. The percentage scores were arcsine transformed for the ANOVA. For ease of interpretation, the SPSS output was transformed back again for this Table.

Condition	Mean percentage correct	Confidence interval (95%)	Standard error
Add-0	98.82	98.06-99.41	0.02
Add-1	93.60	91.72-95.20	0.03
Add-2	92.74	90.41-94.72	0.04

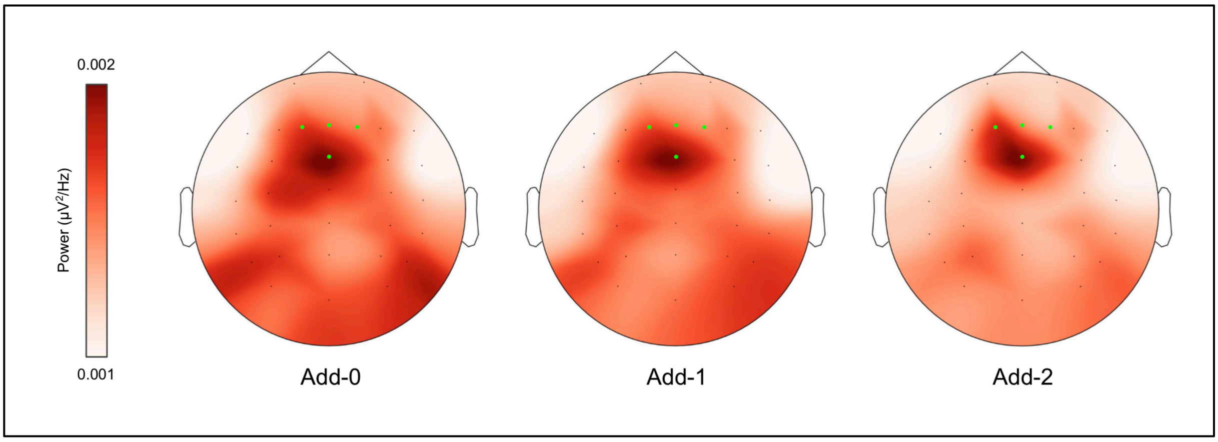

Figure 4. Plots of the (normalised) theta power scores show some variation across the three conditions. Time-window: from 500 ms before to 4.000 ms after the on-screen appearance of a four-digit sequence (see section 2.5.3.1 again). The plots suggest that, unlike expected, theta activity was least focal in the Add-0 condition and most focal in the Add-2 condition. The differences were statistically insignificant. The green dots in the plots mark the positions of electrodes F1, F2, Fz and FCz (also see Appendix B).

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0.75, ε=0.39, so Greenhouse-Geisser correction was applied (Field, 2013). The results of the ANOVA revealed that the main effect of 'Electrode' was significant, $F(12.13, 400.12)=5.53$, $p<0.001$, $\eta_p^2=0.14$. In other words, different electrodes recorded significantly different levels of theta activity. Finally, it was assumed that the sphericity criterion was also violated for the interaction between the factors 'Condition' and 'Electrode' (SPSS could not calculate the results of Mauchly's test for that interaction). The Greenhouse-Geisser estimate of sphericity was much smaller than 0.75, ε=0.14, so Greenhouse-Geisser correction was applied (Field, 2013). The interaction between 'Condition' and 'Electrode' was not significant, $F(8.39, 276.70)=1.10$, $p=0.366$, $\eta_p^2=0.03$. The results of the ANOVA imply that the three theta distributions shown in Figure 4 are not significantly different from each other. The between-subjects factor 'Year of measurement' did not have a significant main effect, $F(1, 33)=2.59$, $p=0.117$, $\eta_p^2=0.07$. The interaction between the factors 'Year of measurement' and 'Condition' was not significant either, $F(1.64, 54.12)=0.33$, $p=0.678$, $\eta_p^2=0.01$, nor were the interactions between 'Year of measurement' and 'Electrode', $F(12.13, 400.12)=1.00$, $p=0.449$, $\eta_p^2=0.03$, and between 'Year of measurement', 'Condition' and 'Electrode', $F(8.39, 276.70)=1.12$, $p=0.349$, $\eta_p^2=0.03$.

3.4. Frontal-midline theta activity and task difficulty

The results of the ANOVA revealed that the effect of 'Condition' on the participants' levels of frontal-midline theta activity was not significant, $F(2, 66)=2.59$, $p=0.083$, $\eta_p^2=0.07$. Mauchly's test showed that the sphericity criterion was satisfied for the factor 'Condition', $\chi^2(2)=4.07$, $p=0.131$. The overall result of the ANOVA notwithstanding, polynomial planned contrasts revealed a significant linear trend in the data, $F(1, 35)=4.86$, $p=0.034$, $\eta_p^2=0.12$. This suggests that the Add-n task induces higher levels of frontal-midline theta activity as *n* grows. Estimated marginal means and their corresponding confidence intervals and standard errors can be found in Table 2. Simple planned contrasts revealed that the difference between the participants' levels of frontal-midline theta activity in the Add-0 condition and their levels of frontal-midline theta activity in the Add-2 condition was statistically significant, $F(1, 33)=4.69$, $p=0.038$, $\eta_p^2=0.13$. The difference between the participants' levels of frontal-midline theta activity in the Add-0 condition and their levels of frontal-midline theta activity in the Add-1 condition, in contrast, was not significant, $F(1, 33)=1.02$, $p=0.321$, $\eta_p^2=0.03$. Likewise, the difference between the participants' levels of frontal-midline theta activity in the Add-1 condition and their levels of frontal-midline theta activity in the Add-2 condition was not significant, $F(1, 33)=1.61$, $p=0.213$, $\eta_p^2=0.05$. The between-subjects factor 'Year of measurement' also did not have a significant main effect, $F(1, 33)=1.92$, $p=0.175$, $\eta_p^2=0.06$. The interaction between 'Year of measurement' and 'Condition' was not significant either, $F(2, 66)=0.13$, $p=0.876$, $\eta_p^2<0.01$.

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Table 2

Estimated marginal means (and their corresponding confidence intervals and standard errors) for the main effect of 'Condition' on the subjects' levels of frontal-midline theta activity. The power scores are quite small. This can be explained by the normalisation procedure that was followed (see section 2.5.3.1 again).

Condition	**Theta power (nV^2/Hz)**	**Confidence interval (95%)**	**Standard error**
Add-0	1.52	1.29-1.76	0.12
Add-1	1.58	1.32-1.83	0.13
Add-2	1.67	1.43-1.92	0.12

4. Discussion

The primary aim of this study was to investigate whether reactive cognitive control processes involve a wider distribution of theta activity in the human brain than proactive cognitive control processes, as Eschmann et al. (2018) concluded on the basis of their research. The results do not seem to point in this direction: the participants' scalp topographical distributions of theta activity did not significantly differ across the three conditions (which were theorised to induce different mixtures of proactive and reactive cognitive control processes). There had never been a follow-up to the experiment by Eschmann et al. (2018) before. It is not unthinkable that their conclusion was incorrect, especially in light of the fact that they used two completely different tasks to evoke proactive and reactive cognitive control processes in their participants. Perhaps the idea that reactive cognitive control processes are accompanied by a wider distribution of theta activity in the human brain than proactive cognitive control processes is actually valid, however. If so, there must exist some explanation for why the results of the present study fail to provide support for that idea. Three possible strands of explanation shall be considered here.

First of all, the three conditions of the Add-n task that the participants were subjected to in this study may not have induced significantly different mixtures of proactive and reactive cognitive control processes. The Add-n task had never been used in the context of the DMC framework before, so it is unclear to what extent experienced researchers in this area would endorse the assumptions that had to be made about the types of cognitive control processes that the Add-0 condition, the Add-1 condition and the Add-2 condition would bring about. Those assumptions revolved around the idea that people's workload expectations for a task influence what kind of cognitive control strategy they will adopt during that task. That idea is based on past research by (among others) the founders of the DMC framework (Speer et al., 2003; Braver et al., 2008; Braver, 2012). Unfortunately, it appears to have been put to the test only once and with only one working memory task: the Sternberg task. More and broader support for it would have been desirable. Even if it is correct that people's workload expectations for a task affect what kind of cognitive control strategy they will adopt during that task, perhaps in the present study the participants' expectations regarding the three conditions of the Add-n task did not vary enough for those conditions to induce significantly different mixtures of cognitive control processes. At the start of the experiment, almost all participants indicated that they thought the Add-0 condition would involve the lowest mental workload and the Add-2 condition would involve the highest mental workload. Perhaps their expectations regarding the three conditions only differed to a very small extent, however. This cannot be excluded, although anecdotal evidence suggests otherwise: during chats in the laboratory, virtually all participants signalled that they dreaded the Add-2 condition much more than the other two conditions and that they thought participating in the Add-0 condition was comparable to taking a break.

