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Research Article

Psychological Science
1–15
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DOI: 10.1177/09567976221110136
www.psychologicalscience.org/PS

A Self-Controlled Mind Is Reflected by Stable Mental Processing

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Abstract

Self-control—the ability to inhibit inappropriate impulses—predicts economic, physical, and psychological well-being. However, recent findings demonstrate low correlations among self-control measures, raising the question of what self-control actually is. Here, we examined the idea that people high in self-control show more stable mental processing, characterized by processing steps that are fewer in number but longer lasting because of fewer interruptions by distracting impulses. To test this hypothesis, we relied on resting electroencephalography microstate analysis, a method that provides access to the stream of mental processing by assessing the sequential activation of neural networks. Across two samples (Study 1: $N = 58$ male adults from Germany; Study 2: $N = 101$ adults from Canada, 58 females), the temporal stability of resting networks (i.e., longer durations and fewer occurrences) was positively associated with self-reported self-control and a neural index of inhibitory control, and it was negatively associated with risk-taking behavior. These findings suggest that stable mental processing represents a core feature of a self-controlled mind.

Keywords

self-control, electroencephalography, microstates, neural networks, resting state, response inhibition, risk taking, open data, open materials, preregistered

Received 2/28/22; Revision accepted 5/25/22

Self-control is a fundamental trait that relates to the regulation of behavior and has been defined as the ability to inhibit impulses in order to achieve long-term goals (Inzlicht et al., 2021). Research has confirmed the adaptive nature of self-control, demonstrating that self-controlled individuals show increased economic, physical, and psychological well-being (de Ridder et al., 2012; Tangney et al., 2004). However, recent findings cast doubt on the validity of both the leading theoretical model of self-control (i.e., the strength model; Vohs et al., 2021) and distinct self-control measures (e.g., Wennerhold & Friese, 2020). Furthermore, by conceptually focusing on the role of inhibitory processes, researchers may have neglected other aspects of self-control (e.g., proactively avoiding temptations or using cognitive reconstruals to alter the experience of temptations; see also the Discussion section, second paragraph, and Fujita, 2011; Inzlicht et al., 2021).

These issues raise questions about how well we have actually understood the construct of self-control. On the basis of overlooked theoretical models and empirical findings, which suggest that self-controlled individuals are less prone to distracting impulses, we hypothesized that self-control is associated with a less distracted mind, characterized by more stable and longer-lasting mental-processing steps. To test this hypothesis, we relied on microstate analysis of resting-state electroencephalography (EEG; Bréchet et al., 2020; da Cruz et al.,

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2020; Nagabhushan Kalburgi et al., 2020). This analysis provides access to the stream of mental processing by assessing the sequential activation of (usually) four large-scale brain networks at a millisecond resolution (for a review, see Michel & Koenig, 2018). We speculate that the temporal stability (i.e., longer durations and fewer occurrences) across the four network types indicates an individual's general mental-processing stability. In order to investigate mental processing free of context, we focused on analyzing task-independent brain networks.

The strength model holds that self-control is a domain-general resource with a limited capacity that varies in individual strength and that high self-control demands lead to depletion of this resource, as indicated by performance decreases during consecutive tasks (Baumeister et al., 2007). However, recent meta-analyses have shown that this depletion effect is much smaller than previously thought (e.g., Vohs et al., 2021), leaving a gap within self-control theory. If self-control is not a limited resource, what is it?

To answer this question, it could help to look at how researchers have measured this construct. Self-report measures such as the Brief Self-Control Scale (BSCS) capture cognitively available aspects of self-control by having participants respond to items like "I am good at resisting temptation" (Tangney et al., 2004). Incentivized risk tasks, like the Balloon Analogue Risk Task (BART; Lejuez et al., 2002), indirectly assess self-control by having participants choose between smaller but secure, and larger but insecure, monetary gains. Finally, researchers have analyzed inhibitory-control-related brain activity during both task-independent and task-dependent processing, arguing that neural measures may provide the most direct indices of self-control. An example is the baseline activation in inhibitory-control-related brain regions (Schiller et al., 2014) and the no-go P300 amplitude, a task-dependent neural index of inhibitory control that is registered while participants are inhibiting prepotent motor responses (Nash et al., 2013). In sum, although existing self-report, behavioral, and neural measures of self-control choose different routes to access the construct, they share the assumption that self-control relates to inhibitory capacity. Yet associations among these measures are commonly weak or absent (Wennerhold & Friese, 2020). The ongoing confusion about the right way to measure self-control emphasizes the need to reconceptualize the construct by identifying other core features of self-control across measures.

