The dynamics of resting-state alpha oscillations predict individual differences in creativity

Naomi Prent a, Dirk J.A. Smit b, *  

a Department of Neurology and Clinical Neurophysiology, Amsterdam University Medical Center Location AMC, Amsterdam Neuroscience, the Netherlands  
b Psychiatry Department, Amsterdam University Medical Center Location AMC, Amsterdam Neuroscience, the Netherlands

ARTICLE INFO

Keywords:  
Alternative uses task  
Temporal correlations  
Self-organized criticality  
Electroencephalography (EEG)  
Neural dynamics

ABSTRACT

The neuronal mechanisms underlying creativity are poorly understood. Arguably, the brain’s ability to switch states would contribute to achieving novel ideas, and thus to creativity. Faster brain-state switching is reflected in the temporal dynamics of functional brain activity. Stronger autocorrelations in brain activity measures can make a brain stay in a certain state for longer periods, whereas low temporal autocorrelations reflect faster state switching. We established the brain’s inherent tendency to switch or stay in a resting, no-task condition using 128 channel electroencephalography (EEG). We assessed temporal autocorrelations of the amplitude modulation of the dominant alpha oscillations (8–13 Hz). Creativity was measured by a self-rating, an examiner-rating and the alternative uses task in 40 healthy young adults, which was scored on dimensions of verbal fluency, originality, elaboration, usefulness, and flexibility. For each dimension, the total number of subject-reported alternative uses that matched the criterion was noted (the quantity measure), as well as the proportion of uses that matched the dimensional criterion. A principal components analysis confirmed the two-component structure of quantity and quality. Partial correlation analysis was used controlling for gender and age, and a cluster permutation test was performed to correct for multiple testing. A significant cluster over right central/temporal brain areas was found with a negative correlation between creativity and temporal autocorrelations were observed (p = 0.028). To our knowledge, this is the first demonstration that individual variation in the dynamics of the dominant alpha oscillations (8–13 Hz) is inherent tendency to switch or stay in a resting state, thus increasing flexibility in thought as one of the key components in creative ideation.

1. Introduction

Creativity is involved in almost every field of life: in art, music, science, economy, and technology. Creativity is our ability to change existing thinking patterns, flexibly break with ongoing trains of thought, and make innovation possible (Dietrich and Kanso, 2010). Sternberg and Lubart (1996) defined creativity as ‘the ability to produce work that is both novel and appropriate’. And according to Guilford (1950), creativity is divergent thinking in which originality, flexibility, and fluency are the main components. Creativity correlates with well-being and adaptive behavior, which as such has led to a large body of investigations into its neurobiological underpinnings. Recent reviews are increasingly converging on brain areas and networks involved in creative ideation and explaining individual differences in creativity (Beaty et al., 2016; Dietrich and Kanso, 2015; Khalil et al., 2019). Relatively under-investigated is how these brain areas affect creativity and the flexibility of thought it requires. It is our aim to investigate whether temporal dynamics in functional brain activity index the propensity to switch brain states, thus increasing flexibility in thought as one of the key components in creative ideation.

Reviews of investigations into the neuronal mechanisms underlying creativity conclude that they are still poorly understood (Dietrich and Kanso, 2010). Creative thinking does not appear to depend on any single mental process or brain region (Dietrich and Kanso, 2010; Stevens and Zabelina, 2019). Idea generation begins with retrieval of common and old ideas, followed by processes of mental simulation and imagination to the actual generation of novel and creative ideas (Schwab et al., 2014). Consequently, it may be assumed that multiple specific neurocognitive processes at multiple brain areas are associated with different types and stages of creativity. According to Dietrich and Kanso (2010), this could be an explanation for highly variegated results of research on brain regions related to creativity.
The most consistent finding in neuroscientific studies of creativity seems to be the increased power of 10 Hz (alpha oscillations) during creative ideation (Fink and Benedek, 2014; Luft et al., 2018; Martindale and Hasenfus, 1978; Martindale and Mines, 1975; Stevens and Zabelina, 2019), although some have argued that the results are inconclusive (Dietrich and Kanso, 2010). Further EEG studies suggested that generation of original ideas is associated with alpha synchronization in the prefrontal cortex (Fink et al., 2011) and in the parietal and temporal sites of the right hemisphere (Schwab et al., 2014), and that creative persons show stronger frontal activity, whereas lower creative individuals showed increased parietal activity. This suggests that lower and higher creative individuals may use different strategies of divergent thinking (Jauk et al., 2012).