Secondly, the epochs that were focused on in the analyses may have been too long. Each epoch ran from 500 ms before to 4.000 ms after the on-screen appearance of a four-digit sequence. If a smaller time-window had been opted for, perhaps significant differences would have been observed between the conditions' scalp topographical distributions of theta activity. Various efforts to repeat the analyses with different epoch length settings did not result in any support for the conclusion of Eschmann et al. (2018) either, however. Perhaps different time-windows should have been looked at for the different task conditions, since the DMC framework posits that proactive and reactive cognitive control processes have different temporal dynamics: the latter tend to be less sustained in nature than the former (Braver, 2012). The time-window for the Add-2 condition, for example, should perhaps have been made shorter than it currently is (with epochs running from, say, 3.500 ms after to 4.000 ms after the on-screen appearance of a four-digit sequence). The DMC framework offers very little guidance in this area, however. This seems problematic, if only because it raises the researcher degrees of freedom for studies on proactive and reactive cognitive control to a very high level. Eschmann et al. (2018) chose their time-windows by examining when most theta activity was recorded during each of their two tasks. It could be argued that, for the sake of comparability, a similar approach should have been adopted here. In any case, it would have been useful if the collected EEG data had been subjected to a time-frequency analysis. Unfortunately, that was beyond the scope of this study.

Thirdly and finally, the individuals who participated in this study may each have had a strong preference for a certain cognitive control strategy (Braver, 2012; Chiew & Braver, 2017). If so, this may have rendered the attempts that were made in this study to manipulate their cognitive control strategies less effective. Factors that may be of influence on one's preferences in the area of cognitive control include one's level of fluid intelligence and one's personality traits (Fales et al., 2008; Burgess & Braver, 2010; Savine et al., 2010; Braver, 2012; Bugg, 2014; Dash et al., 2019; Aguerre et al., 2020). No evidence could be found in the literature for the existence of individuals with highly inflexible modes of cognitive control, however. On the contrary, as was already alluded to in section 1.1, past research suggests that people's modes of cognitive control tend to be highly malleable (Braver et al., 2008). Moreover, even if there would exist individuals who are relatively inflexible in this regard, it seems highly unlikely that the proportion of such individuals in the present study's sample was much larger than the proportion of such individuals in the study of Eschmann et al. (2018): both samples were relatively large for EEG research, and both samples mainly consisted of university students.

Given the above considerations, especially the first two of them, the results of this study cannot be used to convincingly challenge the view that reactive cognitive control processes involve a wider distribution of theta activity in the human brain than proactive cognitive control processes. They do not provide any support for that view either, however: if anything, although it should be stressed that the differences were statistically insignificant and not very pronounced, theta activity appears to have been most widespread in the Add-0 condition (which was theorised to evoke more proactive cognitive control processes than any other condition) and most focal in the Add-2 condition (which was theorised to evoke more reactive cognitive control processes than any other condition). All in all, therefore, it might be advisable to treat the outcome of the study by Eschmann et al. (2018) with some caution pending further research in this area.

It should be pointed out that the difference between the participants' performance in the Add-1 condition and their performance in the Add-2 condition was not statistically significant. This seems to imply that the Add-2 condition was not significantly more challenging than the Add-1 condition. The frontal-midline theta data points in a similar direction. Röber (2019) obtained a highly comparable outcome when she analysed the data that was collected in 2019 (see section 2.1). Based on Kahneman's (2011) description of the Add-n task, however, one would expect the Add-2 condition to be far more challenging than the Add-1 condition. Kahneman does not discuss the Add-2 condition himself, but he writes about the Add-3 condition that it is "much more difficult" than the Add-1 condition and that participating in it is "as hard as people can work – they give up if more is asked of them" (pp. 32-33). The Add-0 condition does not seem to be very challenging, so if participating in the Add-3 condition is "near the limit of what most people can do" (Kahneman, 2011, p. 36) one would expect to see steep drops in performance as *n* incrementally grows from 0 to 3. Part of the data corroborates this: the participants scored much better in the Add-0 condition than in the Add-1 condition. This statistically significant performance difference can probably be explained by the fact that the Add-0 condition merely involves remembering a sequence of digits, whereas the Add-1 condition involves transforming those digits as well. The participants did not score significantly better in the Add-1 condition than in the Add-2 condition. Since there is no reason to believe that the jump from the Add-1 condition to the Add-2 condition is smaller than the jump from the Add-2 condition to the Add-3 condition, this finding suggests that Kahneman's assertions regarding the difficulty of the latter (which, it should be noted, he made in a book that he wrote for a non-scientific audience) may have been a bit overblown. Researchers who plan to make use of the Add-n task in the future can benefit from this insight. It may be advisable for them to make use of a more diverse set of conditions (e.g. Add-1, Add-4 and Add-7) than the one used here. Depending on their aims, they could even consider introducing relatively complex conditions like Multiply-by-n or Add-(n+m).

This study had various strengths, arguably, including a clear focus and a relatively large sample size for EEG research. Unfortunately, this study had some limitations as well. Two limitations were already discussed earlier in this section: the attempted manipulation of the participants' cognitive control strategies may not have been successful, and the epoch length settings that were used in the EEG processing pipeline may have been too crude. A third and final limitation that is worth highlighting, concerns the fact that a rather large number of components had to be dropped during the independent component analysis in the EEG processing pipeline. Multiple attempts (involving multiple ICA algorithms) were made to reduce the number of components that had to be removed, but none of them were successful. Many of the discarded components were related to eye-movement artefacts. To determine whether a component had to be dropped, both its signal and its topoplot were examined (see Appendix D again). It is unfortunate that so many components had to be removed, since valuable information may have been lost with them. The outcome of the analysis of the frontal-midline theta data (which was performed primarily to get an impression of the reliability of the output of the EEG processing pipeline) does not provide much reason for concern, however. As one would expect on the basis of the literature, the polynomial planned contrasts revealed that the Add-n task tends to induce higher levels of frontal-midline theta activity as *n* increases. The results of the simple planned contrasts were also largely in line with the results of the analysis of the participants' task performance, which makes sense: task performance and frontal-midline theta activity both seem to be suitable (albeit imperfect) proxies for task difficulty. In sum, it is unfortunate that many components had to be dropped during the independent component analysis, but there is no concrete reason to believe that the output of the EEG processing pipeline should be strongly mistrusted as a consequence.

To find a definitive answer to the question of whether reactive cognitive control processes are accompanied by a wider distribution of theta activity in the human brain than their proactive counterparts, more research is needed. It should be disclosed that this study's research question was only developed after its design was already largely set in stone. This order of events is far from ideal. Future studies could aim to put the conclusion of Eschmann et al. (2018) to another test with a different task, designed specifically for that purpose. It would be desirable for such studies to make use of more advanced analysis techniques (e.g. wavelet-based time-frequency analysis) than the ones that were applied here. Scholars could also try to find more evidence for the idea that people's workload expectations for a task influence what kind of cognitive control strategy they will adopt during that task. Meanwhile, the founders (and other advocates) of the

DMC framework could try to provide more clarity on the temporal dynamics of proactive and reactive cognitive control processes. It would also be valuable for them to produce an overview of all tasks that they believe can be used to effectively manipulate people's cognitive control strategies. Such an overview could facilitate new work in this area, which will hopefully lead to new insights and a better understanding of the role of theta activity in human cognitive control.

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REFERENCES

Aguerre, N. V., Bajo, M. T., & Gómez-Ariza, C. J. (2020). Dual mechanisms of cognitive control in mindful individuals. *Psychological Research*. https://doi.org/10.1007/s00426-020-01377-2

Andrade, J., & May, J. (2004). *Cognitive psychology.* New York City (New York), United States of America: Garland Science Publishers. ISBN: 1-85996-223-8.

Arellano, A. P., & Schwab, R. S. (1950). Scalp and basal recording during mental activity. *Proceedings of the 1st International Conference of Psychiatry,* 216-219.

Asanowicz, D., Panek, B., & Kotlewska, I. (2021). Selection for action: The medial frontal cortex is an executive hub for stimulus and response selection. *Journal of Cognitive Neuroscience, 33*(8), 1442-1469. https://doi.org/10.1162/jocn_a_01727

Azouz, R., & Gray, C. M. (2003). Adaptive coincidence detection and dynamic gain control in visual cortical neurons in vivo. *Neuron, 37*(3), 513-523. https://doi.org/10.1016/S0896-6273(02)01186-8

Baddeley, A. (1996). Exploring the central executive. *Quarterly Journal of Experimental Psychology, 49*(1), 5-28. https://doi.org/10.1080/713755608

Baddeley, A. D. (2002). Is working memory still working? *European Psychologist, 7*(2), 85-97. https://doi.org/10.1037/0003-066x.56.11.851

Baddeley, A. D., & Hitch, G. J. (1974). Working memory. In G. H. Bower (Ed.), *The psychology of learning and motivation, volume 8* (pp. 47-89). Cambridge (Massachusetts), United States of America: Academic Press. ISBN: 978-0-12-543308-2.