Here, we argue that a core feature of self-control is stable mental processing characterized by fewer but longer-lasting mental-processing steps because of fewer interruptions by distracting impulses. This hypothesis is based on three main pieces of suggestive theoretical and empirical evidence. First, different measures of self-control share the notion that a self-controlled mind is able to shield against mental interruptions, such as distracting events or impulsive urges, in order to maintain a stable, higher-order goal (Schiffer et al., 2015). For example, scoring high on the item "Sometimes I can't stop myself from doing something, even if I know it is wrong" will result in a lower score on the BSCS (Tangney et al., 2004). In line with this notion, the Continuous Performance Test (CPT) measures people's ability to quickly respond to specific stimuli while neglecting distracting ones (Fallgatter et al., 1997). Moreover, in incentivized risk tasks participants have to resist the impulse to obtain potential immediate high-gain rewards in order to maximize their long-term profit (Lejuez et al., 2002). Second, research on attention-deficit/hyperactivity disorder (ADHD), a mental disorder associated with deficient self-control, suggests that an "uncontrolled mind" is reflected by unstable mental processing prone to interruption by distracting impulses (Castellanos et al., 2006). Specifically, the inability to distinguish between relevant and irrelevant information is assumed to lead to increased vulnerability for insignificant information to intrude into the current mental process (Fassbender et al., 2009). These deficiencies impair performance in objective self-control measures, as evidenced by more errors and more variable response

Statement of Relevance

Self-control enables us to regulate our behavior in order to achieve long-term goals. Indeed, scientists have found that people with high self-control live happier and healthier lives. Yet the differences between a self-controlled mind and an impulsive mind have remained unclear. Here, we analyze the relationship between self-report, neural, and behavioral measures of self-control and brain activity when a person's mind is free to wander and no task is at hand. We demonstrate that self-controlled individuals show fewer but longer-lasting mental-processing steps. These results suggest that people with high self-control have more stable mental processes with fewer interrupting thoughts and impulses. Our findings illustrate that analyzing the mental flow of the resting brain can reveal crucial information on the nature of our minds. In the future, assessing individual differences in the stability of mental processing could be helpful in understanding and treating disorders associated with deficient self-control.

times in the CPT (Epstein et al., 2003) and more impulsive decision-making in the BART (Humphreys & Lee, 2011). Third, it has been observed that self-control is negatively associated with mind wandering ($r = -.49$, $p < .001$), a mental-processing style characterized by many interruptions of mental processing and consequently shorter processing steps (Deng et al., 2019). In sum, a broad array of research supports the theoretical assumption that a core feature of self-control is stable mental processing. But how can we actually gain access to an individual's mental processing style to test this hypothesis?

An ideal tool to identify mental-processing steps on a millisecond scale is EEG microstate analysis (Michel & Koenig, 2018). Microstate analysis uses clustering of electrophysiological data to obtain a sequential activation of large-scale brain networks and quantify their temporal characteristics (e.g., average duration, average occurrences per second). This approach is consistent with the notion that self-control is associated with the activation of whole-brain neural networks (Schiller & Delgado, 2010). Microstates arise because of simultaneous activation of specific neuronal assemblies and thus reflect temporarily stable episodes of coherent mental activity (Michel & Koenig, 2018). Based on the idea that microstates represent the individual units that constitute the stream of mental processing, each microstate may be described as a distinct mental processing step. In the resting brain, microstates remain stable for approximately 40 to 120 ms before quickly changing into other networks (Lehmann et al., 1987). Further illustrating microstates' fundamental character, four prototypical types of microstate networks (A–D) account for approximately 80% of the variance in resting EEG recordings of almost every single individual (Michel & Koenig, 2018). Importantly, the average duration of microstate networks in milliseconds and their average number of occurrences per second are highly correlated across microstate types (duration: $r = .79$, occurrence: $r = .51$; Khanna et al., 2014). This suggests that individuals have a general tendency for more (fewer but longer-lasting microstates) or less (more but shorter-lasting microstates) stable mental processing at rest (beyond associations of specific microstates' stability with different levels of consciousness, neuropsychiatric conditions, and cognitive contents; for a review, see Michel & Koenig, 2018).

