Negative mood and mind wandering increase long-range temporal correlations in attention fluctuations

Mona Irrmischer¹*, C. Natalie van der Wal²,³, Huibert D. Mansvelder¹, Klaus Linkenkaer-Hansen¹

¹ Department of Integrative Neurophysiology, Center for Neurogenomics and Cognitive Research (CNCR), Amsterdam Neuroscience, VU Amsterdam, HV Amsterdam, Netherlands, ² Vrije Universiteit (VU) Amsterdam, Department Computer Science, Amsterdam, Netherlands, ³ Centre for Decision Research, University of Leeds Business School, Leeds, United Kingdom

* monairrmischer@gmail.com

Abstract

There is growing evidence that the intermittent nature of mind wandering episodes and mood have a pronounced influence on trial-to-trial variability in performance. Nevertheless, the temporal dynamics and significance of such lapses in attention remains inadequately understood. Here, we hypothesize that the dynamics of fluctuations in sustained attention between external and internal sources of information obey so-called critical-state dynamics, characterized by trial-to-trial dependencies with long-range temporal correlations. To test this, we performed behavioral investigations measuring reaction times in a visual sustained attention task and cued introspection in probe-caught reports of mind wandering. We show that trial-to-trial variability in reaction times exhibit long-range temporal correlations in agreement with the criticality hypothesis. Interestingly, we observed the fastest responses in subjects with the weakest long-range temporal correlations and show the vital effect of mind wandering and bad mood on this response variability. The implications of these results stress the importance of future research to increase focus on behavioral variability.

Introduction

“Mind wandering” refers to cognitions unrelated to the current demands of the external environment and plays a prominent role in daily life [1]. Reflecting on the past or mentally simulating future events are key components of the mind wandering process and central to our self-percept [2,3]. Intrusive thoughts, however, may also cause attention lapses in vital situations demanding sustained attention such as driving [4]. Additionally, long-term stress and emotional burden can lead to an increase of mind wandering, often referred to as rumination [1,5], which has a relation to numerous brain disorders, including depression [6] and social anxiety [7], and is related to decreased task performance for example while reading [8].

Research on attention has a long tradition in investigating how we selectively process one source of information while ignoring others [9]. In the face of limited processing abilities, task
performance is strongly influenced by the level of attention paid to the task \[10\]. Still, competing influences such as additional sensory information \[11\] or mind wandering \[12\] can cause distraction from the task at hand and play a pronounced role in determining behavioral variability, as seen for example in a metronome task requiring continuous responses to tones \[13\]. Nevertheless, most investigations into the link between attention and performance use statistical measures of central tendency, such as mean reaction times \[14,15\], and thereby ignoring large proportions of ongoing variability as noise or unexplained variance \[16\]. It has been shown that impending errors and stimulus-independent thoughts are related to increases in average reaction times \[17,18\] and reaction time variance \[13,19,20\], but the observation that behavioral responses have apparent fluctuations, which tend to occur in non-random clustered fashion \[21,22\] is largely neglected.

The lack of investigations into the temporal structure of trial-to-trial variability in reaction times is surprising considering the growing evidence that the temporal structure of neuronal and behavioral time series contains valuable information about the mechanisms and functions of the systems producing these fluctuations. In fact, if a signal exhibits complex fluctuations, the average is a poor statistical measure as opposed to scaling techniques that relate different scales to each other \[23\], especially if the signal harbors the long-term memory process known as 1/f noise \[16\]. 1/f noise is a hallmark of dynamical systems operating close to the critical point of a phase transition from ordered to disordered states \[24\] and is also a characteristic of many healthy physiological systems with high demands for swift adaptation, e.g., heartbeat \[25\], gait \[26\], speech \[27\] and neuronal oscillations \[28,29\]. In such non-linear dynamical systems operating near the critical state, these dynamics are reflected in the form of long-range temporal correlations \[30–32\]. Indeed, behavioral experiments in humans also show robust non-random clustering of behavioral responses such as detection of weak tactile \[33\] or visual stimuli \[34\], as well as in speech \[35\] and motor timing tasks \[36–38\]. Together, these studies suggest that profoundly important aspects of human cognition and behavior may be dismissed if the observed variability is averaged out and, therefore, not investigated.

Similarly, in attention and mind wandering research it has been shown that the behavioral success is linked to the successful dynamics of attentional resource allocation to task-related external demands as opposed to task-unrelated internal information \[14,39\]. In this study, we therefore combine this notion of resource allocation with response variability and apply it to the mind wandering problem and resulting observable behavioral correlates. We reason that for successful task performance prompt adaptation of the attentional system to the demands at hand is important and requires a mechanism that supports swift transitions.