Beatty, J., & Kahneman, D. (1966). Pupillary changes in two memory tasks. *Psychonomic Science, 5*, 371-372. https://doi.org/10.3758/BF03328444

Bishop, K. M. (2014). Processing load and biopotentials: An evaluation of a consumer electroencephalogram (EEG) [Honours thesis]. Andrews University. https://digitalcommons.andrews.edu/honors/89

Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences, 16*(2), 106-113. https://doi.org/10.1016/j.tics.2011.12.010

Braver, T. S., Gray, J. R., & Burgess, G. C. (2008). Explaining the many varieties of working memory variation: Dual mechanisms of cognitive control. In A. R. A. Conway, C. Jarrold, M. J. Kane, A. Miyake & J. N. Towse (Eds.), *Variation in working memory* (pp. 76-106). New York City (New York), United States of America: Oxford University Press. ISBN: 978-0-195-16864-8.

Brzezicka, A., Kamiński, J., Reed, C. M., Chung, J. M., Mamelak, A. N., & Rutishauser, U. (2019). Working memory load related theta power decreases in dorsolateral prefrontal cortex predict individual differences in performance. *Journal of Cognitive Neuroscience, 31*(9), 1290-1307. https://doi.org/10.1162/jocn_a_01417

Bugg, J. M. (2014). Evidence for the sparing of reactive cognitive control with age. *Psychology and Aging, 29*(1), 115-127. https://doi.org/10.1037/a0035270

Burgess, G. C., & Braver, T. S. (2010). Neural mechanisms of interference control in working memory: Effects of interference expectancy and fluid intelligence. *PLOS ONE*, *5*(9), article e12861. https://doi.org/10.1371/journal.pone.0012861

Buzsáki, G., & Draguhn, A. (2004). Neural oscillations in cortical networks. *Science, 304*(5679), 1926-1929. https://doi.org/10.1126/science.1099745

Carter, C. S., & Krug, M. K. (2012). Dynamic cognitive control and frontal-cingulate interactions. In M. I. Posner (Ed.), *Cognitive neuroscience of attention (second edition)* (pp. 89-98). London, United Kingdom: Guilford Press. ISBN: 978-1-60918-985-3.

Cavanagh, J. F., & Frank, M. J. (2014). Frontal theta as a mechanism for cognitive control. *Trends in Cognitive Sciences, 18*(8), 414-421. https://doi.org/10.1016/j.tics.2014.04.012

Cavanagh, J. F., Zambrano-Vazquez, L., & Allen, J. J. B. (2012). Theta lingua franca: A common mid-frontal substrate for action monitoring processes. *Psychophysiology, 49*(2), 220-238. https://doi.org/10.1111/j.1469-8986.2011.01293.x

Cavanagh, J. F., Frank, M. J., Klein, T. J., & Allen, J. B. J. (2010). Frontal theta links prediction errors to behavioral adaptation in reinforcement learning. *NeuroImage, 49*(4), 3198-3209. https://doi.org/10.1016/j.neuroimage.2009.11.080

Chai, W. J., Hamid, A. I. A., & Abdullah, J. M. (2018). Working memory from the psychological and neurosciences perspective: A review. *Frontiers in Psychology, 9,* article 401. https://doi.org/10.3389/fpsyg.2018.00401

Chiew, K. S., & Braver, T. S. (2017). Context processing and cognitive control: From gating models to dual mechanisms. In T. Egner (Ed.), *The Wiley handbook of cognitive control* (pp. 143–166). Hoboken (New Jersey), United States of America: Wiley-Blackwell. ISBN: 978-1-118-92054-1.

Cohen, M. X. (2011). Error-related medial frontal theta activity predicts cingulate-related structural connectivity. *NeuroImage*, *55*(3), 1373–1383. https://doi.org/10.1016/j.neuroimage.2010.12.072

Conway, A. R. A., Jarrold, C., Kane, M. J., Miyake, A., & Towse, J. N. (Eds.). (2008). *Variation in working memory.* New York City (New York), United States of America: Oxford University Press. ISBN: 978-0-195-16864-8.

Cooper, P. S., Karayanidis, F., McKewen, M., McLellan-Hall, S., Wong, A. S. W., Skippen, P., & Cavanagh, J. F. (2019). Frontal theta predicts specific cognitive control-induced behavioural changes beyond general reaction time slowing. *NeuroImage, 189,* 130-140. https://doi.org/10.1016/j.neuroimage.2019.01.022

Cooper, P. S., Wong, A. S. W., Fulham, W. R., Thienel, R., Mansfield, E., Michie, P. T., & Karayanidis, F. (2015). Theta frontoparietal connectivity associated with proactive and reactive cognitive control processes. *NeuroImage, 108,* 354-363. https://doi.org/10.1016/j.neuroimage.2014.12.028

Dash, T., Berroir, P., Ghazi-Saidi, L., Adrover-Roig, D., & Ansaldo, A. I. (2019). A new look at the question of the bilingual advantage: Dual mechanisms of control. *Linguistic Approaches to Bilingualism,* 1-31. https://doi.org/10.1075/lab.18036.das

Duncan, J., & Manly, T. (2012). A frontoparietal attention system in human and monkey brain: Constructing and assembling the fragments of thought and behavior. In M. I. Posner (Ed.), *Cognitive neuroscience of attention (second edition)* (pp. 143-158). London, United Kingdom: Guilford Press. ISBN: 978-1-60918-985-3.

Engel, A. K., Fries, P., & Singer, W. (2001). Dynamic predictions: Oscillations and synchrony in top-down processing. *Nature Reviews Neuroscience, 2,* 704-716. https://doi.org/10.1038/35094565

Eschmann, K. C. J., Bader, R., & Mecklinger, A. (2018). Topographical differences of frontal-midline theta activity reflect functional differences in cognitive control abilities. *Brain and Cognition, 123,* 57-64. https://doi.org/10.1016/j.bandc.2018.02.002

Eschmann, K. C. J., Bader, R., & Mecklinger, A. (2020). Improving episodic memory: Frontal-midline theta neurofeedback training increases source memory performance. *NeuroImage, 222,* article 117219. https://doi.org/10.1016/j.neuroimage.2020.117219

Eysenck, M. W., & Keane, M. T. (1995). *Cognitive psychology: A student's handbook.* Hove, United Kingdom: LEA Publishers. ISBN: 0-86377-375-3.

Fales, C. L., Barch, D. M., Burgess, G. C., Schaefer, A., Mennin, D. S., Gray, J. R., & Braver, T. S. (2008). Anxiety and cognitive efficiency: Differential modulation of transient and sustained neural activity during a working memory task. *Cognitive, Affective, & Behavioral Neuroscience, 8*(3), 239-253. https://doi.org/10.3758/CABN.8.3.239

Fell, J., & Axmacher, N. (2011). The role of phase synchronization in memory processes. *Nature Reviews Neuroscience, 12*(2), 105-118. https://doi.org/10.1038/nrn2979

Field, A. (2013). *Discovering statistics using IBM SPSS Statistics (fourth edition).* London, United Kingdom: Sage Publications. ISBN: 978-1-4462-4917-8.

Frank, M. G. (2009). Brain rhythms. In M. D. Binder, N. Hirokawa & U. Windhorst (Eds.), *Encyclopedia of neuroscience* (pp. 482-483). Heidelberg, Germany: Springer. ISBN: 978-3-540-29678-2.

Fries, P. (2005) A mechanism for cognitive dynamics: Neuronal communication through neuronal coherence. *Trends in Cognitive Sciences*, *9*(10), 474–480. https://doi.org/10.1016/j.tics.2005.08.011

Fröber, K., & Dreisbach, G. (2012). How positive affect modulates proactive control: Reduced usage of informative cues under positive affect with low arousal. *Frontiers in Psychology, 3,* article 265. https://doi.org/10.3389/fpsyg.2012.00265

Fröhlich, F. (2016). *Network neuroscience.* Cambridge (Massachusetts), United States of America: Academic Press. ISBN: 978-0-12-801560-5.

