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Registered Report

Investigating the relationship between resting-state EEG microstates and executive functions: A null finding



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ABSTRACT

Recent advances in cognitive neurosciences suggest that intrinsic brain networks dynamics are associated with cognitive functioning. Despite this emerging perspective, limited research exists to validate this hypothesis. This Registered Report aimed to specifically test the relationship between intrinsic brain spatio-temporal dynamics and executive functions. Resting-state EEG microstates were used to assess brain spatio-temporal dynamics, while a comprehensive battery of nine cognitive function tasks was employed to evaluate executive functions in 140 participants. We hypothesized that microstates (class C and D) metrics would correlate with an executive functions composite score. Contrary to expectations, our hypotheses were not supported by the data. We however observed a small, non-significant trend with a negative correlation between microstate D occurrences and executive functions scores ($r = -.18$, 95% CI $[-.33, -.01]$) which however did not meet the adjusted threshold for significance. In light of the inconclusive or minor effect sizes observed, the assertion that intrinsic brain networks dynamics – as measured by resting-state EEG microstate metrics – are a reliable signature of executive functioning remains unsupported.

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1. Introduction

Executive functions are a hallmark of human cognition and have been defined as “high-level cognitive processes that enable individuals to regulate their thoughts and actions during goal-directed behaviors” (Friedman & Miyake, 2017). They are thought to be typically recruited when dealing with novel and complex tasks or situations (Miyake et al., 2000), and to rely on a set of large-scale functional brain networks that include frontal and parietal areas (Uddin, 2021). In this Registered Report, we propose to study the links between resting-state (RS) EEG microstates and executive functions.

Executive functions have been difficult to study due to the fact that they encompass a large number of cognitive functions which are inter-related, meaning that they cannot be purely studied with specific cognitive tasks. To overcome this task impurity issue, it has been proposed to use latent variable analyses, which capture only common variance across multiple measures (Friedman et al., 2008; Miyake et al., 2000). A highly influential study in the domain (Miyake et al., 2000) showed that executive functions can be decomposed into three latent variables: mental set-shifting (“shifting”), information updating and monitoring in working memory (“updating”) and inhibition of prepotent responses (“inhibition”). In this model, nine cognitive tasks (three per latent variable) have been chosen and have been found to weakly correlate with one another (r between $-.05$ and $.34$), while the three latent variables show moderate correlation with one another (r between $.42$ and $.63$). These results illustrate the fact that executive functions show both unity and diversity (Friedman & Miyake, 2017). Interestingly, this three-factors model shows some robustness since it has been replicated multiple times in healthy adult samples (Karr et al., 2018).

The neural substrates of executive functions have been largely studied with fMRI. Searching the Neurosynth database (<https://neurosynth.org/>) with the separate terms “executive functions”, “inhibition”, “shifting”, “working memory”, returns overlapping sets of overlapping brain areas that include frontal areas (dorsolateral prefrontal cortex, anterior cingulate cortex, inferior frontal gyrus) and parietal areas (inferior parietal lobule, angular gyrus) (Uddin, 2021), which are part of the fronto-parietal network (FPN), the executive control network (ECN) and the salience network (SN) (Xu et al., 2020). Studies using dynamic functional connectivity (dFC) showed that these networks are dynamically modulated during executive functions tasks such as the Stroop or the n-back (Braun et al., 2015; Douw et al., 2016). These results are consistent with a recent hypothesis that postulates that neural flexibility (i.e., the ability of the brain to change from one state to another) is related to cognitive performance (Hartwigsen, 2018; Uddin, 2021). This hypothesis has been further investigated by correlating fMRI dFC during RS with performance in various cognitive function tasks (Zelazo, 2006; Douw et al., 2016; Jia et al., 2014; Nomi et al., 2017). Taken together, these fMRI dFC studies show that brain networks dynamics may be an intrinsic signature of cognitive performance (Nomi et al., 2017; Uddin, 2021).

Besides fMRI, EEG provides an interesting means of capturing the temporal dynamics of the brain activity at a

higher temporal resolution (Michel & Koenig, 2018; Zappasodi et al., 2019). In particular, EEG microstates analyses have recently gained increasing interest to characterize spatio-temporal electrical brain dynamics (for a review, see Michel & Koenig, 2018). Some authors have even suggested that EEG microstates could be the “atoms of thoughts” (Lehmann et al., 1987; Lehmann & König, 1997) in that they could represent the unitary elements of cognitive processes. Microstates have been defined as semi-stable electric potential configurations on the scalp that last approximately 60–120 msec. Several metrics (e.g., coverage, duration, occurrence) can be computed to describe the dynamics of these microstates that transition between one another (Michel & Koenig, 2018). While several microstates have been described, the literature shows some consistency by repetitively identifying four main microstates, each being a prototypical configuration of the scalp potential field (Michel & Koenig, 2018).

By combining EEG and fMRI analyses, studies have found that these four main microstates (named A, B, C and D) may be associated with specific fMRI RS networks: the auditory (A), the visual (B), the executive control (C) and the attentional (D) networks (Britz et al., 2010; Van de Ville et al., 2010; Custo et al., 2017; Xu et al., 2020). Recent evidences in favor of this hypothesis have also been reported with a study that showed that EEG microstates are closely related to dFC states observed in fMRI and may be relevant markers to study large-scale brain networks dynamics (Abreu et al., 2020). As a result, EEG microstates analyses approach appears to be adapted to study the temporal dynamics of these networks and their relationship with higher cognitive processes (Michel & Koenig, 2018). Especially, microstates C and D (associated with executive control and attentional networks) metrics seem to be related to higher cognitive functions. The number of occurrences or the mean duration of microstate C during a RS correlates negatively with fluid intelligence (Liu et al., 2020; Santarnecchi et al., 2017). It has also been shown that reasoning and arithmetic tasks significantly modify microstates C and D metrics (e.g., occurrences, mean duration and coverage) compared to a RS, revealing that these cognitive microstates are arguably associated with specific cognitive abilities (Seitzman et al., 2017; Zappasodi et al., 2019; Kim et al., 2021).

Taken together, the results of these studies are in favor of an association between brain networks dynamics (investigated through dFC or microstates analyses) and executive functions, albeit with some limitations. First, the executive functions in these studies are usually assessed through only one cognitive task (for example a n-back task or Raven's matrices task). This is a limitation considering the task impurity problem (Friedman & Miyake, 2017), especially on complex tasks where multiple cognitive functions are recruited. As an executive functions model is available and has been validated by several studies (Friedman & Miyake, 2017; Karr et al., 2018; Miyake et al., 2000), one could argue that such a model could best fit the multidimensionality of executive functions. Finally, microstates analyses are well established and provide an interesting method to capture the brain networks dynamics (Michel & Koenig, 2018); however, their links with executive functions are yet to be more thoroughly investigated.

The present project aims to explore for the first time the links between spatiotemporal brain dynamics (RS EEG microstates) and executive functions. This study is based on the results of fMRI and EEG studies that support the hypothesis that neural flexibility is associated with cognitive flexibility and executive functions (Zelazo, 2006; Braun et al., 2015; Douw et al., 2016; Jia et al., 2014; Nomi et al., 2017; Seitzman et al., 2017; Uddin, 2021; Zappasodi et al., 2019). To do so, we measured participants' performance on executive functions tasks and their neural flexibility. Note that in this article, "neural flexibility" will be used to describe the spatio-temporal brain dynamics. In practice, this term will refer to microstate metrics, which have been found to be related to brain network dynamics (Britz et al., 2010; Van de Ville et al., 2010). In order to measure the participants' executive functions, they had to perform nine cognitive tasks. A confirmatory factor analysis (CFA) was then applied to extract the three executive functions factors repeatedly replicated in the literature (Friedman & Miyake, 2017; Karr et al., 2018; Miyake et al., 2000). In order to measure the participants' neural flexibility, microstate metrics were extracted from an EEG recording during a RS. We followed a two-step level clustering procedure, similar to D'Croz-Baron et al. (2019, 2020). Finally, we computed correlation analyses between microstates C and D metrics and an executive functions composite score. The choice of these specific microstates was done according to previous studies that showed associations (1) between microstates (C & D) and functional brain networks such as the executive control or the attentional networks (Britz et al., 2010; Van de Ville et al., 2010; Custo et al., 2017; Xu et al., 2020); (2) between microstates (C & D) and cognitive functions that are related to executive functions such as fluid intelligence or reasoning (Zelazo, 2006; Seitzman et al., 2017; Zappasodi et al., 2019).