The role of the alpha oscillations in creative ideation is less clear. Creative thinking—specifically, being able to produce thoughts that are novel (Bancho and Gaeta, 2012)—may crucially depend on the ability of the brain to produce activity patterns that are independent of previous states. Creative thinking critically depends on a break from habitual thinking and associations (Luft et al., 2018). Arguably, this ability depends on a decorrelation over time of the state of the brain. Research has shown that alpha oscillations in the spontaneously active (resting) brain show clear periods of a particular state, which changes relatively suddenly into novel states. Therefore, subsequent oscillatory states show substantial temporal correlations (Linkenkaer-Hansen et al., 2001; Miller et al., 2009; Palva et al., 2013; Smit et al., 2013; van de Ville et al., 2010), which gets smaller when comparing states across longer periods (i.e., the brain states show a decay in autocorrelation). Brain states may be defined by presence of oscillations (or not) at specific time points, evident in the amplitude envelope of the alpha oscillations (Linkenkaer-Hansen et al., 2001). The amplitude envelope of alpha oscillations shows a clear pattern of bursts that indicate that alpha oscillatory states tend to be alike compared over short periods, but decay over longer periods (Fig. 1). This decay is reflected in the in power-spectra of the amplitude envelope signal, and follows a power-law, $P(f) \propto f^{-\beta}$ where $P$ is power, $f$ is frequency and $\beta$ is the power-law exponent (He, 2014). In double-log PSD plots $\beta$ represents the steepness of the downward linear slope. Positive values of $\beta$ indicate larger power for slow frequencies relative to higher frequencies, resulting in the signal remaining in a similar state for prolonged times. Interestingly, it was observed that individuals show stable and heritable variation in the autocorrelation decay parameter (Linkenkaer-Hansen et al., 2007; Smit et al., 2010).

Previous studies have shown that interindividual variability in the temporal correlations in brain dynamics have been found to predict performance in simple cognitive behavior like finger tapping and the detection of threshold stimuli (Palva et al., 2013; Smit et al., 2013). It is unknown whether brain dynamics may also have an effect on more complex behavior like creativity. Therefore, our aim was to investigate whether temporal correlations in resting-state alpha oscillations are a biomarker of human creativity. Since alpha oscillations have been found to be involved in the suppression of habitual responses and lead to more creative solutions (Luft et al., 2018), we hypothesized that a faster decay in autocorrelation of alpha power would result in increased creative output.

2. Methods

2.1. Subjects

Subjects were recruited within the VU University community. They were selected on their age (18–30 years). Individuals using antipsychotics, sedative drugs, or psychoactive medication like Ritalin, having experienced insomnia the past 3 days, epilepsy, or having ever experienced unconsciousness for more than 5 min were excluded based on self-report. All participants were informed about the nature of the research and signed an informed consent, and were treated in accordance with local law and international treaties. The study was approved by the ethical review committee of the Faculty of Psychology and Education of the VU University Amsterdam.

The sample consisted of 40 participants (20 males), with ages

Fig. 1. Illustration of brain oscillations filtered at 8–13 Hz (black) and the amplitude envelope (red) plotted on a time-condensed scale. (A) Sample of an EEG signal with high spectral exponent $\beta$ of 0.90. Alpha oscillations show strong clustering into bursts. Bursts cause prolonged elevated values in the amplitude envelope. Temporal autocorrelation is evident as high values of the amplitude envelope tend to correlate with high values in the directly following periods. Therefore, the subjects’ signal tends to stay in a particular oscillatory state longer than for others. (B) Example of low exponent $\beta$ of 0.4. Less temporal clustering of alpha oscillations with less pronounced bursts and quicker state-shifting is evident. (C) Power spectra of the amplitude envelope of the alpha oscillations follow a $1/f^{\beta}$ function, which is the same as a linear fit in log-log space. Amplitude envelopes of high and low temporal correlations show a clear differences in the slope of the line. The slope of the least-squares fitted line (negated) is the exponent beta. The spectra showed a downward curve above 2 Hz caused by the 8–13 Hz filtering (see Smit et al., 2013), which is constant across subjects. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)
rangin from 20 to 27 years, and a mean age of 22.55 (SD = 1.77). The majority of the participants (87.5%) were born in the Netherlands, others in Belgium, Russia, France or Iran. Furthermore, 22.5% of the participants had one or both parents born outside Europe. At the time of the research, more than half of the participants followed a university education (57.5%) and others followed college education (20%), high school (7.5%) or did no education (15%). The participants had different educational backgrounds: Behavioral and Social Sciences (30%), Natural Sciences (20%), Health and Movement (15%), Economics, Business and Law (12.5%), Computer Science, Mathematics and Business (12.5%), Art, Culture and History (5%) and Language and Communication (5%). None of the participants had ever experienced psychosis and two participants had a family member who had ever had a psychosis. 92.5% of the subjects were right-handed.

2.2. Materials & procedure

First, a digital survey with general questions (gender, age etc.) was administrated via Qualtrics (Qualtrics, Provo, UT, version 2015) on a computer. Participants were asked to rate their own creative ability on a 10-point scale. This was performed to provide a validity check for the AUT scoring system. Next, the Alternative Uses Task (AUT) (Guilford, 1967) was used for the measurement of divergent thinking. During the task, participants were asked to name as many unusual uses as possible for four various conventional, everyday objects (paperclip, newspaper, brick, and shoe) in 3 min per object.

Next, the participants were connected to the EEG system and the resting-state brain activity was measured. The subject was instructed to sit silently with eyes closed and minimize movement for 3 min, followed by a 3-min measurement with eyes open. This resting-state brain activity measurement was performed again after several minutes—after performing a Wisconsin Card Sorting Task—resulting in a total of 6 min eyes-open and 6 min eyes-closed.