Here, we investigated the hypothesis that self-report, neural, and behavioral measures of self-control show associations with stable mental processing, although these measures may not correlate with each other (Wennerhold & Friese, 2020). In Study 1, we first tested for associations of stable mental processing with self-reported self-control (BSCS; Tangney et al., 2004) in 58 healthy men. Second, we tested for associations with a neural index of inhibitory control (the no-go P300 in the CPT; Fallgatter et al., 1997). Third, we localized neural sources of inhibitory control and investigated whether stable mental processing is associated with cortical activity in these sources (using standardized low-resolution brain electromagnetic tomography [sLORETA]; Pascual-Marqui, 2002). In Study 2, we carried out the same analysis plan as in Study 1 (preregistered at https://osf.io/sajxv/), in order to replicate associations of self-control and stable mental processing in an already-collected sample of 101 participants (58 females). As a conceptual extension, we tested the hypothesis that stable mental processing is negatively associated with risk-taking behavior (BART; Lejuez et al., 2002).

Study 1

Method

Participants. Based on an estimated medium effect size of associations between resting-state microstate characteristics and trait variables in similar research (Schiller, Kleinert, et al., 2020), 56 participants ($\alpha = .05$, power = .85, $r = .35$) were needed to detect a significant effect. To account for potential dropouts, we recruited 61 healthy right-handed men in Freiburg, Germany, all free of current or previous history of physical and psychiatric disorders and of alcohol or drug abuse. Two participants were excluded because of technical problems during EEG measurements, and one participant was excluded because of random response patterns in the go/no-go reaction time task, resulting in a final sample size of 58 for all analyses. The mean age of the sample was 24.09 years ($SD = 4.28$, range = 18–40). Both studies were reviewed and approved by the institutional review board of each university and carried out with the adequate understanding and informed written consent of participants according to the principles expressed in the Declaration of Helsinki.

Procedure. Exclusion criteria were assessed in an online screening questionnaire. Prior to the experimental procedure, participants completed the BSCS (Tangney et al., 2004) online. They then took part in two laboratory sessions, each run by two trained study assistants. In the first session of 90 min, participants were seated in a darkened, electrically shielded cabin for the recording of 64-channel resting EEG. A chin rest was used, and participants were instructed to move as little as possible to minimize artifacts. Resting-state EEG was recorded for 5 min using a routine protocol consisting of 20-s eyes-open periods followed by 40-s eyes-closed periods, repeated five times (Schiller et al., 2014, 2019). This procedure was used in

order to minimize fluctuations in the vigilance states of participants. Instructions were given via intercom. Next, participants completed the CPT (Fallgatter et al., 1997) and other paradigms that are not part of the current study. Participants also completed a second experimental session, in which interactive paradigms were assessed that are evaluated elsewhere. On average, participants received monetary compensation of €45.18 (*SD* = €1.18, range = €43.50–48.10).