Hypotheses. The present study aims to test the hypothesis that intrinsic spatio-temporal brain dynamics is a signature of executive functions. Specifically, our hypotheses postulate that:

Hypothesis 1.a. The number of occurrences of microstate C during RS correlates (non-directional) with the executive functions composite score.

Hypothesis 1.b. The mean duration of microstate C during RS correlates (non-directional) with the executive functions composite score.

Hypothesis 2.a. The number of occurrences of microstate D during RS correlates (non-directional) with the executive functions composite score.

Hypothesis 2.b. The mean duration of microstate D during RS correlates (non-directional) with the executive functions composite score.

2. Methods

We report how we determined our sample size, all data exclusions, all inclusion/exclusion criteria, whether inclusion/

exclusion criteria were established prior to data analysis, all manipulations, and all measures in the study.

2.1. Sample

2.1.1. Sample size calculation

Using the power *r* package (*pwr*, Champely et al., 2018), a power analysis was conducted to calculate the sample size for our main hypotheses. To determine the power analysis parameters, we choose to rely partially on the study conducted by Santarnecchi et al. (2017) that best fit the present statistical plan. In the former article, the authors found correlations of $r = .35$ and $r = .5$ between microstate metrics and performance in a fluid intelligence test. While fluid intelligence is not executive functions *per se*, they share up to 25% common variance (Friedman & Miyake, 2017). Hence, we choose a $r = .30$ (undirected) based on this article, corresponding to medium to large effect size (Cohen, 1992). Coupled with a power at .90 and a significance level of .02, the results gave a sample of $n = 140$.

Note that a CFA on nine executive functions tasks was performed to reproduce the results from the literature (Friedman et al., 2008; Miyake et al., 2000). The model consisted of three-factors (inhibition, shifting, updating) based on the CFA literature (Friedman & Miyake, 2017; Karr et al., 2018; Miyake et al., 2000). To determine the sample size of the CFA (Kline, 2015; Kyriazos, 2018), we used a classical rule of thumb of $N: p > 10$ ratio ($N =$ number of participants, $p =$ number of measures) and $N: q > 20$ ratio ($q =$ number of factors). Furthermore, as recommended by Kyriazos (2018), we performed a CFA power analysis. Using the *simsem* *r* package (Pornprasertmanit et al., 2020), a Monte-Carlo simulation (1000 repetitions) was computed with $N = 140$ participants based on the results and models from Friedman et al. (2008). Using a significance level of $p = .02$, the results of the simulation gave the following parameters $RMSEA = .071$, $CFI = .919$, $TLI = .879$, $SRMR = .063$. These parameters can be considered as sufficient considering the simplicity of the model (three-factors), the chosen sample size (Sharma et al., 2005), and the fact that this model has been replicated several times in healthy adult samples (Karr et al., 2018).

Therefore, 140 healthy adults (age = 18–35 years) were planned to be recruited from the Toulouse University Campus, by email, flyers and newspaper publications. The local ethic committee of Toulouse University approved the study (IRB00011835-2020-09-22-297).

2.1.2. Inclusion criteria and exclusion criteria

Inclusion criteria were: age (18–35 years); affiliation to social insurance; having read the information document about the experiment and signed the informed consent form; native French language. Exclusion criteria were: addiction (alcohol, drugs); major hearing loss; major visual deficit; including hemianopsia and color blindness; neurological or psychiatric pathology; known brain injury, drugs intake targeting the central nervous system.

2.1.3. Pilot sample

Ten participants were recruited in order prior to the stage I of the Registered Report. The goal of this pilot sample was to pre-test code robustness for RS EEG data analyses (pre-processing

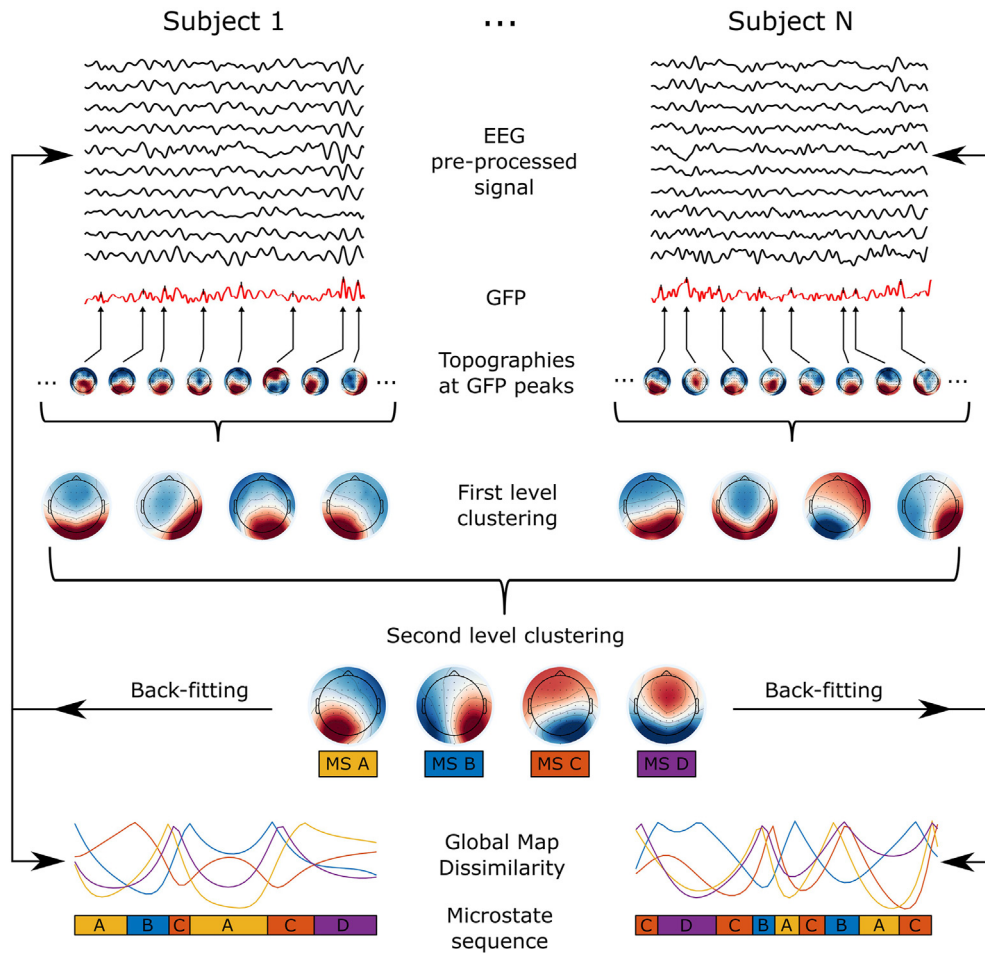


Fig. 1 – Illustration of the microstate pipeline based on pilot data. The GFP of pre-processed EEG signal for each participant is calculated (please note that only ten channels are displayed here). Topographies at GFP peaks are concatenated into one dataset. A first-level clustering is applied to this dataset, participant by participant. Then a second-level clustering is applied on the concatenated results of the first-level clusterings. A back-fitting from this second-level clustering is then performed on participant's samples. Each EEG sample is labeled with the microstate prototype with which it is most similar topographically by using the Global Map Dissimilarity measure. The final result of the pipeline is a temporal sequence of microstates from which metrics can be extracted (i.e., number of occurrences, mean duration). GFP: Global Field Power, MS: microstate.

and microstates analyses). The mean age of the sample was 23.5 (SD = 4.7) years old (8 men), all right-handed. The mean level of education was 16 (SD = 2.5) years. Note that one participant was excluded due to poor EEG signal rated as bad by Automagic (see [Methods](#)). The obtained microstates prototypes from the pilot data can be found in [Fig. 1](#). These ten participants are not part of the final sample.

2.1.4. Final sample

In total, 165 participants were recruited between February 2022 and October 2023. Twenty-five were removed due to exclusion criteria such as not being native French speakers (12), major hearing loss (2), color blindness (2), dyslexia (3), under medication (2). Four more participants were not included because of missing data (2), difficulties to understand the tasks (1) and not being able to attend the second session (1). Therefore, the final sample is constituted of 140 participants (66 women), including

13 left-handed. Mean age was 24.72 (SD = 4.37) years, and mean education level was 15.9 (SD = 1.88) years.