Fuentes-García, J. P., Villafaina, S., Collado-Mateo, D., Cano-Plasencia, R., & Gusi, N. (2019). Chess players increase the theta power spectrum when the difficulty of the opponent increases: An EEG study. *International Journal of Environmental Research and Public Health, 17*(1), article 46. https://doi.org/10.3390/ijerph17010046

Gevins, A., & Smith, M. E. (2000). Neurophysiological measures of working memory and individual differences in cognitive ability and cognitive style. *Cerebral Cortex, 10*(9), 829-839. https://doi.org/10.1093/cercor/10.9.829

Gevins, A., Smith, M. E., McEvoy, L., & Yu, D. (1997). High-resolution EEG mapping of cortical activation related to working memory: Effects of task difficulty, type of processing, and practice. *Cerebral Cortex, 7*(4)*,* 374-385. https://doi.org/10.1093/cercor/7.4.374

Grandjean, J., D'Ostilio, K., Phillips, C., Balteau, E., Degueldre, C., Luxen, A., Maquet, P., Salmon, E., & Collette, F. (2012). Modulation of brain activity during a Stroop inhibitory task by the kind of cognitive control required. *PLOS ONE, 7*(7), article e41513. https://doi.org/10.1371/journal.pone.0041513

Griesmayr, B., Gruber, W. R., Klimesch, W., & Sauseng, P. (2010). Human frontal midline theta and its synchronization to gamma during a verbal delayed match to sample task. *Neurobiology of Learning and Memory, 93*(2)*,* 208-215. https://doi.org/10.1016/j.nlm.2009.09.013

Helfrich, R. F., & Knight, R. T. (2016). Oscillatory dynamics of prefrontal cognitive control. *Trends in Cognitive Sciences, 20*(12), 916-930. https://doi.org/10.1016/j.tics.2016.09.007

Hess, E. H. (1965). Attitude and pupil size. *Scientific American, 212*, 46-54. https://doi.org/10.1038/scientificamerican0465-46

Hess, E. H., & Polt, J. M. (1960). Pupil size as related to interest value of visual stimuli. *Science, 132*(3423), 349-350. https://doi.org/10.1126/science.132.3423.349

Hess, E. H., & Polt, J. M. (1964). Pupil size in relation to mental activity during simple problem-solving. *Science*, *143*(3611), 1090-1092. https://doi.org/10.1126/science.143.3611.1190

Hof, P. R., De Vellis, J., Nimchinsky, E. A., Kidd, G., Claudio, L., & Trapp, B. D. (2008). Cellular components of nervous tissue. In L. Squire, D. Berg, F. Bloom, S. Du Lac, A. Ghosh & N. Spitzer (Eds.), *Fundamental neuroscience (third edition)* (pp. 41-58). Cambridge (Massachusetts), United States of America: Academic Press. ISBN: 978-0-12-374019-9.

Hörsting, J., & Titsing, D. (2021). *EEG operations protocol: Set-up and recording.* University of Twente. https://bmslab.utwente.nl/knowledgebase/eeg-manual/

Hsieh, L.-T., & Ranganath, C. (2014). Frontal midline theta oscillations during working memory maintenance and episodic encoding and retrieval. *NeuroImage, 85*(2), 721-729. https://doi.org/10.1016/j.neuroimage.2013.08.003

Ishihara, T., & Yoshii, N. (1972). Multivariate analytic study of EEG and mental activity in juvenile delinquents. *Electroencephalography and Clinical Neurophysiology, 33*(1)*,* 71-80. https://doi.org/10.1016/0013-4694(72)90026-0

Itthipuripat, S., Wessel, J. R., & Aron, A. R. (2013). Frontal theta is a signature of successful working memory manipulation. *Experimental Brain Research, 224,* 255-262. https://doi.org/10.1007/s00221-012-3305-3

Jablonska, K., Piotrowska, M., Bednarek, H., Szymaszek, A., Marchewka, A., Wypych, M., & Szelag, E. (2020). Maintenance vs. manipulation in auditory verbal working memory in the elderly: New insights based on temporal dynamics of information processing in the millisecond time range. *Frontiers in Aging Neuroscience, 12*, article 194. https://doi.org/10.3389/fnagi.2020.00194

Jensen, O., & Tesche, C. D. (2002). Frontal theta activity in humans increases with memory load in a working memory task. *European Journal of Neuroscience, 15*(8), 1395-1399. https://doi.org/10.1046/j.1460-9568.2002.01975.x

Jonides, J., & Smith, E. E. (1997). The architecture of working memory. In M. D. Rugg (Ed.), *Cognitive neuroscience* (pp. 243–276). Hove, United Kingdom: Psychology Press. ISBN: 0-86377-490-3.

Kahana, M. J., Seelig, D., & Madsen, J. R. (2006). Theta returns. *Current Opinion in Neurobiology, 11*(6)*,* 739-744. https://doi.org/10.1016/s0959-4388(01)00278-1

Kahneman, D. (2011). *Thinking, fast and slow.* London, United Kingdom: Penguin Books. ISBN: 978-0-141-03357-0.

Kahneman, D., & Beatty, J. (1966). Pupil diameter and load on memory. *Science, 154*(3756), 1583-1585. https://www.jstor.org/stable/1720478

Kahneman, D., Beatty, J., & Pollack, I. (1967). Perceptual deficit during a mental task. *Science, 157*(3785), 218-219. https://doi.org/10.1126/science.157.3785.218

Kahneman, D., Peavler, W. S., & Onuska, L. (1968). Effects of verbalization and incentive on the pupil response to mental activity. *Canadian Journal of Psychology, 22*(3), 186-196. https://doi.org/10.1037/h0082759

Kahneman, D., Tursky, B., Shapiro, D., & Crider, A. (1969). Pupillary, heart rate, and skin resistance changes during a mental task. *Journal of Experimental Psychology, 79*(1), 164-167.

Karakaş, S. (2020). A review of theta oscillation and its functional correlates. *International Journal of Psychophysiology, 157,* 82-99. https://doi.org/10.1016/j.ijpsycho.2020.04.008

Kimchi, R. (1982). Mental effort and task interference in auditory attention. *Perception & Psychophysics, 32*(5), 473-480. https://doi.org/10.3758/BF03202778

Kutas, M., & Dale, A. (1997). Electrical and magnetic readings of mental functions. In M. D. Rugg (Ed.), *Cognitive neuroscience* (pp. 197-242). Hove, United Kingdom: Psychology Press. ISBN: 0-86377-490-3.

Lamp, G., Alexander, B., Laycock, R., Crewther, D. P., & Crewther, S. G. (2016). Mapping of the underlying neural mechanisms of maintenance and manipulation in visuo-spatial working memory using an n-back mental rotation task: A functional magnetic resonance imaging study. *Frontiers in Behavioral Neuroscience, 10*, article 87. https://doi.org/10.3389/fnbeh.2016.00087

Logie, R. H. (2016). Retiring the central executive. *Quarterly Journal of Experimental Psychology, 69*(10), 2093-2109. https://doi.org/10.1080/17470218.2015.1136657

Lomax, R. G., & Hahs-Vaughn, D. L. (2012). *An introduction to statistical concepts (third edition).* New York City (New York), United States of America: Routledge. ISBN: 978-0-415-88005-3.

Martins-Klein, B., Alves, L. A., & Chiew, K. S. (2020). Proactive versus reactive emotion regulation: A dual-mechanisms perspective. *Emotion, 20*(1), 87-92. https://doi.org/10.1037/emo0000664

May, J. G., Kennedy, R. S., Williams, M. C., Dunlap, W. P., & Brannan, J. R. (1990). Eye movement indices of mental workload. *Acta Psychologica, 75*(1), 75-89. https://doi.org/10.1016/0001-6918(90)90067-P

McCormick, D. A. (2008). Membrane potential and action potential. In L. Squire, D. Berg, F. Bloom, S. Du Lac, A. Ghosh & N. Spitzer (Eds.), *Fundamental neuroscience (third edition)* (pp. 111-132). Cambridge (Massachusetts), United States of America: Academic Press. ISBN: 978-0-12-374019-9.

Miller, E. K., & Buschman, T. J. (2012). Top-down control of attention by rhythmic neural computations. In M. I. Posner (Ed.), *Cognitive neuroscience of attention (second edition)* (pp. 229-241). London, United Kingdom: Guilford Press. ISBN: 978-1-60918-985-3.

Miller, E., & Wallis, J. (2008). The prefrontal cortex and executive brain functions. In L. Squire, D. Berg, F. Bloom, S. Du Lac, A. Ghosh & N. Spitzer (Eds.), *Fundamental neuroscience (third edition)* (pp. 1199-1222). Cambridge (Massachusetts), United States of America: Academic Press. ISBN: 978-0-12-374019-9.

Niendam, T. A., Laird, A. R., Ray, K. L., Dean, Y. M., Glahn, D. C., & Carter, C. S. (2012). Meta-analytic evidence for a superordinate cognitive control network subserving diverse executive functions. *Cognitive, Affective, & Behavioral Neuroscience*, 12, 241-268. https://doi.org/10.3758/s13415-011-0083-5

Nobre, A. C., Rohenkohl, G., & Stokes, M. G. (2012). Nervous anticipation: Top-down biasing across space and time. In M. I. Posner (Ed.), *Cognitive neuroscience of attention (second edition)* (pp. 159-186). London, United Kingdom: Guilford Press. ISBN: 978-1-60918-985-3.