Measurement of self-reported self-control and a neural index of inhibitory control. We measured self-reported self-control using the BSCS (Tangney et al., 2004), including 13 items on different self-control-related domains (e.g., "I am good at resisting temptation"). For each item, participants indicate how much the item reflects them typically on a 5-point Likert scale (1 = *not at all* to 5 = *very much*), resulting in a final score of 13 to 65 points. The BSCS shows good internal consistency (α = .83–.85) and test–retest reliability after 3 weeks (r = .87), and it predicts a wide range of health-related and social outcomes (Tangney et al., 2004). Additionally, we used the CPT as a standard procedure to assess response inhibition using electrophysiological data (Fallgatter et al., 1997). The task for participants was to press a response button if an "O" was followed by an "X" (O → X; go condition; 40 stimuli) in a series of 400 letters that appeared on screen for 200 ms with an interstimulus interval of 1,650 ms. Response inhibition was required if an "O" was not followed by an "X" (e.g., O → F; no-go condition; 40 stimuli). Other letters were either primers (O; 80 stimuli) or distractors (e.g., B; 240 stimuli). A neural index of inhibitory control was calculated as the baseline-corrected, average event-related P300 response in no-go trials in a time frame of coordinated mental activity in the brain (for details, see the event-related EEG analysis).

EEG recording and preprocessing. Continuous resting-state EEG was recorded in an electrically shielded cabin with a sampling rate of 1000 Hz and an online band-pass filter between 0.1 and 100 Hz using 64 Ag-AgCI active electrodes (actiCAP; Brain Products, Munich, Germany) arranged in the extended 10-20 system on the scalp. The signal was referenced online to an electrode on site FCz, and the grounding electrode was placed at AFz. Electro-oculographic signals were measured by two electrodes at the left and right outer canthi (horizontal movement) and the left infra- and supraorbital (vertical movement). Preprocessing of all EEG data was conducted in the *Brain Vision Analyzer* (Version 2.1.0.327, Brain Products). A notch filter of 50 Hz and an additional band-pass filter of 2 to 20 Hz were applied on resting-state EEG data (Michel & Koenig, 2018), and an additional band-pass filter of 0.1 to 30 Hz was applied in case of event-related EEG data (Schiller et al., 2016). Eye-movement artifacts were removed using a semiautomatic independent component analysis. EEG channels heavily affected by artifacts were interpolated using neighboring electrodes. Remaining artifacts were automatically identified first (maximum amplitude ±100 μV) and corrected manually to eliminate remaining artifacts. Finally, the signal was rederived to average reference.

EEG resting-state microstate analysis. To obtain individual information on the temporal stability of microstate networks at rest (i.e., stable mental processing), microstate analyses were conducted in *EEGLAB* (Delorme & Makeig, 2004) using a plug-in for resting-state microstate analyses by Koenig (2017) that works according to standard procedures (Pascual-Marqui et al., 1995). First, resting EEG signals were down-sampled to 500 Hz and split into segments of 2 s (Khanna et al., 2014). Second, EEG data from all channels (electric potential field maps) were extracted at time points of maximum global field power (GFP), ensuring optimal signal-to-noise ratio (Michel & Koenig, 2018), and submitted to an atomize-agglomerate hierarchical-clustering procedure for the identification of the four most predominant microstate maps in each participant (Murray et al., 2008). In line with the literature, the polarity of maps was ignored as inverted polarities emerge from oscillations of the same underlying electrical source generators (Michel & Koenig, 2018). Third, maps of all participants were included in a second cluster analysis to obtain grand-mean microstate maps, which were manually sorted to fit the standard order (Michel & Koenig, 2018). Grand-mean microstate maps of our data closely resembled the four prototypical resting-state microstate types A, B, C, and D known from the literature (see Fig. 1; Michel & Koenig, 2018). Next, individual microstate maps were assigned to one of the four grand-mean microstate maps according to spatial correlations. Finally, individual maps from GFP peaks were assigned to the best-fitting predominant microstate map, resulting in a continuous temporal series of microstates for each participant from which we extracted the average duration of each microstate type in milliseconds and the average number of occurrences of each microstate type per second. As we were interested in the general, type independent temporal stability of resting-state microstates, *duration* refers to the duration of all four microstate types, and *occurrence* refers to the number of occurrences of all four microstate types per second. Overall, stable mental processing is reflected by longer durations and fewer occurrences of microstates across microstate types (as longer durations naturally go with fewer occurrences).