2.2. Experimental protocol

2.2.1. Overview

The experimental protocol included two laboratory sessions. Both lasted approximately 1 h and thirty minutes, making a total of 3 h to complete the experiment. Participants received a financial compensation of 30 euros once they completed both sessions.

2.2.2. First laboratory session

Before the laboratory session, participants received a mail containing information about the experiment. They were asked to avoid drinking coffee or smoking for 2 h before the laboratory session. They were received at the ISAE-SUPAERO

Neuroergonomics laboratory and were asked to read and sign an informed consent and other basic information about the experiment (average time to complete and description of the protocol and the tasks). The experiment took place in an experimental room with no window and with a stable temperature. The participants faced a 24"-inch screen with a keyboard and a mouse on the table.

During the preparation of the EEG acquisition, participants answered a demographic questionnaire and were briefed about the first session which included a 5-min RS (see below for a more detailed description), thirty minutes of video game playing, and a second 5-min RS. Note that this Registered Report is a part of a larger study, which will investigate the links between executive functions, a video game (Space Fortress, Mané & Donchin, 1989) and microstates. For the sake of efficiency, we only describe the methods used in this Registered Report. The full project and methods can be found in OSF (<https://osf.io/fm58p/>).

2.2.3. Second laboratory session

The participants came back to the laboratory (same experimental room) for a second session in the week following the first session. During this second session, participants performed the cognitive tasks, which consisted of approximately three 30-min runs made of three cognitive tasks each. Based on the works of Friedman et al. (2008), the order of task administration was fixed as follow: *antisaccade*, *letter-memory*, *color–shape*, 5-min break, *number–letter*, *Stroop*, *keep track*, 5-min break, *dual 2-back*, *category switch*, *stop-signal*. Stimuli within the tasks were randomized. The Inquisit software (<https://www.millisecond.com/>) was used to run the tasks and to gather the data.

2.3. Tasks and behavioral measures

2.3.1. Resting-state

Spontaneous brain activity was recorded during a RS. Participants were asked to “relax, refrain from moving, and let your mind wander while staying awake”. The task alternated between 30 sec of eyes open and 30 sec of eyes closed, five times each. An auditory cue was used to announce the switching between eyes open and eyes closed. The alternating order of eyes closed and eyes open blocks is intended to avoid fatigue and maintain vigilance (Langer et al., 2012).

2.3.2. Demographic questionnaire

A questionnaire was given to the participants to gather demographics (i.e., age, gender, education level, handedness, native language).

2.3.3. Executive functions tasks

Participants performed nine cognitive tasks measuring the three main executive functions, namely the inhibition, updating and shifting. The nine tasks have been chosen based on the article of Friedman et al. (2008) in order to perform a similar analysis (three-factors CFA). Note that all the tasks codes come from the millisecond test library (<https://www.millisecond.com/download/library/>) and were run through the Inquisit software. The tasks have been translated in French for the purposes of this experiment and the modified code files are available on <https://osf.io/v2xpy>.

2.3.3.1. **ANTISACCADE (INHIBITION TASK)**. During this task, the participant must focus on a fixation cross in the center of the screen. A yellow square flashes (i.e., a visual cue) on either the right or the left side of the cross. After the flash, an arrow appears on the opposite side of the flash, pointing either left, right or up. The participant must respond to which direction the arrow is pointing through the arrow keys on the keyboard. Note that we did not measure saccades with an eye-tracker. The dependent variable on this task is the proportion of correct responses.

2.3.3.2. **STOP SIGNAL (INHIBITION TASK)**. In this task, the participant must focus on a fixation cross in the center of the screen. Then, an arrow appears pointing either left or right. The participant has to press the corresponding arrow key. However, in some of the trials, the participant hears an auditory signal which indicates that she/he has to inhibit her/his response. This task is extracted from Verbruggen et al. (2019) and default parameters were used. The dependent variable on this task was the stop signal RT (response time).

2.3.3.3. **STROOP (INHIBITION TASK)**. In this task, the participant saw colored stimuli (figures and words). Their goal is to indicate the color of the stimuli. This test is adapted for computers, and keyboard keys are associated with colors (Scarpina & Tagini, 2017). There were congruent (e.g., the word RED written in red) and incongruent (e.g., the word RED written in blue) trials. The dependent variable on this task was the RT difference between congruent and incongruent trials.

2.3.3.4. **KEEP TRACK (UPDATING TASK)**. During this task, the participant must memorize and update words that are specific to certain categories (amongst six in total). The words are presented one by one in the center of the screen. The trials on this task include to keep-track of three to four words simultaneously and are randomized. The dependent variable was the proportion of correctly recalled words.

2.3.3.5. **LETTER MEMORY (UPDATING TASK)**. In this task, the participant views a series of letters that appear one at a time at the center of the screen. Their goal is to memorize the four last letters. This task is modified from Friedman et al. (2008) in which participants have only to memorize the three last letters. This modification choice was done according to a pilot study that revealed a ceiling effect with only three letters to memorize. The dependent variable was the proportion of correctly recalled letters.

2.3.3.6. **DUAL N-BACK (UPDATING TASK)**. In this task, the participant needs to follow a sequence of stimuli in two modalities at the same time (visual and auditory). The *n*-value was set to two (i.e., 2-back task). The participant must determine whether the position of the square in a 3 × 3 grid was the same as the one observed two trials before (visual); and simultaneously determine whether the heard letter is the same as the one presented two trials before (auditory). Note that this is the only task that differs from Friedman et al. (2008) study in which they choose a spatial n-back. The reason is that the spatial n-back is not available on millisecond test library, and

the dual n-back is the closest that we found in this library. The dual n-back task from the present study comes from Jaeggi et al. (2010) and we used identical parameters with only the 2-back. The dependent variable was the proportion of correct responses (yes and no).

2.3.3.7. NUMBER LETTER (SWITCHING TASK). During this task, the participant sees a 2×2 matrix on the computer screen. A pair of characters (ex: '7C') is presented and the participants have to respond either on the letter (consonant vs vowel) or the digit (odd vs even) depending on the position of the characters in the matrix that will randomly change. The dependent variable was the difference of RT between switching trials and non-switching trials.

2.3.3.8. COLOR SHAPE (SWITCHING TASK). In this task, red or green circles or triangles are presented to the participant. The goal is to respond to the type of stimuli depending on the cue (S for Shape vs C for Color). The trials were randomized and the dependent variable on this task was the difference of RT between switching trials and non-switching trials.

2.3.3.9. CATEGORY SWITCH (SWITCHING TASK). During this task, the participants are asked to categorize a word in terms of (a) living criterion (living vs non-living) or (b) size criterion (smaller vs larger than a basketball). A cue determined which categorization needs to be performed, with a heart associated to the living criterion, and a cross associated to the size criterion. The trials were randomized and the dependent variable on this task was the difference of RT between switching trials and non-switching trials.

2.4. Neurophysiological measures

EEG raw data were recorded during the laboratory session with a Biosemi Active-two amplifier. Sixty-four pre-amplified gel electrodes were positioned on a head cap according to the 10–20 system. We selected an appropriate cap size depending on the head circumference of each participant. The sampling rate was 512 Hz and the total duration of the RS acquisition lasted 5 min. All data were recorded using the lab streaming layer (<https://github.com/sccn/labstreaminglayer>) with the dedicated Biosemi LSL application, and were saved in XDF format following the Brain Imaging Data structure (BIDS, Pernet et al., 2019) with LabRecorder (LSL library version: 113).

2.5. Analyses

2.5.1. Executive functions

2.5.1.1. TRANSFORMATIONS AND OUTLIER ANALYSES. The distribution of the dependent variables (RTs and proportion of correct responses) for the nine executive functions tasks were transformed to achieve normality following a procedure based on Friedman et al. (2008). Concerning the RT scores, only values > 200 msec on correct trials were included (the mean percentage of excluded trials is available in supplementary material). To obtain the best measure of central tendency for RT scores, we applied a within-subject trimming procedure that is robust to non-normality (Wilcox & Keselman, 2003): for each participant, observations that

deviated from the median by more than 3.32 times the median absolute deviation were excluded. All accuracy data were arcsine transformed to improve normality. To reduce the influence of extreme scores and improve normality, observations larger than 3 standard deviations (SD) from the group mean were replaced with a fixed value of 3 SD. Skewness and kurtosis for each variable 1.