Note that resting state EEG data was preferred over task-based EEG, as temporal correlation assessment may be affected by the events that are typical of task data reflecting stimulus processing or motor activity (Linkenkaer-Hansen et al., 2004). AUT task execution is likely create such events that break ongoing oscillatory activity and reduces the scaling in the signals (Linkenkaer-Hansen et al., 2004). Here, we aimed to assess the general tendency of the brain to switch states unperturbed by these external or internal events. Also note that we only assessed the eyes-open condition was used for the current analyses, consistent with previous investigations (Smit et al., 2013). Eyes-open was preferred over the eyes-closed measurement, because dominant alpha activity in the visual brain areas during eyes-closed rest obfuscates less pronounced alpha oscillatory activity originating in different brain areas. The Wisconsin card sorting task and eyes-closed rest data were collected to be used in different projects. Statistical Package for Social Scientists (IBM-SPSS Statistics, version 20, 2011) and MATLAB (The Mathworks Inc., Natick, MA, version 2014) were used for data analysis.

A final creativity assessment separate from the AUT scoring was performed by assessing the overall quality of all responses by the examiner (N.P.), who divided the participants into 5 groups from least creative to most creative.

2.3. EEG registration

The electrical brain activity was recorded by the 128 channel system BioSemi Ag/AgCl active electrode configuration. The active ground electrode Common Mode Sensor (CMS) and passive ground electrode Driven Right Leg (DRL) form a feedback loop, resulting in very high quality recordings even at high impedance contact. The sampling frequency was 1024 Hz and the low-pass filter during acquisition 208 Hz. The 128 electrodes were attached to a stretch lycca electrode cap placed on the head of the participant. SignaGel Electrode Gel conducted the signal of the scalp to the electrode. Furthermore, one electrode was placed 2 cm beneath each eye vertically aligned with pupil and one electrode 2 cm outside the outer canthi of each eye of the participant. These 4 electrodes recorded eye movements and blinks. Then, the electrodes were connected to the amplifier and computer and the functioning of the electrodes was checked.

2.4. AUT scoring

The scoring procedure for the Alternative Uses task was based on previous research (Crocley, 2000; Runco and Acar, 2012; Vosburg, 1998). Many studies only counted for Fluency. However, Fluency is only one aspect of divergent thinking and does not guarantee the quality of ideas (Vosburg, 1998), and Fluency may not be as closely tied to creativity as Originality and Flexibility (Runco and Acar, 2012).

The scoring procedure for the Alternative Uses task used a well-defined scoring system for Fluency, Flexibility, Originality, Elaboration, and Usefulness as defined in previous research (Crocley, 2000; Runco and Acar, 2012; Vosburg, 1998). Many studies counted just for Fluency, however, this is only one aspect of divergent thinking and does not fully reflect the quality of ideas (Vosburg, 1998), and may not be as closely tied to creativity as the dimensions of Originality and Flexibility (Runco and Acar, 2012). Because some tests also included Elaboration (Runco and Acar, 2012) and others included Usefulness (Crocley, 2000; Vosburg, 1998), it was decided to include both these indices to the rating scores.

Fluency is the total number of ideas produced for each object. The valid number of ideas (Fluency-valid), with only unusual, nonrepeated ideas, was additionally included. Flexibility is the number of generated categories of ideas for each object. Originality is the novelty of the ideas (i.e., infrequent across subjects). Elaboration is the amount of detail of the responses and Usefulness is the functionality of the idea. The scoring of Fluency and Flexibility require simple counting, whereby every idea and every category are worth 1 point. The scoring of Originality was done by comparing each response to the remainder of the group, such that ideas given by only 5% of the group count for 1 point (i.e., no more than 2 others gave the same answer) were deemed original. Responses rated as detailed received 1 point. For example, the answer ‘you can use a shoe to put in a cup so that the cup does not fall over in the car while driving’ was rated as detailed, because it provided more information than the use as a drink holder. Responses that were rated as functional also received 1 point for the Usefulness scale.

The scores per object were added up to a total score for each category separately. In addition, because all these categories are based on the amount of responses (quantity), and hence more related to fluency than intrinsic response quality, 3 ratios were defined for Originality, Elaboration and Usefulness were made as the number of points per category divided by total number of responses. These were used as separate scores for subsequent analysis and association so as to provide more information about the quality of the responses, and thus provide additional internal consistency.

2.5. EEG analysis

EEG was preprocessed using standard procedures. We filtered the signals 1–45 Hz, removed bad channels, rerereferenced to average reference, inspected for transient artifacts (muscle artifact, swallowing, recording artifacts such as a sudden DC shifts). ICA was used to remove eye movement, blink and other artifacts.