Since dynamical systems operating near a critical state show the greatest propensity of producing swift transitions in the dynamics of the order parameter \[40,41\]—including temporal complexity \[42\]—, we hypothesize that a healthy attentional system may also operate close to a critical point \[24,43,44\]. This could allow it to display meaningful dynamics, related to the stability or variability of the resulting behavior. A key prediction derived from this hypothesis is that transitions in attention occur spontaneously \[14\], and that the resulting dynamics in the observable behavior will be characterized by trial-to-trial dependencies, long-range temporal correlations, as opposed to uncorrelated fluctuations, or no fluctuations at all. Further, the closer the transitions in attention are to the critical point (separating the ordered sub-critical and the disordered super-critical regime) the stronger the long-range temporal correlations in reaction-time fluctuations, in analogy to what has been reported for models of neuronal oscillations \[32\].

We investigate changes in behavioral dynamics through indirect performance probing in a sustained attention task and through direct experience sampling in a cued mind wandering task, and use the detrended fluctuation analysis (DFA) \[45,46\] to quantify the temporal
complexity of reaction-time fluctuations. Further, motivated by the effects of mood on mind wandering [1,5], we show that mood has profound effects on these dynamics.

**Methods**

**Participants**

The participants were recruited at the VU Amsterdam, Dutch or English speaking with no history of neurological complications or substance abuse. Three experiments were performed (see details below), an attention- task with 62 participants (mean age = 25 (SD = 6.2), 32 Female) and an attention- and mood-induction task with 89 participants (mean age = 22.4 (SD = 2.5), 64 Female) and a cued mind wandering task with 35 participants (mean age = 21.3 (SD = 1.2), 25 Female). All participants signed the informed consent, the protocol was approved by the scientific and Ethical Review Board (VCWE) of the Faculty of Psychology and Education, VU Amsterdam.

**Overall study design**

We conducted 3 independent experiments that are explained in detail below. In experiment 1, participants completed a 8 minutes sustained attention task (Continuous Temporal Expectancy Task (CTET), adapted from Connell et al., 2009)). In experiment 2, additional participants underwent a mood manipulation before participating in the same CTET paradigm. Only stimulus display times of the task were slightly longer. In experiment 3, additional participants completed a 12 minutes externally cued mind wandering task. All experiments were conducted in front of a computer screen in an isolated room.

**Continuous Temporal Expectancy Task (CTET).** Participants completed a sustained attention task (adaptation of CTET [47]), which was designed to measure lapses in attention through reaction times and the errors that the participants make. The task consisted of centrally presented photos of flowers shown at regular intervals (600 ms in experiment 1, or 900 ms in experiment 2), resulting in a continuous stream of pictures. Participants were asked to attend to the temporal duration of each stimulus and press the space bar with their dominant hand when a stimulus was presented longer (1200 ms in experiment 1, or 1600 ms in experiment 2) than the standard duration (Fig 1). Long-duration stimuli occurred semi-randomly (every 4th to 10th stimuli) 100 times. Identifying the duration target was easy when fully attending to the stimuli; however, it quickly becomes demanding to fully focus on the boring task and results in great variation as well as occasional misses during the continuous task. This makes the CTET a measure of continuous deployment of attention to the time domain, i.e., time interval between events. The stimuli were made of naturalistic pictures taken from the International Affective Picture System [48], with pictures specifically chosen for their low arousal values. Additionally, the color, brightness, saturation, and size of the scenes were standardized decrease stimulus perceptual differences.

The participant’s ability to monitor the stimulus duration is increased when attention is actively oriented towards it [49], and decreases if top-down attentional effort is diminishing. Lapses in identifying targets may therefore been taken as a correlate of decreased attention, a phenomenon seen in many everyday life applications. Different from conceptually similar attention tasks such as the go/no-go “Sustained attention to response task” (SART [50]), every stimulus is a potential target and only discriminated by its longer presentation-time and not by perceptual features. This solves the problematic issue of target salience and automatically engaged exogenous attention interfering with the continuous attentional aspect which is targeted in this study [51]. In this study, a single block was chosen to tap into long-term sustained attention abilities of the participants.
Mood inductions. In experiment 2, before completing the CTET task the participants had two interventions to induce a positive, negative or neutral mood. They first watched one of three 5 minutes movies. The content of the ‘positive’ movie contained clips of funny sit-coms and playing puppies; the ‘negative’ movie contained clips from war scenes and the ‘neutral’ movie contained clips from a documentary on concrete pipes. The instruction was to pay special attention to the content of the movie, of which they would get a quiz at the end. This was meant to obscure the effect of the mood induction and to let the participants think this experiment was about memory, and not about the effect of mood on mind wandering and attention. The ethics committee approved withholding information about the purpose of the experiment from participants until the experiment was completed. Before and after the movie, the participants completed the Positive and Negative Affect Scale (PANAS, [52,53]) to verify successful mood manipulation. The PANAS comprises two mood scales, one for positive affect and one for negative. Participants indicate to what extend they feel certain emotions using a 5-point scale ranging from not at all (1) to extremely (5). The second mood induction was to bring a vivid memory in mind that makes them feel positive, negative or neutral, and then tell the test leader when they succeeded and vividly felt the emotions that come with this memory. Again, The PANAS was applied to check the success of the manipulation. Both times, the same mood was induced in the participant. At the end they were debriefed about the real purpose of the experiment.