Oja, E., & Yuan, Z. (2006). The FastICA algorithm revisited: Convergence analysis. *IEEE Transactions on Neural Networks, 17*(6), 1370-1381. https://doi.org/10.1109/TNN.2006.880980

Onton, J., Delorme, A., & Makeig, S. (2005). Frontal midline EEG dynamics during working memory. *NeuroImage, 27*(2), 341-356. https://doi.org/10.1016/j.neuroimage.2005.04.014

Pomper, U., & Ansorge, U. (2021). Theta-rhythmic oscillation of working memory performance. *Psychological Science*. https://doi.org/10.1177/09567976211013045

Quinlan, P., & Dyson, B. (2008). *Cognitive psychology.* Harlow, United Kingdom: Pearson Education Limited. ISBN: 978-0-13-129810-1.

Röber, T. E. (2019). *Frontal theta increase in the Add-n task and its relation to working memory capacity* [Bachelor thesis]. University of Twente. http://purl.utwente.nl/essays/78365

Roberts, B. M., Hsieh, L.-T., & Ranganath, C. (2013). Oscillatory activity during maintenance of spatial and temporal information in working memory. *Neuropsychologia, 51*(2), 349-357. https://doi.org/10.1016/j.neuropsychologia.2012.10.009

Román-López, T. V., Caballero-Sánchez, U., Cisneros-Luna, S., Franco-Rodríguez, J. A., Méndez-Díaz, M., Prospéro-García, O., & Ruiz-Contreras, A. E. (2019). Brain electrical activity from encoding to retrieval while maintaining and manipulating information in working memory. *Memory, 27*(8), 1063-1078. https://doi.org/10.1080/09658211.2019.1620287

Sauseng, P., Tschentscher, N., & Biel, A. L. (2019). Be prepared: Tune to FM-theta for cognitive control. *Trends in Neurosciences, 42*(5), 307-309. https://doi.org/10.1016/j.tins.2019.02.006

Sauseng, P., Griesmayr, B., Freunberger, R., & Klimesch, W. (2010). Control mechanisms in working memory: A possible function of EEG theta oscillations. *Neuroscience & Biobehavioral Reviews, 34*(7), 1015-1022. https://doi.org/10.1016/j.neubiorev.2009.12.006

Sauseng, P., Hoppe, J., Klimesch, W., Gerloff, C., & Hummel, F. C. (2007). Dissociation of sustained attention from central executive functions: Local activity and interregional connectivity in the theta range. *European Journal of Neuroscience, 25*(2), 587-593. https://doi.org/10.1111/j.1460-9568.2006.05286.x

Savine, A. C., Beck, S. M., Edwards, B. G., Chiew, K. S., & Braver, T. S. (2010). Enhancement of cognitive control by approach and avoidance motivational states. *Cognition & Emotion, 24*(2), 338-356. https://doi.org/10.1080/02699930903381564

Solso, R. L. (2000). *Cognitive psychology (sixth edition)*. Needham Heights (Massachusetts), United States of America: Allyn & Bacon. ISBN: 0-205-30937-2.

Speer, N. K., Jacoby, L. L., & Braver, T. S. (2003). Strategy-dependent changes in memory: Effects on behavior and brain activity. *Cognitive, Affective, & Behavioral Neuroscience, 3*(3), 155-167. https://doi.org/10.3758/CABN.3.3.155

Stankovski, T., Ticcinelli, V., McClintock, P. V. E., & Stefanovska, A. (2017). Neural cross-frequency coupling functions. *Frontiers in Systems Neuroscience, 11*, article 33. https://doi.org/10.3389/fnsys.2017.00033

Steinhauer, S. R., Condray, R., & Kasparek, A. (2000). Cognitive modulation of midbrain function: Task-induced reduction of the pupillary light reflex. *International Journal of Psychophysiology, 39*(1), 21-30. https://doi.org/10.1016/S0167-8760(00)00119-7

Stone, B. P., Lee, M., Dennis, S., & Nettelbeck, T. (2004). Pupil size and mental load. *Student project.* http://www.psychology.adelaide.edu.au/cognition/aml/aml1/stone_aml1.pdf

Uhlhaas, P. J., Roux, F., Rodriguez, E., Rotarska-Jagiela, A., & Singer, W. (2010). Neural synchrony and the development of cortical networks. *Trends in Cognitive Sciences, 14*(2), 72-80. https://doi.org/10.1016/j.tics.2009.12.002

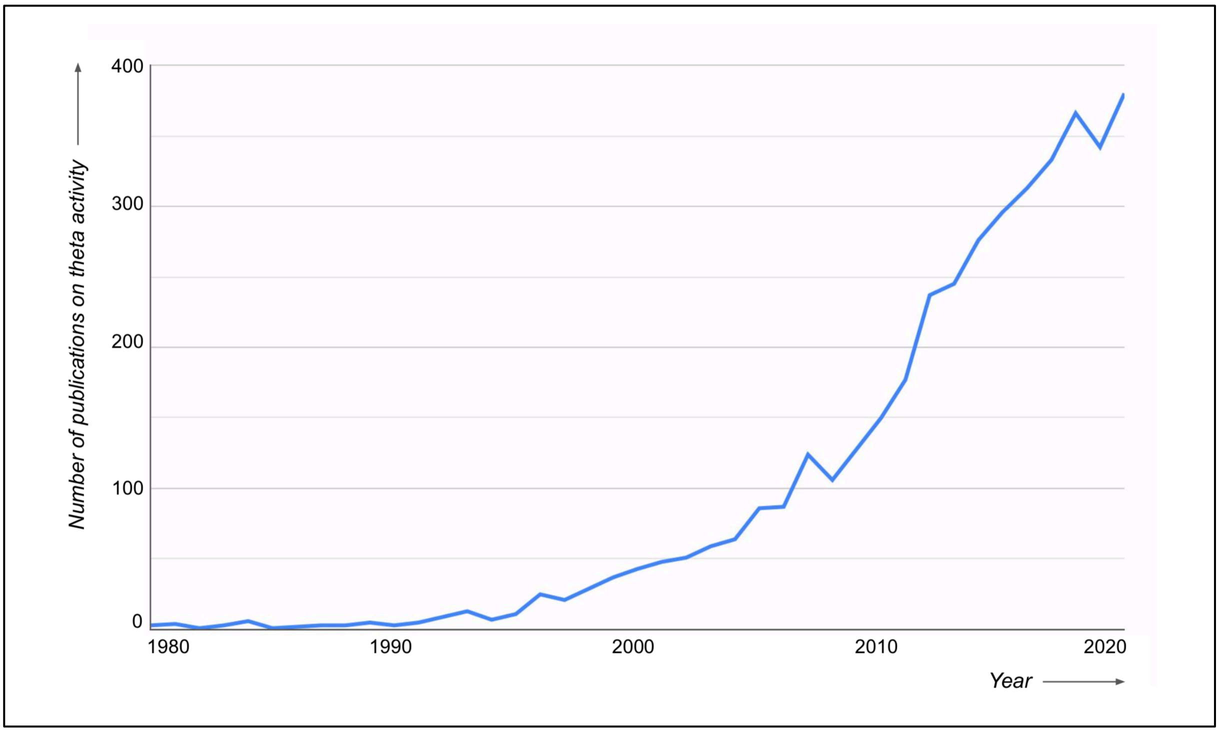
Veltman, D. J., Rombouts, S. A. R. B., & Dolan, R. J. (2003). Maintenance versus manipulation in verbal working memory revisited: An fMRI study. *NeuroImage, 18*(2), 247-256. https://doi.org/10.1016/S1053-8119(02)00049-6

Von Stein, A., & Sarnthein, J. (2000). Different frequencies for different scales of cortical integration: From local gamma to long range alpha/theta synchronization. *International Journal of Psychophysiology, 38*(3), 301-313. https://doi.org/10.1016/s0167-8760(00)00172-0

Wagner, A. D., Bunge, S. A., & Badre, D. (2004). Cognitive control, semantic memory, and priming: Contributions from prefrontal cortex. In M. S. Gazzaniga (Ed.), *The cognitive neurosciences III* (pp. 709-725). Cambridge (Massachusetts), United States of America: MIT Press. ISBN: 0-262-07254-8.

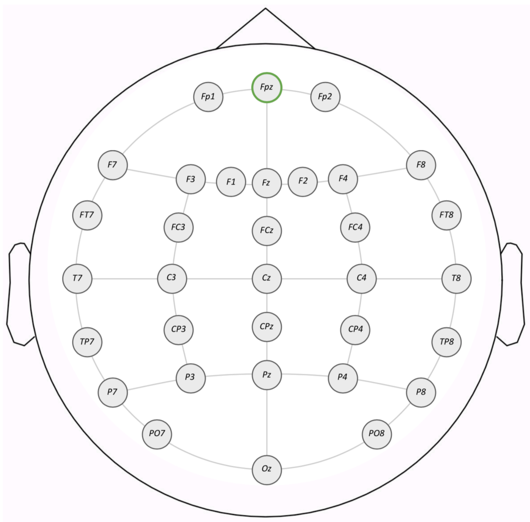
APPENDIX A

Academic interest in theta activity has steadily risen in the course of the past three decades. Please see the figure below, which was made with data that was retrieved from the Scopus database (query: 'theta oscillations'). To create the figure, only publications by psychologists, neuroscientists, biologists and multidisciplinary research teams were taken into consideration.