EEG event-related analysis. To obtain a neural index of inhibitory control, we first identified event-related

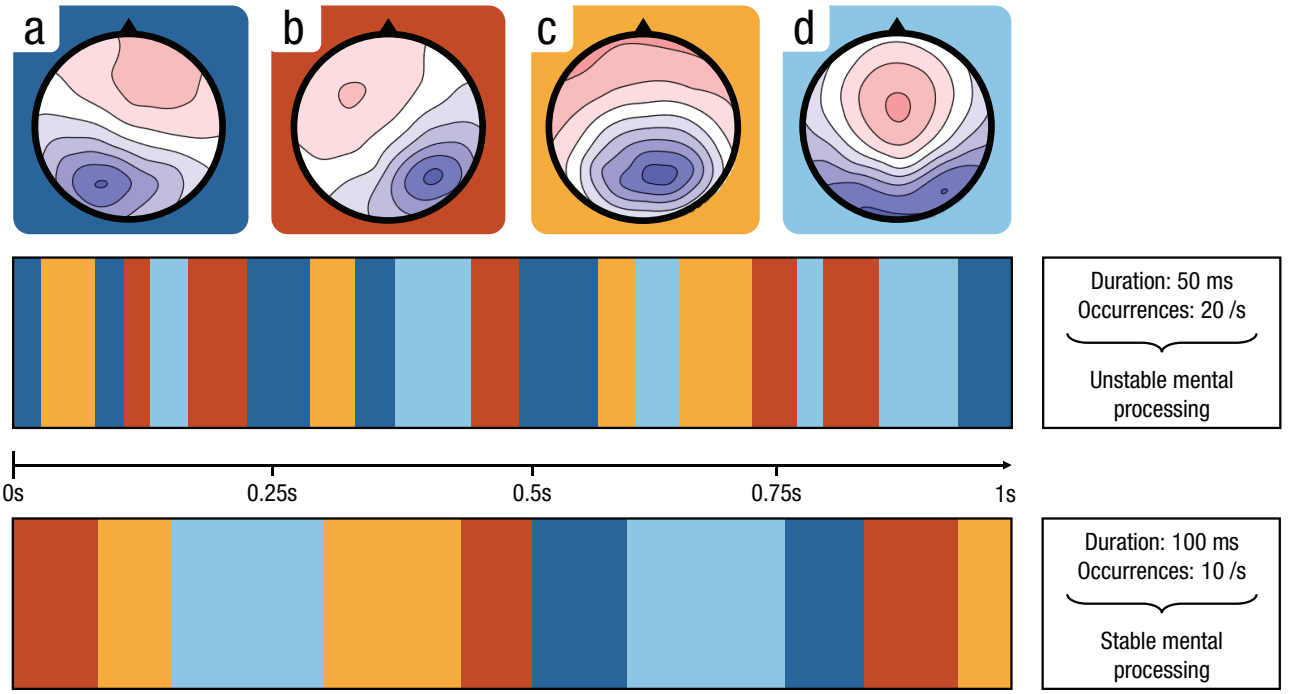

Fig. 1. Grand-mean microstate maps in Study 1 and exemplary microstate sequences. Grand-mean maps of resting-state microstates in Study 1 are shown at the top. Note that the four empirically identified microstate maps closely resemble the prototypical microstate maps known from the literature (Michel & Koenig, 2018). Exemplary 1-s sequences of resting-state microstate networks are shown for an individual with unstable mental processing (middle sequence) and an individual with stable mental processing (bottom sequence). Compared with the individual with unstable mental processing, the individual with stable mental processing shows a longer average microstate duration across network types (100 ms vs. 50 ms) and fewer occurrences of microstates per second (10 vs. 20).