Externally cued mind wandering: Probe-caught paradigms are popular means to investigate mind wandering (for review: [54]) and numerous studies have used thought probes during different tasks to index the degree of mind wandering at specific moments [13,18,55]. In our study, the participants sat in a dimly lit room with their eyes closed and were asked to focus their attention on the sensation of the breathing (bodily movements of the in- and exhalation) for 12 minutes. In semi-random intervals (jitter: 7–20 s, 100 probes in total) a tone asked them to indicate if they achieved that goal or if their mind had wandered away from the breath. Participants responded by promptly indicating the level of attention on a 3-point Likert scale (1-focused on the breath, 2- a little distracted, 3- totally absent).
Behavioral analysis. The observed reaction-time averages were calculated from the point in time when the target stimulus was displayed longer than non-target stimuli. The reaction time, therefore, includes both the time needed to notice the deviant and the time to react. The next stimulus is displayed after 600 ms (experiment 1) or 900 ms (experiment 2), and to prevent that wrong presses to the non-targets stimuli would count as a very slow reaction to the target stimulus, we defined the maximum allowed reaction time up until 100 ms after the next stimuli was presented (700 ms experiment 1, 1000 ms experiment 2). To obtain a comprehensive reaction-time performance we included misses and in the reaction time series and assigned them the longest reaction time allowed (i.e., 700 ms or 1000 ms). Incorporating misses in the time-series avoids short average reaction times in subjects responding very fast but also missing several trials, and importantly, the temporal structure of an actual miss in the time series is preserved for the analysis of temporal correlations. Only serious task performances were taken into the analysis; therefore, we excluded participants who did not press the response key (Experiment 1: \( n = 2 \); Experiment 2: \( n = 1 \)), or who pressed the same button in the entire experiment (Experiment 3: \( n = 1 \)) from the analysis. For parametric tests paired-samples t-tests were used, with a significance level of \( p < 0.05 \). Associations between behavioral measures and long-range temporal correlations (LRTC) (see next section) were calculated using Pearson’s correlation coefficient.

Long-range temporal correlations analysis using the detrended fluctuation analysis. We were interested in understanding individual differences in reaction-time fluctuations as an indirect measure of fluctuations in mind wandering episodes. To this end, we quantified the strength of LRTC in reaction-time series using the detrended fluctuation analysis (DFA) [46]. The reaction-time series were defined by using the sequence of reaction times \( RT(k) \) with \( k \) being the index labeling the \( k \)’th reaction time from a total of \( N \) reaction times (\( k = 1, 2, \ldots N \)). The \( k \)-index plays the role of a pseudo-time in the DFA. In brief, the DFA measures the power-law scaling of the root-mean-square fluctuation of the integrated and linearly detrended signals, \( F(t) \), as a function of time window size, \( t \) (with an overlap of 50% between windows). The DFA exponent (\( \alpha \)) is the slope of the fluctuation function \( F(t) \) and can be related to the power-law scaling exponent of the auto-correlation function decay (\( \gamma \)) and the scaling exponent of the power spectrum density (\( \beta \)) by \( \alpha = \frac{1 + \beta}{2} = \frac{2 - \gamma}{2} \). DFA exponent values between 0.5 and 1.0 reveal the presence of LRTC, whereas an uncorrelated signal has an exponent value of 0.5. The decay of temporal correlations was quantified over a range of 2 to 60 reaction times.

Results

Simulation for the behavioral analysis and theoretical framework. For the behavioral analysis, we work with the assumption that the attention system shows temporal fluctuations in form of LRTC. If these are reflected in behavioral performance over time, it should be possible to capture these dynamics with behavior samples during a sustained attention paradigm. Therefore, in our model, we first tested whether it was possible to quantify the hypothesized attentional dynamics with a low-frequency sampling rate, i.e., the occasional presentation of a target image in the CTET task. Therefore, before conducting the experiments, simulations were carried out to: 1. find the minimum amount of data points needed to reliably estimate DFA exponents (see Methods) and 2. see if the temporal correlations of an underlying signal can be recovered with the infrequent sampling used in the attention paradigm. For this, first a 1/f signal was produced in Matlab using a signal generator with defined underlying LRTC (DFA exponent in the range of 0.6 to 1). This temporal structure is representing the hypothesized fluctuations in attention over time on a scale from entirely focused on external environment to entirely focused on internally generated thoughts and feelings.
commonly referred to as mind-wandering. On top of that signal, time points were marked in accordance with the sampling frequency of the target presentation used in the sustained attention task (Fig 2A). The points of overlap (1/f signal vs. target presentation) were obtained, and the temporal structure of this “behavioral time series” was calculated (Fig 2B). For reliability of the recovery success, the underlying 1/f signal was simulated 100 times for each exponent of the underlying signal ranging from 0.6 to 1, and the DFA fluctuation function fitted from 2 to 60 events. The resulting comparison of original exponent with recovered exponent revealed that it is possible to recover the LRTC of an underlying time series with only 100 sampling points ($p < 0.00001$) (Fig 2C). Less than 100 samples were unfavorable as it led to a regression towards the mean with an underestimation of high and overestimation of low DFA, therefore decreasing the sensitivity of exponent recovery. Thus, the observed reaction-time series resulting from the task can be used as an estimation of the underlying temporal correlation of the participants’ attentional capacities.