APPENDIX B

The standard 10-20 system was used to position the electrodes on the participants' scalps. Please see the figure below. In total, 32 electrodes were used (not including the ground, Fpz, which is marked by a green circle in the figure). Electrode TP8 served as the online reference electrode in the laboratory. An average reference was later switched to in the EEG processing pipeline.



APPENDIX C

Please see the textbox below for a slightly trimmed-down version of the code that was used to process the collected EEG data. The complete script (as well as a number of important related files) can be found online in the GitHub repository that was referred to on page 16 of this work.

```
# ============ SETTINGS ============= #

# To process the EEG data of only a
#  few (rather than all) participants,
#  set 'limitedFocus' to 'True' and
#  enter the identification numbers of
#  the participants whose data you want
#  to examine in 'selectedParticipants'.
limitedFocus = False
selectedParticipants = [1, 2, 3]

# To ensure that a participant's data
#  will never be processed (because it
#  is too noisy, for example), please
#  enter their identification number
#  in 'excludedParticipants' below.
excludedParticipants = [22, 34]

# To avoid generating new ICA solutions
#  for all participants (which is very
#  time-consuming) at step 2.2.10 and to
#  make use of old ICA solutions instead,
#  please set 'completeICA' to 'False'.
completeICA = False

# Different scholars have different
#  views on what constitutes theta
#  activity. To accommodate for this,
#  you can set 'thetaRange' yourself
#  here. The first value (in Hz) is
#  the lower limit. The second value
#  (also in Hz) is the upper limit.
thetaRange = [4.0, 7.0]

# =============== CODE =============== #

### ******************************** ###
###             ~ Part 1 ~           ###
###          Essential set-up        ###
### ******************************** ###

### ----------- Step 1.1 ----------- ###

# We import the Python modules we need.
import mne
import os
```

```
from os import path
from pathlib import Path
from mne.preprocessing import ICA
import pandas as pd
import numpy as np
import pickle

### ----------- Step 1.2 ----------- ###

# We import some useful information
#  that we stored in other files to
#  avoid cluttering up this code file.
mainDirectory = '../..'

# There were 37 participants in total.
#  For each participant, we have one .vhdr
#  file. The paths to all .vhdr files can
#  be found in '/Miscellaneous/File paths.txt'.
#  For the sake of convenience, let us load
#  those paths into an array called 'files'.
files = []
document = open('../../Miscellaneous/File paths.txt', 'r')
document = document.readlines()
for fileName in document:
   files.append(mainDirectory + fileName.strip())

# Were there any bad channels when we
#  recorded our EEG data? To find out,
#  we can use the code provided in
#  '/Code/Other/Bad channel identifica-
#  tion.py'. My findings (per subject)
#  can be found in '/Miscellaneous/Bad
#  channels.txt'. Let us load them into
#  an array called 'badChannelsPerSubject'.
badChannelsPerSubject = []
document = open('../../Miscellaneous/Bad channels.txt', 'r')
document = document.readlines()
for badChannelSet in document:
   badChannelsPerSubject.append(badChannelSet.strip()[5:].split())

# We will use independent component
#  analysis (ICA) to remove noise from
#  our data. I already identified which
#  components should be removed. My
#  findings (per subject) can be found in
#  '/Miscellaneous/Unwanted components.txt'.
#  Let us load them into an array called
#  'unwantedComponentsPerSubject'.
unwantedComponentsPerSubject = []
document = open('../../Miscellaneous/Unwanted components.txt', 'r')
document = document.readlines()
for unwantedComponentSet in document:
   components = unwantedComponentSet.strip()[5:].split()
   unwantedComponentsPerSubject.append(components)

### ******************************** ###
###            ~ Part 2 ~            ###
###     Subject-level computations   ###
### ******************************** ###

### ----------- Step 2.1 ----------- ###
```

```
# For all participant-condition-electrode
#  combinations, we want to calculate power
#  spectral density scores for a wide range
#  of sampling frequencies (0 Hz - 250 Hz).
#  We will do that in this part of the code.
#  We will store the power spectral density
#  scores in an array called 'powerScoresPer-
#  Subject'. We will store the sampling fre-
#  quencies (which will be identical for all
#  participant-condition-electrode tuples)
#  in an array called 'samplingFrequencies'.
powerScoresPerSubject = []
samplingFrequencies = []

### ----------- Step 2.2 ----------- ###

# Let's have a look at all files, and hence
#  all subjects, one by one in a special loop.
for file in files:

   ### ---------- Step 2.2.1 ---------- ###

   # We can derive the identification number
   #  of this subject from the name of their
   #  .vhdr file. We will do that immediately.
   participantNumber = file[-17:-15]

   ### ---------- Step 2.2.2 ---------- ###

   # Did we set 'limitedFocus' to 'True'?
   if limitedFocus:
       # Did the current subject make the selection?
       if int(participantNumber) not in selectedParticipants:
           #  We move on to the next participant.
           continue

   # Should we skip this participant?
   if int(participantNumber) in excludedParticipants:
       # We move on to the next participant.
       continue

   ### ---------- Step 2.2.3 ---------- ###

   # Does the .vhdr file actually exist?
   if not path.exists(file):
       print(print("[ERROR] The file \'{}\' could
                    not be found".format(file)))
       exit()

   # We recorded our data with the Brain-
   #  Vision Recorder software. The files
   #  we refer to in the array we called
   #  'files' (step 1.2) are .vhdr files.
   #  For each participant, the BrainVision
   #  Recorder software we used also gene-
   #  rated two other (eponymous) files that
   #  are also important: a .eeg file and a
   #  .vmrk file. The .vhdr file merely con-
   #  tains metadata. The .eeg file contains
   #  the raw data that we need. The .vmrk
```