Next, EEG signals from the 128 locations were preprocessed with a zero-phase bandpass FIR filter in the frequency bands of alpha (8–13 Hz) oscillations. Next, the amplitude envelope of the filtered signal s(t) and its Hilbert transform. H(S(t)), i = √−1 We assessed temporal correlations by calculating the power spectrum density (PSD) of this amplitude
envelope signal. The PSD was estimated using an FFT with 64s box windows (50% overlap). Power and frequencies from 0.0156 to 2 Hz were converted to log scale with \( \log_{10} \). Exponent \( \beta \) was defined as the absolute value of the slope of the linear regression of power (in dB) on Frequency in \( \log_{10}(Hz) \). Goodness-of-fit of linearity was estimated with \( r^2 \) performed in the regression in the spectral analysis of the amplitude envelope.

2.6. Statistics

First, the different creativity scores, which included Self-rating (SR), Examiner-rating (EX), Fluency (F), Fluency-valid (FV), Flexibility (FX), Originality and Originality-ratio (O and OR), Elaboration and Elaboration-ratio (E and ER), Usefulness and Usefulness-ratio (U and UR) were correlated to examine the convergent validity. Although the AUT has high internal consistency with a Cronbach’s alpha of 0.86 (Vosburg, 1998), we tested the validity of the measure against the self- and examiner ratings by means of correlation analysis.

Principal Component Analysis (PCA) was then used to reveal possible dimensions of creativity and to provide component scores. Finally, components were selected based on the eigenvalue distribution, rotated using promax rotation, and component scores calculated. These were correlated with the power-law exponents of the amplitude modulation of 8.0-13-0 Hz for each of the 128 electrodes measured during the eyes open condition. Standard partial correlation analysis was used controlling for gender and age.

We tested for significance of association using Monte Carlo permutation testing aimed to correct for multiple testing, non-normal distributions, as well as outliers. First, we used the cluster permutation approach of Maris and Oostenveld (2007). In this approach, a spatial grid is defined based on nearness of the electrodes, with only nearest electrodes connected. An (arbitrary) threshold is defined for cluster inclusion (here: \( p_{\text{crit}} = 0.01 \)). Then the correlations and p-values of 128 exponents beta with the creativity phenotype are calculated, and p-values under \( p_{\text{crit}} \) are noted. The correlations of all adjacent significant effects are summed. Providing a summed-R value for each cluster, and selected the largest cluster. Next, we used permutation to shuffle the creativity values, recalculated the correlations and p-values, applied the \( p_{\text{crit}} \) threshold, and calculated the summed-R for the largest cluster. This was repeated 10,000 times to obtain a null distribution for the cluster summed-R statistic, against which the unpermuted summed-R value was tested using the percentile method.

3. Results

3.1. Validation of creativity scores

To examine whether the different creativity variables (Self-rating, Examiner-rating and Alternative Uses Task scores) were correlated, standard Pearson correlation analysis was performed (Table 1). For completeness, means with standard deviations for men, women and the total sample are presented in Table 2. Age did not significantly predict any of the creativity AUT subscores (\( p > 0.30 \)). Sex predicted Elaboration-ratio (\( p = 0.008 \)) but this did not survive multiple the comparisons. Non-Dutch ethnicity did not significantly predict Fluency. The correlations between the count-based scoring scales of the AUT are indicated by the dashed square. Most of these are very strong, with the exception of Elaboration.

The Self-rating variable of creativity correlated significantly with the indices of the AUT (Fluency, Fluency-valid, Elaboration, Flexibility, Originality, and Usefulness). Nonsignificant correlations were found for Elaboration-ratio and Usefulness-ratio. This suggests that the examiner scoring was to a moderate degree consistent with the self-rating, but also that the self-rating is primarily based on the number of ideas generated. The Examiner-rating showed medium-to-large correlations on all the categories of the AUT, but it additionally strongly correlated significantly with Originality ratio, Elaboration ratio and Usefulness ratio. This indicates that the ratios provided a good indication that a second source of variation may be found next to the count-based measures of Fluency, Fluency-valid, Flexibility, Originality, Elaboration, and Usefulness.

Most count-based scores (Fluency, Fluency-valid, Flexibility, Originality, Usefulness) showed significant and strong correlations. Elaboration showed moderate correlations with these scores. This indicates substantial internal consistency between the scoring.

3.2. PCA revealed a quantitative and qualitative component

Principal Component Analysis (PCA) revealed the presence of only 2 components with eigenvalues exceeding unity (eigenvalues of components 1 and 2 were 6.03 and 2.33) with an inflexion point at eigenvalue 3 (Fig. 2). The two-component solution explained a total of 76.0% of the variance, with Component 1 contributing 54.8% and Component 2 contributing 21.2% respectively.