2.5.1.2. CONFIRMATORY FACTORIAL ANALYSIS. The CFA was performed using the *lavaan* R package (Rosseel et al., 2017) and was computed on the z-scored values following the three-factors model from Friedman et al. (2008). To measure model adjustment, the RMSEA, CFI, TLI and SRMR are reported (Kyriazos, 2018).

2.5.1.3. EXECUTIVE FUNCTIONS COMPOSITE SCORE. Finally, an executive functions composite score was calculated for each participant by averaging their z-scores on the nine executive functions tasks.

2.5.2. EEG data pre-processing

All raw and processed data as well as the code to analyze are freely available in a standardized structure (BIDS, Pernet et al., 2019) on <https://osf.io/v2xpy>. Using our own script developed in Matlab (ver. R2020b) from EEGLab functions (Delorme & Makeig, 2004), raw XDF data were imported in Matlab. EEG Data from the entire first RS was selected and pre-processed with the Automagic toolbox (ver. 2.4.3) for MATLAB (Pedroni et al., 2019). This toolbox allowed for automated and standardized pre-processing and quality assessment without any subjective decisions.

2.5.2.1. EEG REFERENCING. A Cz offline referencing was performed before pre-processing in order to improve signal-to-noise ratio, as recommended by Biosemi (<https://www.biosemi.com/faq/cms&drl.htm>).

2.5.2.2. EEG BAD CHANNEL REMOVAL. EEG data were copied and submitted to algorithms whose purpose is to detect bad channels (Pedroni et al., 2019). In these copied EEG data, bad electrodes were identified using EEGLab plugin *clean_rawdata* (http://sccn.ucsd.edu/wiki/Plugin_list_process). This plugin uses three algorithms to detect and removes flatline, low-frequency, and noisy channels. A channel was defined as a bad electrode when recorded data from that electrode correlated at less than .85 to an estimate based on other channels (channel criterion). Furthermore, a channel was defined as a bad channel if it has more line noise relative to its signal compared to all other channels (4 standard deviations). A high-pass filter (.25–.75) was performed to remove channel drift.

2.5.2.3. EEG FILTERING. Data were high-pass filtered (1 Hz) using the *pop_eegfiltnew* EEGLab function. A notch-filter (50 Hz) was also applied to remove European AC line noise.

2.5.2.4. ARTIFACT REMOVAL. Artifact removal was done using EEGLab's *runICA* function. Independent component labels (Pion-Tonachini et al., 2019) was used to classify the components. Components that are classified as muscle, eye, heart,

line noise and channel noise with at least 80 percent confidence were excluded.

2.5.2.5. BAD CHANNEL INTERPOLATION. All channels detected as bad ones were interpolated using the *eeg_interp* EEGLAB function with the spherical interpolation method.

2.5.3. EEG microstates data analysis

Because the eyes closed condition is generally considered most reliable for microstate and functional connectivity analyses (Lehmann et al., 2005; D’Croz-Baron et al., 2019), microstate analyses (Fig. 1) was performed on the pre-processed eyes closed RS data that was concatenated (5×30 sec). Analyses were performed using functions from the Microstates (MST) toolbox (Poulsen et al., 2018) adapted using our own Matlab script. The present study performed a two-level clustering approach, similar to D’Croz-Baron et al. (2019).

2.5.3.1. MICROSTATES PRE-PROCESSING. Additional pre-processing steps were performed on the data before EEG microstates analysis to be in line with previous works (Michel & Koenig, 2018). A band-pass filter (2–20 Hz) was applied and data were re-referenced using the averaged signal from the 64 electrodes. Data were segmented in epochs of 2 sec. Data segments exceeding a certain amplitude threshold ($> 90 \mu\text{V}$) were discarded. If one participant had less than 20 sec left of pre-processed eyes closed EEG data, the whole participant’s data was excluded. After this pre-processing, the mean duration of the EEG pre-processed signal was 148 (SD = 4.2) seconds (see distribution in the Figure in Supplementary material).

2.5.3.2. GLOBAL FIELD POWER. First, the Global Field Power (GFP) was calculated at each timepoint of each participant’s EEG recording. GFP can be defined as the standard deviation of each sample of the EEG signal (across all electrodes) and is thought to reflect the timepoints of stable network activity (Michel & Koenig, 2018). Individual GFP peaks datasets were created, containing all concatenated GFPs peaks within one standard deviation of all GFP samples, with a minimal distance of 10 msec between GFP peaks. These additional selection criteria were used to remove potential GFP peaks induced by remaining artifacts.

2.5.3.3. FIRST LEVEL CLUSTERING. The first level clustering was performed on each individual GFP peaks dataset. A Modified k-means clustering algorithm (polarity invariant) was applied to extract the microstate prototypes of each participant. The algorithm parameters were $k = 4$, 100 repetitions with a maximum of 1000 iterations. Note that the number of four prototypes was chosen according to the literature that repetitively found that four microstates explain a large proportion of variance in the data (Michel & Koenig, 2018). The results of this first level clustering are participant-level prototypes maps that have no particular order, may vary in polarity, be different across participants and would therefore be difficult to compare.

2.5.3.4. SECOND LEVEL CLUSTERING. To account for this limit, a second level clustering was performed at the group level. A modified k-means clustering algorithm (polarity invariant) was applied on a dataset that contains the results of the first level clustering (all four prototypes of each individual participant). The algorithm parameters were $k = 4$, 1000 repetitions with a maximum of 1000 iterations.

2.5.3.5. BACK-FITTING. Finally, a back-fitting of the four group-level microstate prototypes was performed on the individual continuous eyes closed RS EEG data. During this step, each EEG sample was labeled according to the microstate that is the least topographically dissimilar. This was done using the polarity invariant Global Map Dissimilarity (GMD) measure (Poulsen et al., 2018). After the initial labeling, some very short microstate segments might exist due to unstable topographies. Therefore, a temporal smoothing with a minimum-duration criterion of 30 msec was applied. The smoothing algorithm repeatedly scan through the microstate segments and changed the label of time frames in these small segments to the next most likely microstate class, as measured by GMD. This was done until no microstate segment was shorter than the 30 msec threshold Poulsen et al. (2018).

2.5.3.6. MICROSTATE METRICS. The result of the microstate pipeline consisted of a sequence of microstates during the eyes closed RS EEG signal for each participant. From this sequence, four metrics were computed (for details, see Poulsen et al., 2018): microstate mean duration, microstate occurrence, microstate coverage, global explained variance (GEV). The microstate mean duration represents the average duration of a given microstate class, calculated in milliseconds. The microstate occurrence represents the average number of times per second a microstate is dominant. The microstate coverage represents the fraction of time a given microstate is active in the whole signal. The GEV represents to what extent a given microstate can explain the data. The complete pipeline code is available on <https://osf.io/v2xpy>.

2.5.4. Statistical analysis plan

2.5.4.1. HYPOTHESIS. Our main hypothesis postulated that cognitive microstate metrics are associated with executive functions. Therefore, this hypothesis was tested by doing the following statistical analyses:

Hypothesis 1.a. A Bravais–Pearson correlation between the number of occurrences of microstate C during RS and executive functions composite score.

Hypothesis 1.b. A Bravais–Pearson correlation between the mean duration during of microstate C RS and executive functions composite score.

Hypothesis 2.a. A Bravais–Pearson correlation between the number of occurrences of microstate D during RS and executive functions composite score.

Table 1 – Distribution of scores in executive functions tasks.

Task	Mean ^a	SD ^a	Skewness ^b	Kurtosis ^b
Antisaccade	460 msec	64 msec	–1.05	.88
Stop signal	203 msec	38 msec	–.43	.85
Stroop	100 msec	86 msec	–.55	.02
Dual N-back	88.0%	7.2%	–.17	.87
Letter-memory	72.3%	20.0%	.13	–.14
Keep-track	80.6%	11.1%	.58	.34
Category-switch	190 msec	113 msec	–.47	.14
Color-shape	127 msec	111 msec	–1.20	1.13
Number-letter	401 msec	242 msec	–1.33	1.85

^a Mean and SD have been calculated on individual preprocessed data.