**Result experiment 1: The temporal dynamics of reaction times are inversely related to performance**

To test if the observed behavior during the sustained attention task exhibited LRTC, we computed the DFA exponent on the reaction time series (see Methods). Participants showed large individual variation in scaling exponents with a mean of $\alpha = .65$ (SD $= .09$). Interestingly, DFA exponents correlated strongly and positively with the mean reaction time across subjects ($R^2 = .52$, $p = .00002$), indicating that better performance was associated with a suppression of complex reaction-time fluctuations (Fig 3).

**Control analysis.** To verify that it was truly the temporal structure of the reaction time series that correlated with the mean reaction times, we randomly shuffled the reaction times and repeated the DFA analysis of the shuffled data. The correlation of DFA with mean reaction time disappeared ($R^2 = .03$, $p = .79$). Additionally, after shuffling the mean DFA of all

![Fig 2. A model of attention fluctuations to explain non-random fluctuations in reaction times.](https://doi.org/10.1371/journal.pone.0196907.g002)
participants dropped from $\alpha = .65$ to .55, as expected from a time series with a random temporal structure (see Methods).

**Results experiment 2: Mood manipulation**

In experiment 2 we tested if it is possible to manipulate the dynamics observed in Experiment 1 with a positive, neutral or negative mood induction. To test the success one-way ANOVA’s were performed on the PANAS scores obtained before and after the first mood induction (movie) and after the second mood induction (imagination). The positive affect test of the PANAS showed that after the interventions the positive group was higher in positive affect (significant between-groups main effect after the movie ($F(2) = 4,958, p < .01$) and after imagination ($F(2) = 15,346, p < .001$, see Table 1). The negative affect test of the PANAS showed that after the interventions the negative group was higher in negative affect (significant between-groups main effect after the movie ($F(2) = 7,186, p < .01$), and imagination ($F(2) = 26.888, p < .001$, see Table 2). Taken the results together, we conclude that the mood induction was successful.

**Results experiment 2: Positive mood is associated with faster performance and reduced temporal complexity of reaction times**

In experiment 2, we replicated the findings of experiment 1, and show that even with longer stimulus display times, the DFA exponents of the reaction times correlate strongly and positively with the mean reaction time across subjects ($R^2 = .56, p < 000001$). Interestingly,
dividing the outcome of the attention task in the three mood inductions showed that performance improves as the mood improves from a mean reaction time of 838 ms (SD = 75) in the negative condition to 788 ms (SD = 102) in the neutral (t65 = 2.07, p = .042) and to 774 ms (SD = 98) in the positive condition (t40 = 2.39, p = .022) (Fig 4A). Interestingly, not only the mean reaction times are influenced by mood but also the temporal structure of the behavioral time series. Negative mood was associated with more complex variation in reaction times (α = .73, SD = .11) compared to positive mood (α = .65, SD = .1; t40 = 2.53, p = .016), and a trend compared to neutral (α = .67, SD = .11; t65 = 1.9, p = .073), showing that mood also changed the variability in the reaction time series (Fig 4B).

Results experiment 3: Probe-caught mind wandering dynamics show LRTC

Indirect probing in the form of sustained attention tasks has the limitation that it is unknown if the participants really had increased mind wandering or not. Therefore, we investigated if subjectively perceived mind wandering also shows these dynamics. Participants were asked to focus their attention on the sensation of the breathing and indicate the level of success upon probing on a 3-point Likert scale (1- focused on the breath, 2- a bit focused/a bit distracted, 3- totally absent/mind wandering). Missed responses were counted as totally absent (3). We found that the average score of attention over the entire experiment was 1.73 (SD = .43), showing that participants were able to focus on the breath, with occasional distractions. Importantly, we found that these mind wandering periods also exhibited long-range temporal correlations (average α = .82 (SD = .12)). These LRTC of responses are inversely related to mind wandering: the more often participants reply that they were mind wandering the higher the DFA, showing that also subjectively felt focus is associated with reduced temporal complexity (R² = .43, p = .01) (Fig 5).