Table 2

| Total | Men | Women |
|-------|-----|-------|
|        | M     | SD    | M     | SD    |
| Self-rating | 6.73  | 1.69  | 6.60  | 1.90  |
| Examiner-rating | 3.05  | 1.06  | 3.01  | 1.00  | 3.05  | 1.15 |
| Fluency | 29.15 | 11.69 | 32.70 | 12.34 |
| Fluency-valid | 25.08 | 10.49 | 27.50 | 10.51 |
| Flexibility | 24.03 | 9.84  | 26.20 | 9.67  |
| Originality | 5.97  | 4.17  | 6.60  | 4.41  |
| Elaboration | 5.57  | 4.35  | 4.10  | 3.74  |
| Usefulness | 22.05 | 9.85  | 23.60 | 10.13 |
| Originality-ratio | .19   | .11   | .19   | .10   | .20   | .14 |
| Elaboration-ratio | .21   | .17   | .13   | .10   | .29   | .18 |
| Usefulness-ratio | .76   | .20   | .73   | .23   | .79   | .16 |

Note. Significant correlations (\( p < 0.05 \)) are indicated in bold.
Table 3  
Pattern matrix for PCA with Promax rotated two-component solution.

| Component   | 1     | 2     |
|-------------|-------|-------|
| Self-rating | .501  | .220  |
| Examinerrating | .440 | .671  |
| Fluency     | 1.017 | .316  |
| Fluency-valid| 1.005 | .070  |
| Flexibility | .981  | .013  |
| Originality | .794  | .188  |
| Elaboration | .096  | .832  |
| Usefulness  | .913  | .133  |
| Originality-ratio | .357 | .506  |
| Elaboration-ratio | -.419 | .950  |
| Usefulness-ratio | .040 | .719  |

Note. Major loadings are indicated in bold.

Fig. 2. PCA scree plot based on the creativity variables suggests a two-factor solution based on the inflexion point at eigenvalue 3.

To aid in the interpretation of these components, promax rotation with Kaiser normalization was performed. There was a moderate positive correlation between the 2 components (r = 0.33). Components were allowed to correlate as they were both expected to reflect underlying constructs of creativity. Both components show loadings on all variables, however, most variables showed a substantial loading from only one component (Table 3). This pattern is consistent with a correlated two-component solution. Variables related to the number of responses (i.e., count-based scores) showed strong loadings on Component 1 (Self-ratings, Fluency, Fluency-valid, Flexibility, Originality, Usefulness); variables related to the quality of the answers showed strong loadings on Component 2 (Examiner-rating, Elaboration, Elaboration-ratio, Originality-ratio, Functionality-ratio). Based on the type of creativity variable each component correlated with most highly, the two components may be interpreted as Quantity and Quality as underlying constructs of creativity.

Subsequently, the variables Quantity and Quality component scores were created by means of the regression method. Total Creativity was defined as the sum score of the Quantity and Quality z-scores. Three one-way between-groups analyses of covariance were conducted to investigate whether gender or age had an effect on the variables Quantity, Quality, and Total Creativity. The variables were normally distributed and there was no violation of homogeneity of variance between the groups (p > 0.05). There was no significant effect of gender, F(1, 37) = 2.49, p = 0.12, partial $\eta^2 = 0.06$, and age, F(1, 37) = 0.42, p = 0.52, partial $\eta^2 = 0.01$, for Quantity. This was also applied to the effect of gender, F(1, 37) = 2.59, p = 0.12, partial $\eta^2 = 0.07$, and age, F(1, 37) = 0.34, p = 0.56, partial $\eta^2 = 0.01$, for Quality. And also for Total Creativity there was no significant effect for gender, F(1, 37) = 0.00, p = 0.99, partial $\eta^2 = 0.00$, and age, F(1, 37) = 0.53, p = 0.47, partial $\eta^2 = 0.01$.

3.3. Power-law characterisation of alpha-band amplitude modulation

One outlier was observed with an average $\beta$ exponent of 1.27, which was not removed as permutation testing was used for significance. Non-Dutch ethnicity did not significantly affect the $\beta$ exponents and was further disregarded.

Fig. 3 shows the distribution of average $\beta$-exponents over the brain, with a minimum value of 0.32 to a maximum value of 0.56. The average values for $\beta$ were significantly larger than 0 across all channels in a one-sample t-test, $M > 0.32$, $t(39) > 7.96$, $p < 0.001$, showing that these scaling exponents reflect the presence of long-range temporal correlations. High $\beta$ exponents have relatively more low-frequency power corresponding to stronger temporal correlations, which reflect more persistent brain states than low exponents (Smit et al., 2013). The effect of gender varied across the 128 channels, abs($t(38)$) < 2.27, $p > 0.03$, and age seemed to have no effect on any channel, abs($t(38)$) < 1.50, $p > 0.14$. None of these effects were significant after FDR-correction for multiple testing (Benjamini and Hochberg, 1995). A goodness-of-fit of linearity $r^2$ was estimated in the power-law regression for the spectral analysis. The fit statistic explained more than 75% of the variance across 128 channels of the grand average spectrum.

3.4. Brain state switching correlates with creativity

We investigated whether individual variation in brain state switching as reflected in the exponents were correlated with the creativity components Quantity, Quality, and Total Creativity. The distribution of correlations with these creativity components, controlling for gender and age, is shown in Fig. 4. The strongest correlations were found over the right temporal areas. These correlations were mostly negative, which means that relatively high exponents (i.e., lower decay in temporal correlation and slower brain-state switching) are related to low creativity and low exponents (faster decay in temporal correlations and faster brain-state switching) are related to a high creativity (see Fig. 5).