potentials (ERPs) in response to the go- and no-go conditions in the CPT (−200 to 1,000 ms after stimulus presentation). ERPs were baseline corrected (baseline: −200 to 0 ms after stimulus presentation) and averaged. A topographic-consistency test (Koenig et al., 2011) showed that there was no communality in EEG signals across participants earlier than 50 ms after stimulus onset, which is why we chose a time frame of 50 to 1,000 ms after stimulus presentation for further analyses. Next, we used an event-related microstate analysis (e.g., Schiller et al., 2016) to identify sequences of microstate networks in response to the go and no-go conditions of the CPT. For this purpose, ERPs were submitted to a modified *k*-means clustering procedure (300 random trials; minimum length of 30 ms; conserving the polarity of the maps) in the software *CARTOOL*, using global map dissimilarity as an index of topographic difference between maps to identify the most dominant topographic networks (Brunet et al., 2011). Then we generated grand-mean sequences of these networks for the go and no-go conditions using a topographic-fitting procedure. The ideal number of seven microstate networks was identified via a synthetic meta-criterion for the best-fitting microstate solution provided by *CARTOOL* (Custo et al., 2017; Michel & Koenig, 2018). In line with previous research, we found a prolonged latency of the P300 peak and a more anterior activation in the no-go condition compared with the go condition (Fallgatter et al., 1997). Notably, we identified an additional, more anterior microstate network in the no-go condition in a time frame of 300 to 423 ms after stimulus presentation, which was not found in the go condition (evaluated in detail elsewhere). A neural index of inhibitory control was calculated as the baseline-corrected average amount of electrical activity (i.e., GFP) in this time frame of coordinated mental activity following response inhibition.

EEG source-localization analysis. The sLORETA (Pascual-Marqui, 2002) solution space, which has been used in many EEG studies (e.g., Leota et al., 2021; Nash et al., 2013; Schiller, Domes, & Heinrichs, 2020; Schiller et al., 2014), consists of 6.239 voxels (voxel size: 5 × 5 × 5 mm) and is restricted to cortical gray matter and hippocampi, as defined by the digitized Montreal Neurological Institute probability atlas. The sLORETA functional images represent the estimated electrical activity at each voxel as squared magnitude (i.e., power) of computed current density (unit: amperes per square meter, or A/m^2). sLORETA

estimates the electrical neuronal activity without assuming a predefined number of sources. Our aim was to identify the intracerebral sources underlying the association of the no-go P300 and stable mental processing. For that purpose, we averaged all scalp maps within the time periods covered by the P300 microstate in the go and no-go conditions of the CPT (i.e., 300–423 ms after stimulus onset; fixed time window across participants) and then estimated the individual sLORETA images. Using the regularization method in the sLORETA software, we chose the transformation matrix with the signal-to-noise set to 10. To reduce confounds that have no regional specificity, we normalized sLORETA images for each participant and for each condition to a total power of 1 and then log-transformed them before statistical analyses.

Statistical analysis. The goal of the current study was to evaluate associations of self-control measures (self-reported self-control and a neural index of inhibitory control) with stable mental processing (i.e., longer durations and fewer occurrences of microstate networks). We calculated two-tailed linear mixed models with microstate characteristics (i.e., duration, occurrence) as dependent variables, self-control measures as independent variables, and random intercepts across participants (no random slope used; see also Atluri et al., 2018). To test whether characteristics of specific microstate types (A, B, C, or D) showed stronger or weaker associations with indices of self-control, we added interactions with dummy variables of microstate types to the respective model in a next step, allowing for a direct comparison of effects between microstate types (see Table S1 in the Supplemental Material for a full exemplary analysis). All metric variables were *z*-standardized prior to analyses. Marginal *R*-squared values (R^2_m) were calculated following the procedure recommended by Nakagawa and Schielzeth (2013).