Control analysis. First, we tested the confidence of the participants in the accuracy of their mind wandering rating on a 5-point Likert scale (1- strongly disagree to 5- strongly agree). The average score of 3.88 (SD = 0.8) shows that participants believed their scores to be reflecting their subjective experience. Then, again we performed the control correlation

| Table 1. Results PANAS (positive affect). |
|------------------------------------------|
| Positive Mood Manipulation Check | Neutral mood induction (N = 46) | Positive mood induction (N = 20) | Negative mood induction (N = 22) | One-way ANOVA p value | Tukey post hoc tests (neu-pos, neu-neg, pos-neg) |
|------------------------------------------|
| Measurement1 (pre-movie) | 3.01 | 3.38 | 3.14 | | |
| Measurement2 (post-movie) | 2.80 | 3.31 | 2.76 | .009 | .013, .970, .022 |
| Measurement3 (post-imagine) | 2.42 | 3.51 | 2.36 | .000 | .000, .964, .000 |

Table 2. Results PANAS (negative affect).

| Negative Mood Manipulation Check | Neutral mood induction (N = 46) | Positive mood induction (N = 20) | Negative mood induction (N = 22) | One-way ANOVA p value | Tukey post hoc tests (neu-pos, neu-neg, pos-neg) |
|---------------------------------|
| Measurement1 (pre-movie) | 1.99 | 1.89 | 1.83 | | |
| Measurement2 (post-movie) | 1.54 | 1.52 | 2.16 | .001 | .996, .002, .007 |
| Measurement3 (post-imagine) | 1.36 | 1.47 | 2.57 | .000 | .781, .000, .000 |

https://doi.org/10.1371/journal.pone.0196907.t001

https://doi.org/10.1371/journal.pone.0196907.t002
analysis with randomly shuffled values (disrupting the original underlying temporal structure while keeping mean values the same), which showed that the correlation of DFA with mean response disappeared again ($R^2 = -.18$, $p = .30$). Additionally, the temporal structure of reaction time series differed between positive—negative ($t(40) = 2.39, p = .022$). Error bars represent 95% confidence intervals.

**Discussion**

In this study, we tested the hypothesis that spontaneous transitions in attention can be characterized by LRTC. Assuming that a healthy attention system is adapted to allow self-organized switches in response to changing environmental (or internal) demands and, therefore, could operate near a critical state, we applied a measure of temporal correlations to behavior time series. Through indirect performance probing in a sustained attention task and direct experience sampling of mind wandering episodes, we showed that both behavioral time series display long-range temporal correlations. Further, we showed that better performance is associated with less complexity in the response variation. In addition, we could actively manipulate the temporal structure and performance by inducing different moods in the participants.
In this study, we investigated if the variance caused by lapses in attention and mind-wandering episodes are meaningful and can be quantified with the use of scaling techniques to estimate LRTC, also known as $1/f$ noise [16]. For this, we first show that it is possible to retrieve underlying LRTC in a signal with irregular sampling frequency (as used in our attention task) to allow behavioral correlates as a measure for attentional focus. To quantify the temporal complexity of the system we applied the detrended fluctuation analysis (DFA) [45,46], and achieved a robust estimation of underlying temporal correlation. We showed that the observed behavioral responses have non-random clustered fluctuations in the form of LRTC, as opposed to uncorrelated fluctuations, or no fluctuations at all.

According to our hypothesis, a healthy attention system—like many other physiological systems, including neuronal oscillations [28,29], operate near a critical state [24,43,44]. It is plausible that the fluctuations in focus of attention—and hence in the reaction times—may find an explanation also within the framework referred to as "rapid transition processes" [56], which has been successful in accounting for the temporal complexity of different sleep stages and levels of consciousness [57–59]. Importantly, the metric of LRTC applied to reaction-time series is efficient in identifying a direct relationship between individual differences in performance and temporal variability in performance. Therefore, we show that applied to sustained attention and mind wandering LRTC might be related to the dynamics of the allocation of limited attentional resources; possibly from task-unrelated (internal)
demands such as mind wandering to task-related (or external) processes such as responding to the task. The closer the transitions in attention are to the critical point (separating the ordered sub-critical and the disordered super-critical regime), the stronger the long-range temporal correlations in the behavior. The closer a state is to criticality (higher LRTC) it may be more optimized for a broad range of different demands including transitions from environmental and internal sources [60], while reducing these fluctuations might be more beneficial for a single focus, as needed during the present attention task. Indeed, we also see a reduction in LRTC in neuronal oscillations in response to task performance [61,62]. A reduction in exponents indicates less autocorrelations and, therefore, less influence on future dynamics [63,64], hence possibly less distractions from the focused task at hand, such as off-task mind wandering.