↓

```
#  file contains information about events
#  (e.g. button presses and stimulus on-
#  sets) that occurred during the experi-
#  ment. Let us check whether the .eeg
#  file and the .vmrk file, which should
#  be located in the same folder as the
#  corresponding .vhdr file, also exist.
eegFile = file[:len(file) - 4] + 'eeg'
vmrkFile = file[:len(file) - 4] + 'vmrk'
if not path.exists(eegFile):
    print(print("[ERROR] The file \'{}\' could
                 not be found".format(eegFile)))
    exit()
elif not path.exists(vmrkFile):
    print(print("[ERROR] The file \'{}\'
                 could not be found".format(vmrkFile)))
    exit()

### ---------- Step 2.2.4 ---------- ###

# We load the data. Since we make use
#  of BrainVision data, we should apply
#  a non-standard read function here.
raw = mne.io.read_raw_brainvision(file, preload=True)

# We can inspect the loaded data.
if False:
    print(raw.info)
    print(raw.info.ch_names)

### ~~~~~~~~ Pre-processing ~~~~~~~~ ###

### ---------- Step 2.2.5 ---------- ###

# We have 32 EEG channels and 2 MISC
#  channels. The two MISC channels are
#  labeled 'hEOG' and 'vEOG'. They only
#  contain useful data for the first 20
#  participants or so. We want to treat
#  each data file in a similar manner,
#  so let us simply discard the two
#  MISC channels for all participants.
raw.drop_channels(['hEOG', 'vEOG'])

### ---------- Step 2.2.6 ---------- ###

# When we recorded our data, we used TP8
#  as our reference electrode. It would
#  be better to make use of an average
#  reference, however, since that would
#  reduce a potential bias towards brain
#  activity in the left hemisphere. We
#  add TP8 to our set of electrodes and
#  then calculate an average reference.
mne.add_reference_channels(raw, ref_channels=['TP8'], copy=False)
raw.set_eeg_reference(ref_channels='average')

### ---------- Step 2.2.7 ---------- ###

# We should indicate how the EEG electrodes
#  were positioned on the subject's head (i.e.
```

```
#  what electrode montage we used). We
#  made use of the so-called 10-20 system.
raw.set_montage(mne.channels.make_standard_montage('standard_1020'))

# We can visualise our electrode montage.
if False:
    raw.plot_sensors(kind='topomap', ch_type='eeg', block=True)
    raw.plot_sensors(kind='3d', ch_type='eeg', block=True)

### ---------- Step 2.2.8 ---------- ###

# During the experiment, many events
#  (e.g. button presses and stimulus
#  onsets) occurred. Let us extract all
#  event information for the current
#  participant from the data and store
#  it in an array called 'events'.
events, notNeeded = mne.events_from_annotations(raw)

# Each type of event is described by a
#  so-called 'stimulus code'. Different
#  types of events are described by
#  different stimulus codes. Let us in-
#  dicate what each stimulus code means.
event_dictionary = \
    {'Required1': 1, 'Required2': 2,
     'Required3': 3, 'Required4': 4,
     'Required5': 5, 'Required6': 6,
     'Required7': 7, 'Required8': 8,
     'Required9': 9, 'Pressed0': 210,
     'Pressed1': 201, 'Pressed2': 202,
     'Pressed3': 203, 'Pressed4': 204,
     'Pressed5': 205, 'Pressed6': 206,
     'Pressed7': 207, 'Pressed8': 208,
     'Pressed9': 209,  'PressedSB': 211,
     'Add0_StimulusAppears': 100,
     'Add0_StimulusDisappears': 150,
     'Add1_StimulusAppears': 101,
     'Add1_StimulusDisappears': 151,
     'Add2_StimulusAppears': 102,
     'Add2_StimulusDisappears': 152,
     'Practice': 155}

# There is one stimulus code that we did
#  not include in the above dictionary
#  yet: '10' (meaning: 'Required0'). That
#  code was (by accident) not included in
#  the data for participant 1. It was in-
#  cluded in the data for the remaining 36
#  participants, however, so we will add
#  the code to their event dictionaries.
if int(participantNumber) != 1:
    event_dictionary['Required0'] = 10

# We can visualise which events
#  occurred at which points in time.
if False:
    figure = mne.viz.plot_events(events,
                                 event_id=event_dictionary,
                                 sfreq=raw.info['sfreq'],
                                 first_samp=raw.first_samp)
```

```
### ---------- Step 2.2.9 ---------- ###

# Were there any bad channels when
#  we recorded this participant's
#  brain activity? At step 1.2 above,
#  we loaded this information into an
#  array called 'badChannelsPerSubject'.
#  Let us extract the information that
#  we need from that array and link it
#  to the current subject's EEG data.
#  We will interpolate the bad channels
#  later, at step 2.2.14 of this code.
raw.info['bads'] = badChannelsPerSubject[int(participantNumber) - 1]

### ---------- Step 2.2.10 --------- ###

# Eye blinks, eye movements, heartbeats
#  and environmental factors may have
#  caused there to be artefacts (bits
#  of noise) in our data. We can try to
#  get rid of those artefacts by means
#  of a technique known as independent
#  component analysis (ICA). If we set
#  'completeICA' to 'True' earlier, we
#  will now generate a new ICA solution
#  for this participant. Please note that
#  this may take some time (~90 seconds).
if completeICA:

    #  We first make a copy of our data, which
    #  we will use to create an ICA solution.
    raw_copy = raw.copy()

    # We need to remove all major frequency
    #  drifts from the copy of our data, since
    #  such frequency drifts can make it hard
    #  to create an ICA solution. The reason
    #  we made a copy of our data earlier, is
    #  that we do not want to remove any drifts
    #  from our original data yet at this point.
    raw_copy.load_data().filter(l_freq=0.1, h_freq=30)

    # We will now create the ICA solution for
    #  the current participant's data. We make
    #  use of the 'FastICA' algorithm, since I
    #  found (after several trial sessions) that
    #  this algorithm tends to converge faster
    #  than its key competitors: the 'infomax'
    #  algorithm and the 'Picard' algorithm.
    #  Since 'FastICA' does not converge for
    #  participant 27 (for unknown reasons),
    #  we will use 'Picard' for that subject.
    algorithm = 'fastica'
    if int(participantNumber) == 27:
        algorithm = 'picard'
    numberOfComponents = raw.info['nchan']-len(raw.info['bads'])-1
    ica = ICA(n_components=numberOfComponents,
              random_state=91, method=algorithm)
    ica.fit(raw_copy)
```
↓

```
    # Let us store the ICA solution in a folder
    #  called '/Output/ICA solutions' so we can
    #  use it again in the future.
    with open('../../Output/ICA solutions/P' +
              participantNumber + '.data', 'wb') as filehandle:
        pickle.dump(ica, filehandle)

# If we set 'completeICA' to 'False' earlier,
#  we will not generate a new ICA solution for
#  this participant. Instead, we will make use
#  of a solution that we already found earlier.
if not completeICA:

    # Let us load the ICA solution from
    #  the folder we stored it in earlier.
    with open('../../Output/ICA solutions/P' +
              participantNumber + '.data', 'rb') as filehandle:
        ica = pickle.load(filehandle)

# When we created our ICA solution for the
#  current participant, we essentially
#  tried to split up that participant's
#  EEG data into various independent parts
#  (or 'components'). We can now examine
#  all of those components one by one.
if False:
    raw.load_data()
    ica.plot_components()
    ica.plot_sources(raw, block=True)

# We may want to get rid of some of the
#  components we have identified, such
#  as components that seem to have captured
#  ECG or EOG (rather than EEG) activity. I
#  already identified all unwanted components
#  for each subject. We loaded this information
#  into an array called 'unwantedComponentsPer-
#  Subject' at step 1.2. Let us extract the
#  information that we need from that array.
ica.exclude = [int(i) for i in
        unwantedComponentsPerSubject[int(participantNumber) - 1]]

# We are now ready to apply the ICA solution
#  that we created to our original data. This
#  essentially means that we are now ready to
#  reconstruct our original EEG data, this
#  time with much less noise. Let us do this.
ica.apply(raw)

### ---------- Step 2.2.11 --------- ###

# We now filter all major frequency
#  drifts from our data, to further
#  enhance the data's overall quality.
raw.load_data().filter(l_freq=0.1, h_freq=30)

### ~~~~~~~~~~~ Epoching ~~~~~~~~~~~ ###

### ---------- Step 2.2.12 --------- ###

# An epoch is a segment of EEG data
```

```
#  that is centred around an event.
#  Let us extract epochs from this
#  subject's data. By default, one
#  epoch will be created for each
#  event. We cannot change this, even
#  though we are only interested
#  in epochs centred around a spe-
#  cific type of event: 'Add[N]_Stim-
#  ulusAppears' with N ∈ {0, 1, 2}.
#  We can determine how long each
#  epoch should be, however. The
#  settings that are used here were
#  chosen because they seem suitable
#  for the epochs we are interested
#  in. For details, please see
#  sections 2 and 4 of my thesis.
epochs = mne.Epochs(raw, events,
                    event_id=event_dictionary,
                    tmin=-0.5, tmax=4.0, preload=True)

### ---------- Step 2.2.13 --------- ###

# We already tried to clean our data
#  in various ways, but unfortunately
#  there may still be some artefacts
#  left. We will now throw away all
#  epochs that contain major artefacts.
#  If the difference between the
#  highest recorded amplitude and
#  the lowest recorded amplitude in
#  an epoch is larger than 150 µV, we
#  reject that epoch. Brain activity
#  fluctuations are unlikely to cause
#  such large amplitude fluctuations.
reject_criteria = dict(eeg=150e-6)

# If the difference between the
#  highest recorded amplitude and
#  the lowest recorded amplitude in
#  an epoch is smaller than 0.1 µV,
#  we reject that epoch. Brain ac-
#  tivity fluctuations typically
#  give rise to larger amplitude
#  fluctuations, so it seems there
#  has been a measurement error.
flat_criteria = dict(eeg=1e-7)

# Now that we have specified our epoch
#  rejection criteria, let us get rid of
#  all epochs that meet those criteria.
originalNumberOfEpochs = len(epochs)
epochs.drop_bad(reject=reject_criteria, flat=flat_criteria)

# We can print some statistics
#  about how many epochs were dropped.
if False:
    epochs.plot_drop_log()
    remainingNumberOfEpochs = len(epochs)
    percentageDropped = (originalNumberOfEpochs -
                         remainingNumberOfEpochs) /
                         (originalNumberOfEpochs/100)
```
↓

```
    print("Percentage of epochs that
           were dropped: {}".format(percentageDropped))