^b Skewness and Kurtosis have been calculated on z-scores. SD: standard deviation; Bold: deviation from normal distribution.

Hypothesis 2.b. A Bravais–Pearson correlation between the mean duration of microstate D during RS and executive functions composite score.

2.5.4.2. **MULTIPLE COMPARISONS CORRECTION.** To account for multiple comparisons, a Holm–Bonferroni correction was applied on p-values of the different statistical analyses (four p-value in total).

2.5.5. Data removal and missing data

Participants that met any of the following conditions were removed from the final analyses: participant in the exclusion criteria; experiment not completed; missing data (behavioral or neurophysiological); insufficient EEG data quality assessed by Automagic and qualified as “bad” (Pedroni et al., 2019).

3. Results

3.1. Behavioral analyses

3.1.1. Score distribution on executive functions tasks and executive functions composite score

The executive functions tasks score distribution can be found in Table 1 and in Supplementary Fig. 1. Considering a typical threshold of 1 for Skewness, only the Antisaccade, Color-Shape and Number-Letter tasks exhibited a right skewed distribution. Considering a Kurtosis threshold of 2, all score distributions were considered to represent a normal distribution.

The distribution of the executive functions composite score (mean of the nine z-scored executive functions task scores) was normal ($p = .75$, Kolmogorov–Smirnov Test), with excellent Skewness (–.27) and Kurtosis (.09).

3.1.2. Confirmatory factorial analysis on executive functions tasks

The confirmatory factor analysis (CFA) was performed on 140 participants. Using the three factors model of Friedman and Miyake (2017), we were unable to compute the CFA due to latent variables not being positive definite, suggesting that the theoretical structure of the model is not supported by our

data. From the correlation matrix, we can assume that the inhibition factor cannot be correctly extracted due to the low correlation between the inhibition tasks. This assumption is further validated because of incoherent correlations between the inhibition factor and other factors (see Supplementary Material). As a complementary explanation, we decided to compute a nested-factors and a one-factor models, which are presented in the Exploratory Analyses section.

3.2. Microstate analyses

3.2.1. Microstate metrics distribution

Four metrics were calculated for each of the four prototypical microstates: Global Explained Variance (GEV), occurrences, mean duration, and coverage. In the sample, the GEV ranged from 8 to 23%, with a total mean GEV of 74%, meaning that the four microstate prototypes explained 74% of the signal variance during the eyes-closed RS. The mean number of occurrences per second across the four microstates was relatively consistent, with means between 2.45 and 3.46 per second (Hz). Mean duration of active microstates varied from 77 to 99 msec. Finally, mean coverage of individual microstates ranged from 18 to 34% of the overall data. Details of descriptive results can be found in Table 2.

3.2.2. Microstate metrics and executive functions (main hypotheses)

Hypothesis 1.a. The correlation analysis between the number of occurrences of microstate C during RS and the executive functions composite score revealed a non-significant correlation ($r = -.096$, 95% CI [–.257, .072], $R^2 = .009$, $pcorr = .84$).

Hypothesis 1.b. The mean duration of microstate C during RS was found to have a non-significant correlation with the executive functions composite score ($r = .081$, 95% CI [–.086, .244], $R^2 = .007$, $pcorr = .84$).

Hypothesis 2.a. The correlation between the number of occurrences of microstate D during RS and the executive functions composite score was found to be negative, but not significant ($r = -.177$, 95% CI [–.332, –.010], $R^2 = .031$, $pcorr = .15$).

Hypothesis 2.b. The mean duration of microstate D during RS showed a non-significant correlation with the executive functions composite score ($r = .055$, 95% CI [–.126, .205], $R^2 = .003$, $pcorr = .84$).

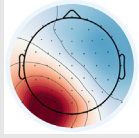
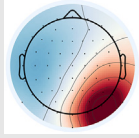
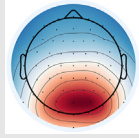
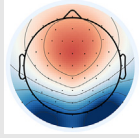
The corresponding graphical representation of these correlations can be found in Fig. 2.

3.3. Exploratory analyses

3.3.1. One-factor and nested-factors executive functions models

We computed a CFA model with the nine tasks contributing to one factor (executive functions latent score), with the lavaan package (Rosseel et al., 2017). Results from this CFA indicated

Table 2 – Microstate metrics (mean \pm SD [range]).

Metric	Microstate A	Microstate B	Microstate C	Microstate D
Topography				
GEV (%)	8 \pm 4 [1–24]	9 \pm 4 [2–27]	19 \pm 8 [1–51]	23 \pm 9 [7–49]
Occurrences (Hz)	2.47 \pm .64 [.74–3.82]	2.45 \pm .60 [.92–3.70]	3.27 \pm .64 [.92–4.48]	3.46 \pm .52 [2.29–4.67]
Mean duration (msec)	73.65 \pm 12.21 [54.98–127.27]	74.58 \pm 12.13 [54.61–137.17]	89.42 \pm 18.77 [61.88–168.42]	99.07 \pm 29.01 [66.31–210.43]
Coverage (%)	18 \pm 6 [4–37]	18 \pm 6 [6–42]	29 \pm 9 [6–57]	34 \pm 9 [15–63]

an acceptable fit for the model to the data. The chi-square test of the model fit was not significant, $\chi^2(27) = 33.904$, $p = .169$, suggesting that the model did not deviate significantly from the observed data. The Comparative Fit Index (CFI) and the Tucker–Lewis Index (TLI) were .916 and .888, respectively, both approaching the commonly recommended threshold of .9 for good fit. The Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) were .043 and .065 respectively, both being inferior to the

recommended maximum threshold of .08, indicating a good fit. Factor Loadings on this model can be found in Fig. 3. The nested-factors model can be found in supplementary material.

3.3.2. Correlation between executive functions composite score and executive functions latent score

Because the executive functions composite score (mean z-score of all the nine cognitive tasks) may be a limiting way to measure executive functions, we decided to compare it with

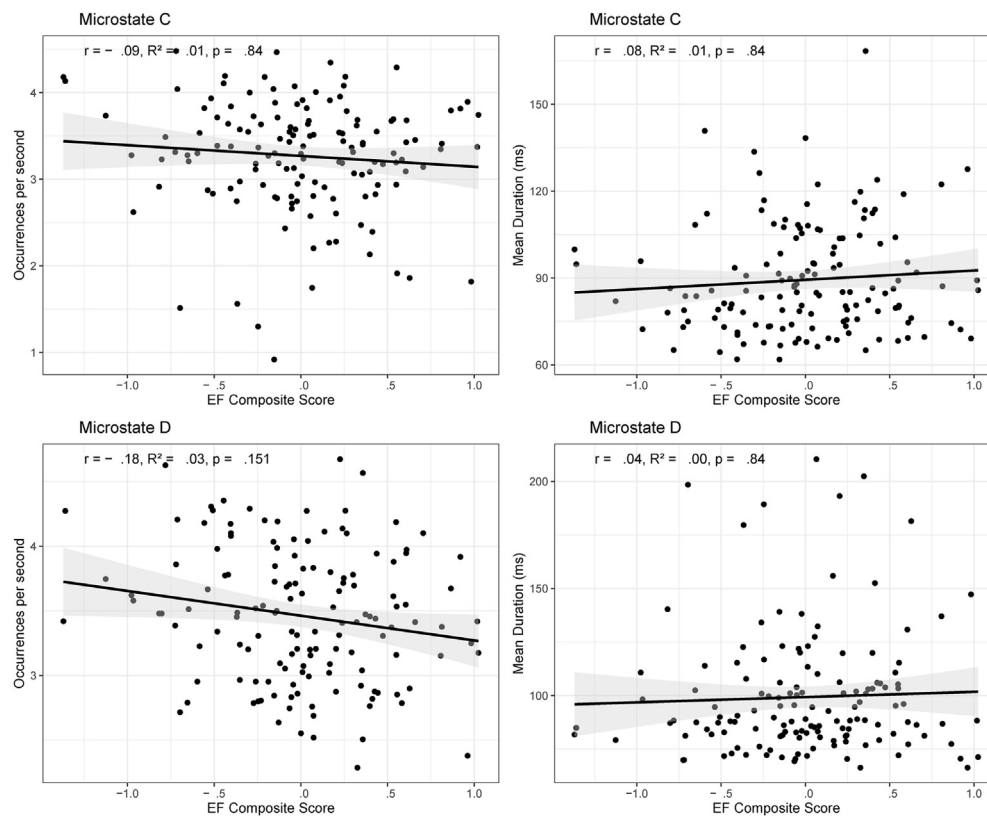


Fig. 2 – Correlations of microstates C and D with the executive functions composite score. The Holm–Bonferroni correction is applied on p -values. The lines represent the linear fit, and the gray shades the standard error. EF: Executive Functions