It is important to stress that the control analysis showed that the temporal structure measured was not only caused by increased variance produced by the increase in reaction times, or mind-wandering episodes, but that additionally these episodes come with an increased temporal structure related to the success in performance. The latter is lost if the order of responses is shuffled: The reaction-time average and variability stay the same while the temporal structure decreases.

We know that mind wandering [1,5] and our ability to keep attention on a task can be largely influenced by our mood [8]. Therefore, we tested if we could actively manipulate the temporal structure of performance by inducing different moods in the participants. We show that indeed positive mood was associated with better performance and decreased LRTC. Bad mood is associated with increased mind wandering [1], with one reason being that we turn ‘inside’ in an attempt to gain insight into why we feel bad [65] a process accentuated by the observation that bad mood additionally biases the mind for further negative thinking [66]. In accordance with our hypothesis participants most likely were more often distracted or pulled out of the single external focus required for the sustained attention task to more internal mood-related mind wandering or distractions. Interestingly, these switches did not occur ‘at random’ but are temporally related.

**Outlook**

The implications of these results stress the importance of future research to investigate the temporal structure of behavioral variability instead of only central tendency measurements. It is also interesting to apply neuroimaging techniques to understand the neural correlations of these individual differences in performance variability, as scaling techniques have successfully been applied to both EEG [62,67,68] and fMRI investigations [69,70].

**Author Contributions**

**Conceptualization:** Mona Irrmischer, C. Natalie van der Wal, Klaus Linkenkaer-Hansen.

**Data curation:** Mona Irrmischer, C. Natalie van der Wal.

**Formal analysis:** Mona Irrmischer.

**Methodology:** Mona Irrmischer, Klaus Linkenkaer-Hansen.

**Project administration:** C. Natalie van der Wal.

**Resources:** C. Natalie van der Wal.

**Supervision:** Huibert D. Mansvelder, Klaus Linkenkaer-Hansen.

**Writing – original draft:** Mona Irrmischer.
Writing – review & editing: Huibert D. Mansvelder, Klaus Linkenkaer-Hansen.

References
1. Killingsworth MA, Gilbert DT. A wandering mind is an unhappy mind. Science. 2010. p. 932. https://doi.org/10.1126/science.1192439 PMID: 21071660
2. Buckner RL, Andrews-Hanna JR, Schacter DL. The brain’s default network: anatomy, function, and relevance to disease. Ann N Y Acad Sci. 2008; 1124: 1–38. https://doi.org/10.1196/annals.1440.011 PMID: 18400922
3. Smallwood J, Brown K, Baird B, Schooler JW. Cooperation between the default mode network and the fronto-parietal network in the production of an internal train of thought. Brain Res. Elsevier B.V.; 2012; 1428: 60–70. https://doi.org/10.1016/j.brainres.2011.03.072 PMID: 21467693
4. He J, Becic E, Lee YC, McCarley JS. Mind wandering behind the wheel: Performance and oculomotor correlates. Hum Factors. 2011; 53: 13–21. https://doi.org/10.1177/0018720810391530 PMID: 21469530
5. Hamilton JP, Furman DJ, Chang C, Thomason ME, Dennis E, Gotlib IH. Default-mode and task-positive network activity in major depressive disorder: implications for adaptive and maladaptive rumination. Biol Psychiatry. Elsevier Inc.; 2011; 70: 327–33. https://doi.org/10.1016/j.biopsych.2011.02.003 PMID: 21459364
6. Papageorgiou C, Wells A. An empirical test of a clinical metacognitive model of rumination and depression. Cognit Ther Res. Springer; 2003; 27: 261–273.
7. Mellings TMB, Alden LE. Cognitive processes in social anxiety: the effects of self-focus, rumination and anticipatory processing. Behav Res Ther. 2000; 38: 243–257. https://doi.org/10.1016/S0005-7967(99)00040-6 PMID: 10665158
8. Lyubomirsky S, Kasri F, Zehm K. Dysphoric rumination impairs concentration on academic tasks. Cogn Ther Res. 2003; 27: 309–330. https://doi.org/10.1023/A:1023918517378
9. Driver J. A selective review of selective attention research from the past century. Br J Psychol. 2001; 92 Part 1: 53–78. https://doi.org/10.1348/000712601162103
10. Sarter M, Gehring WJ, Kozak R. More attention must be paid: The neurobiology of attentional effort. Brain Research Reviews. 2006. pp. 145–160. https://doi.org/10.1016/j.brainresrev.2005.11.002 PMID: 16530842
11. Theeuwes J. Top-down and bottom-up control of visual selection. Acta Psychol (Amst). Elsevier B.V.; 2010; 135: 77–99. https://doi.org/10.1016/j.actpsy.2010.02.006 PMID: 20507828
12. Smallwood J, Schooler JW. The Science of Mind Wandering: Empirically Navigating the Stream of Consciousness. Annu Rev Psychol. 2015; 66: 487–518. https://doi.org/10.1146/annurev-psych-010814-015331 PMID: 25293689
13. Seli P, Cheyne JA, Smilek D. Wandering minds and wavering rhythms: Linking mind wandering and behavioral variability. J Exp Psychol Hum Percept Perform. 2013; 39: 1–5. https://doi.org/10.1037/a0030954 PMID: 23244048
14. Kelly a MC, Uddin LO, Biswal BB, Castellanos FX, Milham MP. Competition between functional brain networks mediates behavioral variability. Neuroimage. 2008; 39: 527–37. https://doi.org/10.1016/j.neuroimage.2007.08.008 PMID: 17919929
15. Diniz A, Wijnants ML, Torre K, Barreiros J, Crato N, Bosman AMT, et al. Contemporary theories of 1/f noise in motor control. Hum Mov Sci. Elsevier B.V.; 2011; 30: 889–905. https://doi.org/10.1016/j.humov.2010.07.006 PMID: 21196059
16. Gilden DL. Cognitive emissions of 1/f noise. Psychol Rev. 2001; 108: 33–56. https://doi.org/10.1037/0033-295X.108.1.33 PMID: 11212631
17. Kane MJ, McVay JC. What Mind Wandering Reveals About Executive-Control Abilities and Failures. Curr Dir Psychol Sci. 2012; 21: 348–354. https://doi.org/10.1177/0963721412454875
18. Smallwood J, Beach E, Schooler JW, Handy TC. Going AWOL in the brain: mind wandering reduces cortical analysis of external events. J Cogn Neurosci. 2008; 20: 458–69. https://doi.org/10.1162/jocn.2008.20037 PMID: 18004943
19. Bastian M, Sackur J. Mind wandering at the fingertips: Automatic parsing of subjective states based on response time variability. Front Psychol. 2013; 4. https://doi.org/10.3389/fpsyg.2013.00573 PMID: 24046753
20. Esterman M, Noonan SK, Rosenberg M, Degutis J. In the zone or zoning out? Tracking behavioral and neural fluctuations during sustained attention. Cereb Cortex. 2013; 23: 2712–2723. https://doi.org/10.1093/cercor/bhs261 PMID: 22941724
21. VERPLANCK WS, Collier GH, COTTON JW. Nonindependence of successive responses in measurements of the visual threshold. J Exp Psychol. Not Available; 1952; 44: 273–82. https://doi.org/10.1037/0054948 PMID: 13000069