### ---------- Step 2.2.14 --------- ###

# At step 2.2.9, we marked all of
#  the bad channels for this subject.
#  Instead of simply dropping those
#  channels and pretending they were
#  never part of our electrode montage,
#  we will try to repair them by looking
#  at the EEG data that was recorded by
#  other (good) channels in the same
#  area. This technique is known as
#  interpolation. We make use of the
#  so-called spherical spline method.
epochs.interpolate_bads()

### ---------- Step 2.2.15 --------- ###

# We could visualise the epochs around,
#  for example, all events that are
#  of type 'Add0_StimulusAppears'. For
#  the sake of conciseness, the code that
#  would allow us to do so has not been
#  included in this trimmed-down version.

### ~~~~~~~~~ Power scores ~~~~~~~~~ ###

# We will now calculate the power scores
#  for this participant, one condition at
#  a time. We will store the scores in an
#  array called 'powerScoresPerCondition'
#  and the sampling frequencies in an array
#  called 'samplingFrequenciesPerCondition'.
#  Please note that the latter is actually
#  a bit redundant: we use the same sampling
#  frequencies across all three conditions.
powerScoresPerCondition = []
samplingFrequenciesPerCondition = []

for condition in range(0, 3):
    epochsForThisCondition = epochs['Add' +
                                str(condition) + '_StimulusAppears']
    powerScoresForThisCondition, samplingFrequenciesForThisCondition =
            mne.time_frequency.psd_multitaper(epochsForThisCondition,
                 picks=['eeg'])
    powerScoresForThisCondition =
            np.mean(powerScoresForThisCondition, axis=0)

    # We store the power scores and sampling
    #  frequencies for this condition in
    #  the arrays we initialised earlier.
    powerScoresPerCondition.append(powerScoresForThisCondition)
    samplingFrequenciesPerCondition.append(samplingFrequencies-
            ForThisCondition)

    # We can visualise the topographical
    #  distribution of theta activity for
    #  the current participant-condition tuple.
    if False:
```

```
            mne.viz.topomap.plot_psds_topomap(
                psds=powerScoresForThisCondition,
                freqs=samplingFrequenciesForThisCondition,
                bands=[(thetaRange[0],thetaRange[1],'Theta')],
                dB=False, normalize=False, show=True, ch_type='eeg',
                pos=epochsForThisCondition[0][0].info)

    # We normalise the power
    #  scores for this participant.
    sumOfAllPowerScores = \
        powerScoresPerCondition[0].sum(axis=-1, keepdims=True) + \
        powerScoresPerCondition[1].sum(axis=-1, keepdims=True) + \
        powerScoresPerCondition[2].sum(axis=-1, keepdims=True)
    powerScoresPerCondition[0] /= sumOfAllPowerScores
    powerScoresPerCondition[1] /= sumOfAllPowerScores
    powerScoresPerCondition[2] /= sumOfAllPowerScores

    # We store the power scores and sampling
    #  frequencies for this participant in
    #  the arrays we initialised earlier for
    #  this specific purpose at step 2.1.
    powerScoresPerSubject.append(powerScoresPerCondition)
    samplingFrequencies.append(samplingFrequenciesPerCondition)

### ******************************** ###
###            ~ Part 3 ~            ###
###      Sample-level computations   ###
### ******************************** ###

### ----------- Step 3.1 ----------- ###

# We now have power spectral density scores
#  for all participant-condition-electrode
#  combinations. We want to combine those
#  scores into a single array, which
#  contains one (average) power score per
#  condition-electrode-frequency combination.
#  We start by creating an array that
#  contains a list of power scores for each
#  condition-electrode-frequency combination.
powerScores_FullSample_notAveragedPerFrequency = [[[[] for i in
range(1126)] for j in range(32)] for k in range(3)]
for condition in range(0, 3):
    for participant in range (0, len(powerScoresPerSubject)):
        for electrode in range (0,32):
            for frequency in range(0, 1126):
                powerScores_FullSample_notAveragedPer-
                      Frequency[condition][electrode][frequency].\
                    append(powerScoresPerSubject[participant]\
                      [condition][electrode][frequency])

# We now create an array that contains a
#  single (average) power score for each
#  condition-electrode-frequency combination.
powerScores_FullSample_averagedPerFrequency = [[[] for j in range(32)]
for k in range(3)]
for condition in range(0, 3):
    for electrode in range (0,32):
        for frequency in range(0, 1126):
            listOfPowerScores = powerScores_FullSample_notAveraged\
                PerFrequency[condition][electrode][frequency]
```

```
            averagePowerScore = sum(listOfPowerScores) /
                len(listOfPowerScores)
            powerScores_FullSample_averagedPerFrequency[condition]\
                [electrode].append(averagePowerScore)

### ----------- Step 3.2 ----------- ###

# Let us now extract a single average theta
#  power score per electrode, per condition,
#  per participant from all of our data.
#  We will store the new scores in an array
#  called 'powerScores_perParticipant_theta'.
powerScores_perParticipant_theta = []

thetaScoreIndices = []
for frequencyIndex in range(0, len(samplingFrequencies[0][0])):
   if thetaRange[0] <= samplingFrequencies[0][0][frequencyIndex]
      <= thetaRange[1]: thetaScoreIndices.append(frequencyIndex)

for participant in powerScoresPerSubject:
   conditions = []
   for condition in participant:
       electrodes = []
       for electrode in condition:
           thetaScores = []
           for scoreIndex in range(0, len(electrode)):
               if scoreIndex in thetaScoreIndices:
                   thetaScores.append(electrode[scoreIndex])
           averageElectrodeScore_theta =
               sum(thetaScores) / len(thetaScores)
           electrodes.append(averageElectrodeScore_theta)
       conditions.append(electrodes)
   powerScores_perParticipant_theta.append(conditions)

### ******************************** ###
###            ~ Part 4 ~            ###
###      A focus on theta activity   ###
### ******************************** ###

### ----------- Step 4.1 ----------- ###

# We can now use the calculated power
#  scores to generate three theta topoplots:
#  one for each condition. We save the three
#  theta topoplots as PDF files in a folder
#  called '/Output/Theta topoplots'.
for condition in range(0, 3):
   powerScoresForThisCondition =
      np.array(powerScores_FullSample_averagedPerFrequency[condition])
   samplingFrequenciesForThisCondition =
      np.array(samplingFrequencies[0][0])
   fig = mne.viz.topomap.plot_psds_topomap(psds=powerScoresForThis\
       Condition, freqs=samplingFrequenciesForThisCondition,
       bands=[(thetaRange[0],thetaRange[1],'Theta')], dB=False,
       normalize=False, show=True, ch_type='eeg', pos=epochsForThis\
       Condition[0][0].info)
   fig.savefig(fname="../../Output/Theta topoplots/
                       Add-" + str(condition) + ".pdf", format='pdf')

### ----------- Step 4.2 ----------- ###
```

```
# We extract the theta power scores for
#  further processing in SPSS. We store the
#  extracted theta power scores in a folder
#  called '/Output/Theta power scores'. We
#  do so twice, in two different formats:
#  the 'wide' format and the 'long' format.
#  We start by creating a 'wide' table. We
#  save it in the above-mentioned folder as
#  an Excel-file called 'Wide format.xlsx'.
pythonTable_wide = []
for participantNumber in range (0,
                         len(powerScores_perParticipant_theta)):
   realParticipantNumber = participantNumber + 1
   for excludedParticipant in excludedParticipants:
       if realParticipantNumber >= excludedParticipant:
           realParticipantNumber += 1
   newRow = [realParticipantNumber]
   for conditionNumber in range (0,
        len(powerScores_perParticipant_theta[participantNumber])):
       for electrodeNumber in range (0,
            len(powerScores_perParticipant_theta[participantNumber]\
                [conditionNumber])):
              thetaPowerAverage = powerScores_perParticipant_theta\
                 [participantNumber][conditionNumber][electrodeNumber]
              newRow.append(thetaPowerAverage)
   pythonTable_wide.append(newRow)
columns = ['Participant']
numberOfConditions = len(powerScores_perParticipant_theta[0])
numberOfElectrodes = len(powerScores_perParticipant_theta[0][0])
for conditionNumber in range(0, numberOfConditions):
   for electrodeNumber in range(0, numberOfElectrodes):
       columns.append('Add' + str(conditionNumber) +
                      '_Electrode' + str(electrodeNumber + 1))
pandasTable_wide = pd.DataFrame(pythonTable_wide, columns=columns)
pandasTable_wide.to_excel("../../Output/Theta power
                          scores/Wide format.xlsx")

# We continue by  creating a 'long' table.
#  We save it (in the same folder) as an
#  Excel-file called 'Long format.xlsx'.
pythonTable_long = []
for participantNumber in range (0,
                         len(powerScores_perParticipant_theta)):
    realParticipantNumber = participantNumber + 1
    for excludedParticipant in excludedParticipants:
       if realParticipantNumber >= excludedParticipant:
           realParticipantNumber += 1
    for conditionNumber in range (0,
        len(powerScores_perParticipant_theta[participantNumber])):
          for electrodeNumber in range (0,
              len(powerScores_perParticipant_theta[participantNumber]\
                [conditionNumber])):
                 thetaPowerAverage = powerScores_perParticipant_theta\
                  [participantNumber][conditionNumber][electrodeNumber]
                 newRow = [realParticipantNumber, conditionNumber,
                  electrodeNumber+1, thetaPowerAverage]
                pythonTable_long.append(newRow)
pandasTable_long = pd.DataFrame(pythonTable_long,
 columns=['Participant', 'Condition', 'Electrode', 'Theta power score'])
pandasTable_long.to_excel("../../Output/Theta power
                          scores/Long format.xlsx")
```

■

APPENDIX D

Please see the table and the figures below for examples of the types of components that were typically removed during the independent component analysis. A single participant's data was used here. Thirty components were generated, ten of which (33.3%) were selected for removal.

Component	Primary reason for removal	Clarification
1	Signal	Nearly flat signal
2	Signal	Nearly flat signal
3	Signal and topography	Ocular activity
4	Signal and topography	Ocular activity
5	Topography	Ocular activity
6	Topography	Muscle movements or heart activity
7	Topography	Muscle movements or heart activity
8	Signal	Noisy signal
9	Topography	Muscle movements
10	Topography	Muscle movements