The cluster permutation test (Maris and Oostenveld, 2007) revealed a two-lead significant cluster for the Qualitative component (channels B24 and B25) and a three lead cluster with Total Creativity (B24, B25, B15), both over right temporal areas ($p = 0.037$ and $p = 0.027$ respectively).
The tendency for faster decorrelation between brain states in the right central brain area. The negative relationship suggests that brains with a higher amplitude modulation of alpha oscillations at right temporal channel B23 of log transformed power (in dB) plotted against log beta is a sign of temporal correlations in brain oscillations. The regression lines for lower (β = 0.48) and higher (β = 0.61) creative individuals are depicted above the zero line in Fig. 4. Previous EEG studies of creativity suggested that generation of original ideas is associated with alpha synchronization in the prefrontal cortex (Fink et al., 2011) and in the parietal and temporal sites of the right hemisphere (Schwab et al., 2014). Since these studies investigated within-subject effects, they are hard to match to the current results, but they do suggest the involvement of alpha oscillations. The maximal effect at the right central areas may reflect the activity in the sensory motor network which is recruited during execution the AUT (Feng et al., 2019). Using fMRI activity in rest, Feng et al. showed that activity in the bilateral post-central gyrus are positively correlated to creative ideation in the alternative uses task. On the network level, they showed evidence for the involvement of several resting-state networks and their integration in creative ideation. In our view, these results complement the current findings, in which the temporal decorrelation (and thus fast state-switching) observed over the right central areas could drive the network to quickly switch into a novel organization.

Although the current results pointed to the involvement of a focused area the right hemisphere, we do not believe that the right central location warrants any firm conclusion about the precise localization. In addition, it may be likely that many other brain areas are involved in the complex behavior elicited by the AUT, but may simply have failed to reach significance due to sample fluctuation. Alternatively, our results may reflect only one aspect in creative ideation, namely the tendency of the brain to switch oscillatory states, which may not be necessary for idea content creation. We also note that tendency to switch brain states was assessed in EEG during rest, and not during AUT task execution. The resting condition was preferred over the task condition as the latter is likely to consist of many cognitive processes acting in parallel and serial, such as reading, verbalizing, motor execution and executive functions. These task-based processes are known to modulate ongoing oscillations and reduce temporal correlations (Linkenkaer-Hansen et al., 2004). A more elaborate design of EEG during AUT task execution with clear serial bounds into reading, ideation, and reporting phases could solve that problem.

Our results seem to contrast with a recent study that reported positive correlations between dwell times in brain states and self-reported openness to experience (Beaty et al., 2018). These authors found that subjects with higher scores on openness—related to creativity—showed longer dwell times in correlational patterns present in resting-state fMRI networks, including the default mode and cognitive control networks. However, these results were obtained using a different methodology, namely, by examining states of consistent cross-connectivity patterns across RSNs, whereas our analysis focused on temporal dynamics or

**3.5. EEG power and peak frequency**

The more standard EEG measures of EEG alpha power and alpha peak frequency did not correlate significantly with any of the creativity scores (uncorrected p > 0.01). The results for total creativity are shown in Fig. 6.

**4. Discussion**

The current research investigated whether long-range temporal correlations in resting-state alpha oscillations is associated with human creativity. Creativity was measured by multiple variables (Self-rating, Examiner-rating and the Alternative Uses Task) and PCA revealed a two (correlated) component structure interpreted as Quantity and Quality. In accordance with the expectation, significant negative correlations were found between the exponents and creativity (for Quantity and Total Creativity, and a near significant effect for Quality) over the right central brain area. The negative relationship suggests that brains with a tendency for faster decorrelation between brain states—which we hypothesized reflect a more flexible brain—are more creative. More standard measures of EEG, alpha power and peak frequency, did not correlate with the three creativity measures.

Previous EEG studies of creativity suggested that generation of original ideas is associated with alpha synchronization in the prefrontal cortex (Fink et al., 2011) and in the parietal and temporal sites of the right hemisphere (Schwab et al., 2014). Since these studies investigated within-subject effects, they are hard to match to the current results, but they do suggest the involvement of alpha oscillations. The maximal effect at the right central areas may reflect the activity in the sensory motor network which is recruited during execution the AUT (Feng et al., 2019). Using fMRI activity in rest, Feng et al. showed that activity in the bilateral post-central gyrus are positively correlated to creative ideation in the alternative uses task. On the network level, they showed evidence for the involvement of several resting-state networks and their integration in creative ideation. In our view, these results complement the current findings, in which the temporal decorrelation (and thus fast state-switching) observed over the right central areas could drive the network to quickly switch into a novel organization.