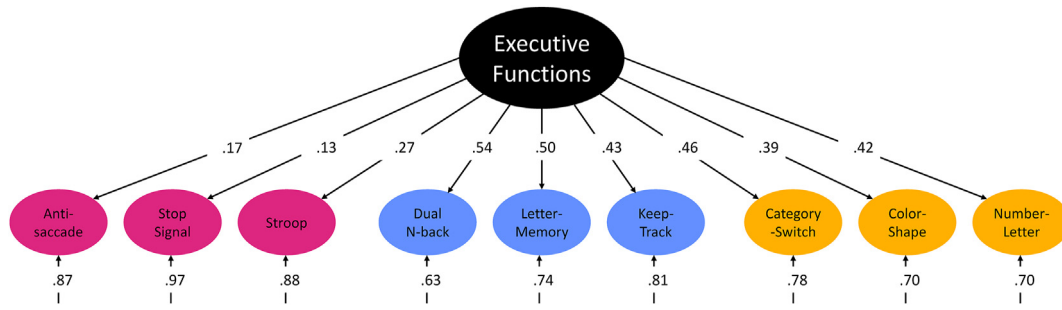


Fig. 3 – Factor Loadings for the one-factor model. Numbers on arrows are standardized factor loadings (middle) and residual variances (below). Inhibition, updating and shifting tasks are represented in pink, blue and yellow respectively. The executive functions factor is in black.

Table 3 – Demographic predictors of the executive functions composite score. Bold: $p < .02$

Predictor	Beta	CI (95%)	t	Partial R^2	p
β_1 age	-.04	[-.06, -.03]	-4.89	.151	<.001
β_2 education	.06	[.02, .10]	2.96	.061	.003
β_3 handedness	.08	[-.17, .33]	.63	.003	.53
β_4 gender	-.14	[-.29, .003]	-1.92	.027	.054

Table 4 – Predictors of the executive functions composite score. MS: microstate; Bold: $p < .02$

Predictor	Beta	CI (95%)	t	Partial R^2	p
β_1 age	-.05	[-.06, -.03]	-5.36	.177	<.001
β_2 education	.06	[.01, .10]	2.66	.051	.008
β_3 MS C duration	-.001	[-.007, .005]	-.40	.001	.688
β_4 MS C occurrences	-.004	[-.23, .23]	-.003	.000	.997
β_5 MS D duration	-.001	[-.005, .003]	-.35	.001	.727
β_6 MS D occurrences	-.21	[-.46, .04]	-1.65	.020	.098

the latent score obtained from the CFA (one-factor model). The executive functions latent score was calculated for each participant using *lavPredict* function Rosseel et al. (2017). It showed a strong and significant positive correlation with the executive functions composite score ($r = .957$, $p < .001$).

3.3.3. Demographics variables contributing to executive functions composite score

To measure the impact of demographics variables, a General Linear Model (GLM, estimated using Maximum Likelihood) was conducted to predict executive functions composite score as follows:

$$EF = \beta_0 + \beta_1(\text{Age}) + \beta_2(\text{Education}) + \beta_3(\text{Handedness}) + \beta_4(\text{Gender}) + \epsilon$$

The model's explanatory power was moderate ($R^2 = .20$). Age and education appear to be the only significant predictors of the executive functions composite score, showing a negative association with age (partial $R^2 = .151$), and a positive association with education (partial $R^2 = .061$). Complete results of this model can be found in Table 3.

3.3.4. Microstates analysis: GLM with covariates

Based on our previous analyses, we identified age and education as important factors influencing the executive functions composite score. Furthermore, our initial analyses to test our hypotheses were based on Bravais–Pearson correlations and did not consider potential interactions among the microstate metrics. To address this limitation and gain a more comprehensive understanding of these relationships, we conducted a follow-up analysis using a General Linear Model (GLM). This GLM included both the microstate metrics from our hypotheses, the age and education level as covariates to

predict the executive functions composite score. The GLM equation is presented below:

$$EF = \beta_0 + \beta_1(\text{Age}) + \beta_2(\text{Education}) + \beta_3(\text{MSC}_d) + \beta_4(\text{MSC}_o) + \beta_5(\text{MSD}_d) + \beta_6(\text{MSD}_o) + \epsilon$$

The model's explanatory power was moderate ($R^2 = .21$). Age and education appear to be the only significant predictors of the executive functions composite score, showing a negative association with age (partial $R^2 = .18$), and a positive association with Education (partial $R^2 = .05$). Complete results of this model can be found in Table 4.

3.3.5. Correlations between executive functions composite score and other microstate metrics

Exploratory correlation analyses were conducted between the executive functions composite score and mean duration, occurrences or coverage of all four microstates. All correlations were non significant and are reported in supplementary material.

4. Discussion

4.1. Summary of findings

In this Registered Report, we sought to investigate the relationship between intrinsic brain activity and cognitive functions. Precisely, we used the EEG microstates method to test the hypothesis of a relationship between brain spatio-temporal dynamics at rest and executive functions.

Based on previous studies, we choose the executive functions tasks from the Miyake & Friedman's model (Friedman & Miyake, 2017). We were not able to reproduce their three-

factors executive functions model (inhibition, switching and updating), although we showed in an exploratory section that a composite score in these tasks highly correlates with loadings on a one factor executive functions model. Initially, we postulated that this composite score would correlate with RS EEG microstates C and D metrics (mean duration and occurrences). Our results do not support these hypotheses. Considering the relatively large sample size, we can conclude that the microstates C and D metrics are not a reliable signature of executive functions, at least in the way these functions have been evaluated in this study. It is however pertinent to highlight that, albeit not reaching statistical significance, there was a negative correlation between the microstate D occurrences and the executive functions composite score ($r = -.18$, $p = .15$, 3% of explained variance). To gain deeper insight into the relationship between microstate metrics and executive functions, we conducted exploratory analyses taking the form of a GLM. This analysis focused on predicting this composite score with several RS microstate metrics (microstate C and D occurrences and mean duration) measured prior to the tasks, as well as demographics (age and education). Again, this analysis revealed that none of the RS microstate metrics are significant predictors of the executive functions composite score.

In this discussion, we will first focus on the results of the confirmatory factorial analyses for the executive functions models. Then we will discuss and compare the studies that have investigated the relationships between microstate metrics and executive functions, and put them into perspective with our results. Finally, we will conclude on the strength and limitations of this Registered Report, and on future directions.

4.2. Three-factors versus nested-factors versus one-factor executive functions model

Our attempt to reproduce the three-factors executive functions model, namely inhibition, shifting and updating, was unsuccessful. This contrasts with the framework proposed by Friedman and Miyake (2017), and may be attributed to (1) methodological differences, (2) small correlations among inhibition tasks that could have prevented the extraction of the inhibition-specific factor and (3) sample characteristics.

First, this study cannot be considered as a replication of the (Friedman & Miyake, 2017) model *per se*. Indeed, there are some differences in the number of trials and blocks per task, as well as a French translation. Furthermore, for the inhibition tasks, our adaptation of the Stroop task involved a keyboard response format instead of providing vocal responses (Fennell & Ratcliff, 2019). Additionally, our version of the Stop-Signal (Verbruggen et al., 2019) included arrows and auditory tones instead of animals or non-animals and auditory tones as used in Friedman et al. (2008). In this task, some participants also reported an inclination to await auditory tones during trials of the Stop-Signal task, despite explicit instructions advising against such behavior. Indeed, this waiting behavior is likely to involve other cognitive processes among these participants. Taken together, the aforementioned methodological and behavioral differences with Miyake & Friedman work might have led to different scoring for the inhibition tasks performance.