In a first set of analyses, we tested for associations of self-reported self-control with the duration and occurrence of resting-state microstates using the procedure described above. In a second set of analogous analyses, we tested for associations of a neural index of inhibitory control with the duration and occurrence of microstates. Next, we added both indices of self-control as joint predictors in one linear mixed model to test whether a higher percentage of variance in the duration and occurrence of resting-state microstates could be explained by combining self-report and neural measures of self-control. To test for the reliability of our results, we repeated the main analyses using microstate characteristics adjusted for the total EEG time available (to control for EEG quality; see Table S2 in the Supplemental Material). Furthermore, we found associations of the mean spectral EEG power of the delta, theta, alpha, and beta frequency band with microstate duration and self-control indices (see Table S3 in the Supplemental Material). Therefore, we controlled for power values by adding them as additional predictors to our main analyses. We also tested for the robustness of our findings by excluding outliers with regard to microstate characteristics (see Table S4 in the Supplemental Material). All analyses yielded highly comparable results. Last, we examined whether source-localized brain activity during response inhibition in the CPT was associated with the temporal stability of resting-state microstates by regressing the sLORETA images of the no-go condition on the average duration of resting-state microstates. We restricted this voxel-by-voxel regression analysis to voxels, which were more active during the no-go condition than the go condition (461 voxels encompassing mostly frontocingulate regions; $p < .01$; see Table S5 in the Supplemental Material). Correction for multiple testing was implemented by means of a nonparametric randomization approach, which estimated the empirical probability distributions and the corresponding critical probability thresholds (corrected for multiple comparisons; $r > .37$, $p < .05$).

Results

Descriptive statistics. As expected, we found considerable heterogeneity of self-control across different measurement domains. Self-reported self-control as measured with the BSCS amounted to an average of 37.60 points ($SD = 6.90$, range = 19–51); the neural index of inhibitory control as measured by the average amplitude of the P300 during response inhibition amounted to an average of 5.73 μV ($SD = 2.23$, range = 1.78–12.64). Self-reported self-control was not significantly associated with the neural index of inhibitory control ($r = .11$, 95% confidence interval [CI] = [–.16, .35], $p = .431$).

On average, there were 158.88 s of artifact-free resting-state EEG data available for microstate analyses ($SD = 31.39$, range = 54.10–219.00). In close accordance with previous findings, the four prototypical microstate types accounted for an average of 77.87% of EEG signals ($SD = 3.26$, range = 70.40–84.20). See Figure 1 for grand-mean microstate maps and exemplary sequences of microstates for individuals with stable and unstable mental processing (see Table S6 in the Supplemental Material available online for descriptive statistics of Study 1). Supporting the assumption that people display a general tendency for more or less stable mental processing, durations (A × B: $r = .58$, 95% CI = [.38, .73], $p < .001$; A × C: $r = .59$, 95% CI = [.40, .74], $p < .001$; A × D: $r = .60$, 95% CI = [.40, .74], $p < .001$; B × C: $r = .64$, 95% CI = [.45, .77], $p < .001$; B × D: $r = .59$, 95% CI = [.40, .74], $p < .001$; C × D: $r = .58$, 95% CI = [.37, .73], $p < .001$)

and occurrences (A × B: $r = .59$, 95% CI = [.40, .74], $p < .001$; A × C: $r = .39$, 95% CI = [.14, .59], $p = .003$; A × D: $r = .39$, 95% CI = [.15, .59], $p = .002$; B × C: $r = .57$, 95% CI = [.36, .72], $p < .001$; B × D: $r = .45$, 95% CI = [.21, .63], $p < .001$; C × D: $r = .54$, 95% CI = [.32, .70], $p < .001$) of all four microstate types showed considerable positive correlations. This confirms that the temporal stability of one microstate network naturally goes along with the temporal stability of all other microstate networks.

Adding a random intercept across participants to a model of microstate duration increased the model fit ($p < .001$), confirming the need for linear mixed model analyses. Correspondingly, a high intraclass correlation coefficient (ICC) of .600 indicated that durations of the four microstate types were correlated, which again means that people tend to have higher or lower durations of microstates across microstate types. The same pattern applies for microstate occurrences (increase in model fit with $p < .001$; ICC = .493).