Although the current results pointed to the involvement of a focused area the right hemisphere, we do not believe that the right central location warrants any firm conclusion about the precise localization. In addition, it may be likely that many other brain areas are involved in the complex behavior elicited by the AUT, but may simply have failed to reach significance due to sample fluctuation. Alternatively, our results may reflect only one aspect in creative ideation, namely the tendency of the brain to switch oscillatory states, which may not be necessary for idea content creation. We also note that tendency to switch brain states was assessed in EEG during rest, and not during AUT task execution. The resting condition was preferred over the task condition as the latter is likely to consist of many cognitive processes acting in parallel and serial, such as reading, verbalizing, motor execution and executive functions. These task-based processes are known to modulate ongoing oscillations and reduce temporal correlations (Linkenkaer-Hansen et al., 2004). A more elaborate design of EEG during AUT task execution with clear serial bounds into reading, ideation, and reporting phases could solve that problem.

Our results seem to contrast with a recent study that reported positive correlations between dwell times in brain states and self-reported openness to experience (Beaty et al., 2018). These authors found that subjects with higher scores on openness—related to creativity—showed longer dwell times in correlational patterns present in resting-state fMRI networks, including the default mode and cognitive control networks. However, these results were obtained using a different methodology, namely, by examining states of consistent cross-connectivity patterns across RSNs, whereas our analysis focused on temporal dynamics or
autocorrelation patterns within a single signal. Lower temporal autocorrelations can co-exist with strong cross-regional connectivity. Other research (Simola et al., 2017) reported positive correlations between the DFA exponent of alpha oscillations and cognitive flexibility. However, these authors investigated flexibility in closed-form (convergent) cognitive go–no-go task, which is different from the open-ended AUT measuring divergent creativity.

We conclude that we have shown, for the first time, that individuals with higher creativity are marked by decreased temporal autocorrelations in resting-state alpha oscillations over right central/temporal cortex. The decreased temporal autocorrelations result in less persistent brain states, compared to less creative individuals. This increased flexibility in the intrinsic dynamics of the brain may contribute to an explanation why individuals differ in their behavior and creative abilities, and how innovative ideas and solutions are formed.

CRediT authorship contribution statement

Naomi Prent: Formal analysis, Investigation, Writing - original draft, Writing - review & editing. Dirk J.A. Smit: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Supervision.

Acknowledgements

We are grateful to Dio van der Mee for assisting in collecting the data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuropsychologia.2020.107456.

References

Beaty, R.E., Benedek, M., Silvia, P.J., Schacter, D.L., 2016. Creative cognition and brain network dynamics. Trends Cognit. Sci. 20, 87–95. https://doi.org/10.1016/j.tics.2015.10.004.
Beaty, R.E., Chen, Q., Christensen, A.P., Qin, J., Silvia, P.J., Schacter, D.L., 2018. Brain networks of the imaginative mind: dynamic functional connectivity of default and cognitive control networks relates to openness to experience. Hum. Brain Mapp. 39, 811–821. https://doi.org/10.1002/hbm.23884.
Benjamin, Y., Hochberg, Y., 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. J. Royal Stat. Soc. Ser. B Methodol. 57, 289–300.
Crapley, A.J., 2000. Defining and measuring creativity: Are creativity tests worth using? Roeper Rev. 23, 72–79. https://doi.org/10.1080/0278319009554069.
Dietrich, A., Kanno, R., 2010. A review of EEG, ERP, and neuroimaging studies of creativity and insight. Psychol. Bull. 136, 822–848. https://doi.org/10.1037/ a0019749.
Feng, Q., He, L., Yang, W., Zhang, Y., Wu, X., Qin, J., 2019. Verbal creativity is correlated with the dynamic reconfiguration of brain networks in the resting state. Front. Psychol. 10, 894. https://doi.org/10.3389/fpsyg.2019.00894.
Fink, A., Benedek, M., 2014. EEG alpha power and creative ideation. Neurosci. Biobehav. Rev. 44, 111–123. https://doi.org/10.1016/j.neubiorev.2012.12.002.
Fink, A., Schwab, D., Papousek, I., 2011. Sensitivity of EEG upper alpha activity to cognitive and affective creativity interventions. Int. J. Psychophysiol. 82, 233–239. https://doi.org/10.1016/j.ijpsycho.2011.09.003.
Guilford, J.P., 1967. The Nature of Human Intelligence. McGraw-Hill, New York, NY.
Guilford, J.P., 1950. Creativity. Am. Psychol. 5, 444–454.
He, B.J., 2014. Scale-free brain activity: past, present, and future. Trends Cognit. Sci. 18, 480–487. https://doi.org/10.1016/j.tics.2014.04.003.
Jauk, E., Benedek, M., Neubauer, A.C., 2012. Tackling creativity at its roots: evidence for different patterns of EEG alpha activity related to convergent and divergent modes of task processing. Int. J. Psychophysiol. 84, 219–225. https://doi.org/10.1016/j. ijpysci.2012.02.012.
Khall, R., Godde, B., Karim, A.A., 2019. The link between creativity, cognition, and creative drives and underlying neural mechanisms. Front. Neural Circ. 13 https://doi.org/10.3389/fncir.2019.00018.
Linkenkaer-Hansen, K., Nikouline, V.V., Palva, J.M., Ilmoniemi, R.J., 2001. Long-range temporal correlations and scaling behavior in human brain oscillations. J. Neurosci. 21, 1370–1377.
Linkenkaer-Hansen, K., Nikulin, V.V., Palva, J.M., Kaila, K., Ilmoniemi, R.J., 2004. Stimulus-induced change in long-range temporal correlations and scaling behaviour of somatosensory oscillations. Eur. J. Neurosci. 19, 203–218. https://doi.org/10.1111/j.1460-9568.2004.03116.x.
Linkenkaer-Hansen, K., Smit, D.J.A., Barkil, A., van Beijsterveldt, T.E.M., Brussaard, A.B., Boomsma, D.I., van Ooster, A., de Geus, E.J.C., 2007. Genetic contributions to long-range temporal correlations in ongoing oscillations. J. Neurosci. 27, 13882–13889. https://doi.org/10.1523/JNEUROSCI.3083-07.2007.
Luft, C.D.B., Zioga, I., Thompson, N.M., Banissy, M.J., Bhattacharya, J., 2018. Right temporal alpha oscillations as a neural mechanism for inhibiting obvious associations. Proc. Natl. Acad. Sci. 115, E12144–E12152. https://doi.org/10.1073/pnas.1811465115.
Maris, E., Oostenveld, R., 2007. Nonparametric statistical testing of EEG- and MEG-data. J. Neurosci. Methods 164, 177–190. https://doi.org/10.1016/j.jneumeth.2007.03.024.