Consequently, these differences may have contributed to small correlations between inhibition tasks, which could explain the difficulties to obtain a latent inhibition factor. It is however worth noting that Friedman and Miyake (2017) have also encountered difficulty in extracting this inhibition-specific factor in some of their samples, which led them to propose a nested-factor model to capture both unity (common executive functions factor that predicts all nine tasks) and diversity with shifting and updating-specific factors (Friedman & Miyake, 2017). To shed light on the unique position of inhibition in the Executive Functions framework, two competing interpretations have been proposed: either inhibition is central for all Executive Functions (Valian, 2015), or there is nothing special about inhibition (Banich & Depue, 2015; Munakata et al., 2011, see Friedman & Miyake, 2017 for a discussion on this topic). In exploratory analyses, we also tested this bifactor model, but underwent the same difficulties as in the three-factors model and were unable to reproduce it (see supplementary material).

Finally, a recent systematic review on executive functions models has shown that executive functions models (*e.g.*, one-factor, nested-factors, three-factors, etc.) do not consistently converge and meet fit criteria across diverse samples, especially when considering different ages (Karr et al., 2018). In their review, the authors draw the conclusion that unidimensionality models of executive functions may be a better fit among child/adolescents' samples while multidimensionality may be more appropriate in adult samples. Our study was composed of 140 young adults (mean age of 24.7 years) with relatively high education level (mean of 15.9 years), which could also constitute an explanation as to why we were unable to fit the three-factors or the nested-factors models.

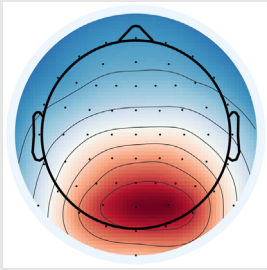
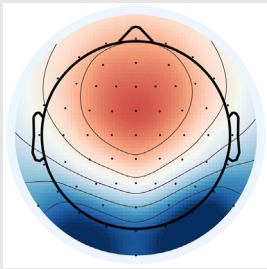
However, our data successfully supported a unidimensional model (one-factor). In this model, the tasks that seem to contribute most to this one factor are first updating tasks (mean factor loading = .49), then shifting tasks (mean factor loading = .42), and finally inhibition tasks (mean factor loading = .19). Furthermore, we showed that the individual loadings on this one-factor highly correlated with the composite score (mean of all nine tasks), hence validating the use of this metric in our initial hypotheses.

4.3. Microstate metrics and executive functions

4.3.1. Microstate C (hypothesis 1)

To date, few studies have examined the relationship between microstate C metrics at rest and executive functions as measured by performance in cognitive tasks (Table 5). Most pertinent among these is the study of Santarnecchi et al. (2017), which served as a reference for calculating our sample size. In this study, they found a notable negative correlation between microstate C occurrences and Gf-1 (fluid intelligence component). Similarly, Liu et al. (2020) found a significant negative correlation between microstate C mean duration and the raw scores on the same fluid intelligence task. Because fluid intelligence and executive functions seem to be closely related (Friedman & Miyake, 2017; Roca et al., 2010; Santarnecchi et al., 2021), we hypothesized that microstate C metrics might correlate with executive functions.

Table 5 – Summary of study results, including our own, investigating the correlations between RS microstates C or D metrics and cognitive tasks or questionnaires.

Microstate	Metric	Behavioral metric	N	r	p	R ² (%)	Reference
	MD	Fluid intelligence C1 ^a	68	−.089	.349	.7	Santarnecchi et al. (2017)
		Fluid intelligence C2 ^a	68	.036	.705	.1	Santarnecchi et al. (2017)
		RAPM score	54	−.32	.018	10.2	Liu et al. (2020)
		VSMT performance	36	.326	.052	10.6	Penalver-Andres et al. (2022)
		Executive functions score	140	.081	.79	.7	Present study
		Occ	Fluid intelligence C1 ^a	68	−.503	.002	25.3
		Fluid intelligence C2 ^a	68	−.132	.136	1.7	Santarnecchi et al. (2017)
		VSMT performance	36	.372	.026	13.8	Penalver-Andres et al. (2022)
	MD	Fluid intelligence C1 ^a	68	.189	.046	3.5	Santarnecchi et al. (2017)
		Fluid intelligence C2 ^a	68	.033	.726	.1	Santarnecchi et al. (2017)
		VSMT performance	36	−.277	.102	7.7	Penalver-Andres et al. (2022)
		Executive functions score	140	.040	.79	.2	Present study
	Occ	Fluid intelligence C1 ^a	68	.126	.186	1.5	Santarnecchi et al. (2017)
		Fluid intelligence C2 ^a	68	−.114	.232	1.3	Santarnecchi et al. (2017)
		VSMT performance	36	−.146	.396	2.1	Penalver-Andres et al. (2022)
		Cognitive flexibility score	203	−.361	.001	13.0	Du et al. (2022)
	Executive functions score	140	−.177	.151	3.1	Present study	

^a Components 1 and 2 were calculated with a Principal Component Analysis on the results of the Raven's Advanced Progressive Matrices (RAPM), Sandia Matrices and Bomat. VSMT: Visual Surfing Motor task. MD: Mean Duration. Occ: Occurrences. Bold: $p < .02$.

Contrary to our expectations, our results did not support this hypothesis as we observed no significant correlation, either for mean duration or occurrences metrics. The observed discrepancy in our findings compared to these studies is likely to arise from differences between fluid intelligence tasks (Raven's matrices, Sandia matrices, Bomat; Matzen et al., 2010; Hossiep et al., 1999) and executive functions tasks. In the Santarnecchi et al. (2017) study, they used Principal Component Analysis to extract two fluid intelligence components respectively indexing, according to them, executive functions (Gf-1) and activity in the visual system (Gf-2). One interpretation could be that the fluid intelligence component (Gf-1) extracted in their study is fundamentally independent of how the executive functions were measured in our study.

However, some of their results are in line with our own. It is important here to distinguish between the two metrics, which are mean duration and occurrences. Santarnecchi et al. (2017) observed a significant negative correlation for microstate C occurrences and Gf-1, yet no such correlation was reported for

microstate C mean duration. In contrast, Liu et al. (2020) found a significant negative correlation for microstate C mean duration and did not provide correlation data for microstate C occurrences. Consequently, although both studies appear methodologically similar, they reveal contradictory results, suggesting that the association between RS EEG microstate C metrics and fluid intelligence remains ambiguous.

Another study worth mentioning (Penalver-Andres et al., 2022) found significant or near significant – albeit positive – correlations between both metrics and the performance in a complex motor task, in contrast to previous studies. However, the task used in this case (Visual Surfing Motor Task) may be vastly different from fluid intelligence or executive functions tasks.

Collectively, findings across these studies, including our own, underscore the inconsistencies in the relationship between microstate C metrics at rest and cognitive task performance (see Table 5). As a complementary explanation, one should acknowledge that these contradictory results may also be attributable to small sample sizes in these studies. It has

indeed been shown that such sample size may induce false positives (Button et al., 2013) and simulations have shown that correlations tends to stabilize around 160 subjects (see Schönbrodt & Perugini, 2013). In conclusion, given the early stage of research and the current ambiguity of evidence, it seems premature to speculate on the underlying physiological mechanisms that may connect RS EEG microstate C metrics with executive functions.

4.3.2. Microstate D (hypothesis 2)

Based on previous reviews (Michel & Koenig, 2018) that suggested that microstate D is related to the fronto-parietal network activity, and that flexibility within this network is associated with cognitive flexibility (Zelazo, 2006; Braun et al., 2015; Douw et al., 2016; Jia et al., 2014; Nomi et al., 2017; Seitzman et al., 2017; Uddin, 2021; Zappasodi et al., 2019), we hypothesized that RS EEG microstate D metrics would correlate with executive functions. Here again, our data do not support our hypotheses. Our empirical findings revealed no statistically significant correlations between the mean duration or occurrences of this microstate at rest and the executive functioning composite score. Although not significant, a minor negative correlation for the occurrences is worth mentioning since it is in line with a recent study by Du et al. (2022). In this study, they measured executive functions with the Cognitive Flexibility Inventory (Dennis & Vander Wal, 2010) in a large cohort ($N = 200$) and showed a significant negative correlation between the results in this questionnaire and the microstate D occurrences at rest. While their correlation is interesting because of their large sample size, one should note that the behavioral score is not a performance in an executive function task, but a subjective evaluation of cognitive flexibility with a questionnaire. Santarnecchi et al. (2017) and Penalver-Andres et al. (2022) works, mentioned earlier, also revealed a negative but non-significant correlation between occurrences of this microstate at rest and task performance, within the range of what we report here.