22. Wertheimer M. An investigation of the “randomness” of threshold measurements. J Exp Psychol. 1953; 45: 294–303. https://doi.org/10.1037/h0055277 PMID: 13052865

23. Hardstone R, Poi S-S, Schiavone G, Jansen R, Nikulin V V, Mansvelder HD, et al. Detrended fluctuation analysis: A scale-free view on neuronal oscillations. Front Physiol. Frontiers Media SA; 2012; 3 NOV. https://doi.org/10.3389/fphys.2012.00450 PMID: 2326132

24. Bak P. Complexity and Criticality. How nature works. Springer; 1996. pp. 1–32.

25. Goldberg AL, Amaral L a N, Hausdorff J, M, Ivanov P. C, Peng C-K, & Stanley HE, Goldberg AL, Amaral L a N, Hausdorff J, M, Ivanov P. C, Peng C-K, et al. Fractal dynamics in physiology: alterations with disease and aging. Proc Natl Acad Sci U S A. 2002; 99 Suppl 1: 2466–72. https://doi.org/10.1073/pnas.012579499 PMID: 11875196

26. Daliri MR. Automatic diagnosis of neuro-degenerative diseases using gait dynamics. Measurement. 2012; 45: 1729–1734. https://doi.org/10.1016/j.measurement.2012.04.013

27. Voss RF, Clarke J. 1/F Noise in Music and Speech. Nature. 1975. pp. 317–318. https://doi.org/10.1038/258317a0

28. Montez T, Poi S-S, Jones BF, Manshanden I, Verbunt JPA, van Dijk BW, et al. Altered temporal correlations in parietal alpha and prefrontal theta oscillations in early-stage Alzheimer disease. PNAS. 2009; 106: 1614–1619. https://doi.org/10.1073/pnas.0811699106 PMID: 19164579

29. Palva S, Linkenkaer-Hansen K, Näätänen R, Palva JM. Early neural correlates of conscious somatosensory perception. J Neurosci. 2005; 25: 5248–58. https://doi.org/10.1523/JNEUROSCI.0141-05.2005 PMID: 15917465

30. Eguiluz VM, Chialvo DR, Cecchi G a., Baliki M, Apkarian a. V. Scale-free brain functional networks. 2003; 1–4. https://doi.org/10.1103/PhysRevLett.94.018102 PMID: 15698136