Fig. 6. Left panels: distribution of alpha oscillation peak frequency (A) and power (B) from the eyes-open resting EEG. Right panels: the correlation topography of alpha oscillation peak frequency (C) and of power (D) with total creativity. No correlation reached significance after correction (p > 0.014 uncorrected).
Martindale, C., Hasenfus, N., 1978. EEG differences as a function of creativity, stage of the creative process, and effort to be original. Biol. Psychol. 6, 157–167. https://doi.org/10.1016/0301-0511(78)90018-2.

Martindale, C., Mines, D., 1975. Creativity and cortical activation during creative, intellectual and EEG feedback tasks. Biol. Psychol. 3, 91–100. https://doi.org/10.1016/0301-0511(75)90011-5.

Miller, K.J., Sorensen, L.R., Ojemann, J.G., den Nijs, M., 2009. Power-law scaling in the brain surface electric potential. PLoS Comput. Biol. 5, e1000609. https://doi.org/10.1371/journal.pcbi.1000609.

Palva, J.M., Zhigalov, A., Hirvonen, J., Korhonen, O., Linkenkaer-Hansen, K., Palva, S., 2013. Neuronal long-range temporal correlations and avalanche dynamics are correlated with behavioral scaling laws. Proc. Natl. Acad. Sci. 110, 3585–3590. https://doi.org/10.1073/pnas.1216855110.

Runco, M.A., Acar, S., 2012. Divergent thinking as an indicator of creative potential. Creativ. Res. J. 24, 66–75. https://doi.org/10.1080/10400419.2012.652929.

Runco, M.A., Jaeger, G.J., 2012. The standard definition of creativity. Creativ. Res. J. 24, 92–96. https://doi.org/10.1080/10400419.2012.650092.

Schwab, D., Benedek, M., Papoušek, I., Weiss, E.M., Fink, A., 2014. The time-course of EEG alpha power changes in creative ideation. Front. Hum. Neurosci. 8 https://doi.org/10.3389/fnhum.2014.00310.

Simola, J., Zhigalov, A., Morales-Munoz, I., Palva, J.M., Palva, S., 2017. Critical dynamics of endogenous fluctuations predict cognitive flexibility in the Go/NoGo task. Sci. Rep. 7 https://doi.org/10.1038/s41598-017-02759-5.

Smit, D.J.A., Boersma, M., Bijlertveldt, C.E.M., Posthuma, D., Boomsma, D.I., Stam, C. J., Geus, E.J.C., 2010. Endophenotypes in a dynamically connected brain. Behav. Genet. 40, 167–177. https://doi.org/10.1007/s10519-009-9330-8.

Smit, D.J.A., Linkenkaer-Hansen, K., de Geus, E.J., 2013. Long-range temporal correlations in resting-state alpha oscillations predict human timing-error dynamics. J. Neurosci. 33, 11212–11220.

Sternberg, R., Lubart, T., 1996. Investing in creativity. Am. Psychol. 51, 677–688. https://doi.org/10.1037/0003-066X.51.7.677.

Stevens, C.E., Zabelina, D.L., 2019. Creativity comes in waves: an EEG-focused exploration of the creative brain. Curr. Opin. Behav. Sci., Creativity 27, 154–162. https://doi.org/10.1016/j.cobeha.2019.02.003.

Ville, D.V.D., Britz, J., Michel, C.M., 2010. EEG microstate sequences in healthy humans at rest reveal scale-free dynamics. Proc. Natl. Acad. Sci. 107, 18179–18184. https://doi.org/10.1073/pnas.1007841107.

Vosburg, S.K., 1998. Mood and the quantity and quality of ideas. Creativ. Res. J. 11, 315–324. https://doi.org/10.1207/s15326934crj1104_5. 