The small effect sizes (1–3% of explained variance) reported in these studies, including ours, would be consistent with existing neuroimaging literature investigating the relationships between RS brain activity and cognitive functions. Indeed, a recent study conducted by Marek et al. (2022) underlined that Brain Wide Associations Studies (BWAS) using fMRI, typically necessitate large samples (over 1000 participants) because these relationships have small effect sizes, ranging from 1 to 5% of explained variance.

On another note, a recent systematic review on the functional significance of EEG microstates concluded that the microstate D is likely to be associated with executive functions, including working memory and attention (Tarailis et al., 2023). However, the studies cited in this review differ methodologically from ours because they used a different type of protocol. Indeed, it is important to distinguish between (1) protocols that assess cognitive recruitment by means of direct comparisons such as those in this review that use contrasts (RS brain activity vs task-related brain activity) and (2) protocols that establish correlations between RS brain activity and subsequent performance in a cognitive task (such as our

study). This distinction is essential, as it influences the interpretive framework for understanding the functional significance of microstates. The studies mentioned in this review highlight that microstate D activity is different whether the participants are performing an executive task compared to a RS (Bréchet et al., 2019; Kim et al., 2021; D'Croz-Baron et al., 2021; Wang et al., 2021; Zappasodi et al., 2019). Consequently, these findings underscore the necessity for a more nuanced interpretation of the interplay between microstates D activity and executive functions.

To integrate our results into the larger body of research, we suggest that RS EEG microstate D occurrences may be a correlate of executive functions. However, the extent of this relationship appears to be limited, reflecting the small effect sizes reported in the different aforementioned studies. Therefore, although our data do not robustly support the hypothesized correlation, they do not rule out the possibility of a significant relationship existing in a more subtle way than previously anticipated.

4.3.3. Considerations on measurement reliability

In this section, we delve into factors that might have influenced the measures (e.g., microstate metrics or composite executive functions score) and consequently, correlations results.

A first element to mention is the EEG preprocessing pipeline to extract microstates. These include, but are not limited to, filtering, use of ICA to remove components, GFP peak extraction algorithm, temporal-smoothing with a minimum duration of 30 sec, etc. For example, the *a priori* choice to extract four microstates was challenged in recent studies (Koenig et al., 2024; Tarailis et al., 2023; Zanesco, 2023). Unfortunately, the field of research associated with microstates currently lacks a publication showing the impact of EEG preprocessing on microstate metrics. Given the growth and advancements in this field (Tarailis et al., 2023), it is anticipated that future studies will tackle this issue. In this regard, a multiverse analysis (see Steegen et al., 2016) could be an interesting way of approaching this question.

Second, microstate metrics could have been influenced by thoughts during the RS. Indeed, some studies have used a questionnaire to measure spontaneous thoughts (the Amsterdam Resting State Questionnaire, Díaz et al., 2014). These studies showed correlations between the modality or content of thought (e.g., verbal vs visual; past vs future, etc.) and microstates C and D metrics, even though these correlations were small, between $-.19$ and $.37$ (Pipinis et al., 2017; Zanesco et al., 2021).

Third, the chosen metrics (for correlation analyses) in this study might vary over time. With regards to EEG microstate metrics, our study measured EEG RS and the executive functions battery in two separate sessions (with a maximum of one week interval). Consequently, one could argue that the microstate metrics could have changed considerably between the two sessions. The reliability, or test–retest of microstates has been the subject of previous investigations (Antonova et al., 2022; Khanna et al., 2014; Popov et al., 2023). The most recent study to date and the most statistically powerful ($n = 542$, Kleinert et al., 2024) revealed an intraclass correlation

coefficient between .67 and .92 for short-term (two days) and long-term intervals (approximately two months), with mean duration and occurrences having the highest correlations. With regards to the executive functions composite score, studies have also investigated the test–retest of specific executive functions tasks such as the antisaccade, the n-back or the letter-memory (Ettenhofer et al., 2006; Paap & Sawi, 2016; Soveri et al., 2018). While the intraclass correlation coefficients reported for specific task were between .69 and .88 (for around three to eight weeks between the two sessions), they showed a higher correlation when computing a latent executive functions construct, which could be similar to our composite executive functions score.

In conclusion, although the reliability of both the microstate measures and the executive function scores appears relatively high, potential influences such as EEG pre-processing, content of thought during RS, and day-to-day intra-individual variability cannot be ruled out. These factors may have influenced the correlation coefficients in either direction.

4.4. Relevance of the registered report, limitations and future directions

We would like to argue that the Registered Report format was appropriate for this study, which follows a hypothetico-deductive approach. It is indeed important to mention that we have tested our hypotheses with a small sample pilot study ($N = 10$, Chenot, 2021). The results indicated strong correlations between the executive functions composite score and several microstate metrics, including microstate C and D mean duration ($r = .68$ and $r = .62$, respectively) and microstate D occurrences ($r = -.52$). Compared with our final results with a larger sample, these results are manifestly inflated and raise once again the question of the impact of statistical power and sample size (Button et al., 2013). Considering the reproducibility crisis in neurosciences and psychology (Collaboration, 2015; Poldrack et al., 2017), we argue that the Registered Report format is an essential tool. Indeed, this enabled this study, first, to rigorously test these hypotheses with a substantial sample. Second, we are able to publish the results regardless of their significance, thus mitigating the risk of publication bias. The open-access database constituted during this study presents itself as a rich repository for further exploration and is available here: <https://osf.io/v2xpy>.

Despite the strengths of pre-registration, the present study is not without limitations. First, even with a substantial sample size, this study is not able to clearly elucidate the relationship between RS microstate D activity and executive functions. Our results, together with the existing literature, indicate that a large-scale study with more statistical power may be required to clarify this relationship more thoroughly. A power analysis based on our observed correlation coefficient ($r = -.18$, $p = .02$, power = .9) revealed that a future study would need a sample size of 395 participants to achieve adequate power.

A second limitation lies in the way that executive functions have been measured. While our study aimed to assess

an executive functions composite score, previous research has been more narrowly focused on specific cognitive functions such as working memory or reasoning (Tarailis et al., 2023). This divergence in approach may lead us to question whether a composite or a latent score on an executive functions battery is the most appropriate method to investigate the functional significance of microstates. It may be argued that microstate metrics could correlate more strongly with specific cognitive functions rather than with a global executive functions construct, especially considering that the unidimensionality and multidimensionality of executive functions is still under debate (Karr et al., 2018). Future research may provide a more comprehensive understanding of this aspect.

Finally, the lack of EEG data collection during the nine executive functions tasks is a limitation. Indeed, with such recordings, we would have had the opportunity to evaluate the same hypothesis, but for task-related brain activity instead of intrinsic brain activity. It is however worth noting that EEG recordings were captured during a more complex task (Space Fortress, Mané & Donchin, 1989). Testing the hypothesis of a relationship between microstates activity during this multi-tasking game and its associated performance is however beyond the scope of the present paper and will be the subject of a later publication.

5. Conclusion

This study marks a significant step toward understanding the relationships between intrinsic spatio-temporal brain dynamics and executive functioning. In a relatively large sample, our results do not support a significant relationship between microstate C metrics measured at rest and performance in executive functions tasks. This finding underscores that the functional significance of this microstate probably lies elsewhere. While the relationship between microstate D metrics at rest and executive functions warrants further investigation in a larger cohort, our results suggest that the association, if present, is likely to be minimal. In light of the inconclusive or minor effect sizes observed, it remains difficult to postulate, as originally hypothesized, that the intrinsic spatio-temporal brain dynamics - measured by microstates C and D activity at rest - are a reliable signature of executive functioning.

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Open practices

The study in this article has earned Open Data, Open Materials and Preregistered badges for transparent practices. The data, materials and preregistered studies are available at: <https://osf.io/>.

CRediT authorship contribution statement

Quentin Chenot: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Caroline Hamery:** Writing – review & editing, Visualization, Software, Formal analysis, Data curation. **Moritz Truninger:** Writing – review & editing, Visualization, Validation, Software, Methodology, Formal analysis, Data curation. **Nicolas Langer:** Writing – review & editing, Validation, Software, Resources, Methodology, Formal analysis. **Xavier De boissezon:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition. **Sébastien Scannella:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.cortex.2024.05.019>.

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