31. van Orden GC, Kello CT, Anderson GG, Holden JG, Van Orden GC. The emergence of cognitive function. J Exp Psychol Gen. 2007; 136: 551–68. https://doi.org/10.1037/0096-3445.136.4.551 PMID: 17999570

32. Weissman DH, Roberts KC, Visscher KM, Woldorff MG. The neural bases of momentary lapses in attention. Nat Neurosci. 2006; 9: 971–8. https://doi.org/10.1038/nn1727 PMID: 16767087

33. Contoyiannis YF, Diakonos FK. Criticality and intermittency in the order parameter space. Phys Lett Sect A Gen At Solid State Phys. 2000; 268: 286–292. https://doi.org/10.1016/S0375-9601(00)00180-8

34. Contoyiannis YF, Diakonos FK, Malakis A. Intermittent dynamics of critical fluctuations. Phys Rev Lett. APS; 2002; 89: 35701.

35. Kinouchi O, Copelli M. Optimal dynamical range of excitable networks at criticality. Nat Phys. 2006; 2: 348–351. https://doi.org/10.1038/nphys289
44. Shew WL, Yang H, Petermann T, Roy R, Plenz D. Neuronal avalanches imply maximum dynamic range in cortical networks at criticality. J Neurosci. 2009; 29: 15595–600. https://doi.org/10.1523/JNEUROSCI.3864-09.2009 PMID: 20007483

45. Linkenkaer-Hansen K, Nikouline V V, Palva JM, Ilmoniemi RJ. Long-range temporal correlations and scaling behavior in human brain oscillations. J Neurosci. 2001; 21: 1370–7. PMID: 11160408

46. Peng K, Havlin S., Stanley H., and. Goldberger A. Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series. Chaos. 1995; 5.

47. O'Connell RG, Dockree PM, Robertson IH, Bellgrove MA, Foxe JJ, Kelly SP. Uncovering the Neural Signature of Lapsing Attention: Electrophysiological Signals Predict Errors up to 20 s before They Occur. J Neurosci. 2009; 29: 8604–8611. https://doi.org/10.1523/JNEUROSCI.5967-08.2009 PMID: 19571151

48. Lang P. J., Bradley M. M., & Cuthbert B. N. International affective picture system (IAPS): Technical manual and affective ratings. NIMH Center for the Study of Emotion and Attention. 1997. 39–58.

49. Nobre A, Correa A, Coull J. The hazards of time. Current Opinion in Neurobiology. 2007. pp. 465–470.

50. Robertson IH, O'Connell R. Vigilant attention. Attention and Time. 2012. https://doi.org/10.1093/acprof:oso/9780199563456.003.0006

51. Irremischer M, Sangiuliano Intra F, Mansvelder HD, Poil S-S, Linkenkaer-Hansen K. Strong long-range temporal correlations in beta/gamma oscillations are associated with poor sustained visual attention performance. Eur J Neurosci. 2017; 38: 42–49. https://doi.org/10.1111/ejn.13672

52. Eke a, Herman P, Kocsis L, Kozak LR. Fractal characterization of complexity in temporal physiological signals. Physiol Meas. 2002; 23: R1–R38. https://doi.org/10.1088/0967-3334/23/1/201 PMID: 11876246

53. Lyubomirsky S, Nolen-Hoeksema S. Self-perpetuating properties of dysthmic rumination. [Internet]. Journal of Personality and Social Psychology. 1993. pp. 339–349. https://doi.org/10.1037/0022-3514.65.2.339 PMID: 8366423
66. Koster EHW, De Raedt R, Goeleven E, Franck E, Crombez G. Mood-Congruent Attentional Bias in Depression: Maintained Attention to and Impaired Disengagement From Negative Information. Emotion. 2005; 5: 446–455. https://doi.org/10.1037/1528-3542.5.4.446 PMID: 16366748

67. Allegrini P, Menicucci D, Bedini R, Fronzoni L, Gemignani A, Grigolini P, et al. Spontaneous brain activity as a source of ideal 1/f noise. Phys Rev E. APS; 2009; 80: 61914.

68. Allegrini P, Paradisi P, Menicucci D, Gemignani A. Fractal complexity in spontaneous EEG metastable-state transitions: New vistas on integrated neural dynamics. Front Physiol. 2010; https://doi.org/10.3389/fphys.2010.000128

69. Tagliazucchi E, Balenzuela P, Fraiman D, Chialvo DR. Criticality in Large-Scale Brain fMRI Dynamics Unveiled by a Novel Point Process Analysis. Front Physiol. 2012; 3: 1–12. https://doi.org/10.3389/fphys.2012.00001

70. Tagliazucchi E, Sinitchkin M, Laufs H, Chialvo DR. The voxel-wise functional connectome can be efficiently derived from co-activations in a sparse spatio-temporal point-process. Front Neurosci. 2016; https://doi.org/10.3389/fnins.2016.00381 PMID: 27601975