Associations of self-reported self-control and stable mental processing. As hypothesized, the duration of resting-state microstates was positively related to self-reported self-control, $b = 0.419$, 95% CI = [0.230, 0.609], $SE = 0.095$, $t(56) = 4.41$, $p < .001$, $R^2_m = .177$ (see Fig. 2). To test whether this effect was driven by specific microstate types, we tested for an interaction of self-reported self-control with microstate types. We found a significantly higher model fit after including interactions with microstate types to the model ($p = .046$) because of a weaker association of self-reported self-control with the duration of type A compared with type B ($p = .006$). However, durations of all four microstate types were positively associated with self-reported self-control, supporting our assumption of a type-independent association of microstate network stability and self-control (see Table S7 in the Supplemental Material for correlations). Furthermore, the occurrence of resting-state microstates was negatively related to self-reported self-control, $b = -0.370$, 95% CI = [−0.552, −0.188], $SE = 0.091$, $t(56) = -4.05$, $p < .001$, $R^2_m = .137$ (see Fig. 2). Again, adding interactions with microstate types to the model resulted in a higher model fit ($p = .012$), revealing a stronger (negative) association of self-reported self-control with the occurrence of type A compared with types B ($p = .002$), C ($p = .016$), and D ($p = .018$). However, occurrences of all four microstate types were negatively associated with self-reported self-control, again demonstrating the type-independent association of microstate network stability and self-control. Adding to the reliability of our findings, effects were robust when controlling for EEG quality (see Table S2 in the Supplemental Material) and when removing outliers with regard to microstate characteristics (see Table S4 in the Supplemental Material). Taken together, these results suggest that self-controlled individuals show a higher stability of mental processing in the brain when no task is at hand.

Associations of a neural index of inhibitory control and stable mental processing. In a second set of analyses, we used a neural index of inhibitory control (amount of electrical activity in the time frame of the no-go P300, obtained from the CPT) to predict the duration of microstates in a mixed model. As expected, the neural index of inhibitory control was positively related to microstate duration, $b = 0.265$, 95% CI = [0.056, 0.473], $SE = 0.104$, $t(56) = 2.54$, $p = .014$, $R^2_m = .070$ (see Fig. 2). All microstate types contributed equally to this effect, as there was no increased model-fit testing for an interaction with microstate types ($p = .166$). Furthermore, the neural index of inhibitory control was negatively related to microstate occurrence, $b = -0.241$, 95% CI = [−0.438, −0.045], $SE = 0.098$, $t(56) = -2.45$, $p = .017$, $R^2_m = .059$ (see Fig. 2), indicating that participants with fewer occurrences of microstates show an increased electrophysiological response-inhibition capacity. Again, all microstate types contributed equally to this effect, as there was no increased model-fit testing for an interaction with microstate types ($p = .096$). These findings suggest that an increased P300 response during response inhibition is associated with stable mental processing (see Fig. 2; see Table S7 in the Supplemental Material for correlations; see Table S4 for outlier analyses demonstrating the robustness of these associations).

To test for their combined predictive power for stable mental processing, we used self-reported self-control and the neural index of inhibitory control as joint predictors for the duration (and occurrence) of microstates in multiple-predictor linear mixed models. Both measures of self-control showed incremental validity on top of each other for the prediction of the duration of microstates—self-reported self-control: $b = 0.396$, 95% CI = [0.214, 0.578], $SE = 0.091$, $t(55) = 4.32$, $p < .001$; neural index of inhibitory control: $b = 0.223$, 95% CI = [0.041, 0.404], $SE = 0.091$, $t(55) = 2.44$, $p = .018$, $R^2_m = .226$—and the occurrence of microstates—self-reported self-control: $b = -0.348$, 95% CI = [−0.523, −0.173], $SE = 0.088$, $t(55) = -3.96$, $p < .001$; neural index of inhibitory control: $b = -0.205$, 95% CI = [−0.380, −0.030], $SE = 0.088$, $t(55) = -2.33$, $p = .024$, $R^2_m = .179$. Compared with single-predictor models using only self-reported self-control as a predictor, adding the neural index of inhibitory control increased the amount of variance explained in microstate duration by 4.6% (from 17.7% to 22.3%) and in microstate occurrence by 4.2% (from 13.7% to 17.9%). These results illustrate independent associations of stable mental processing with both perceptions and neural processes related to self-control.

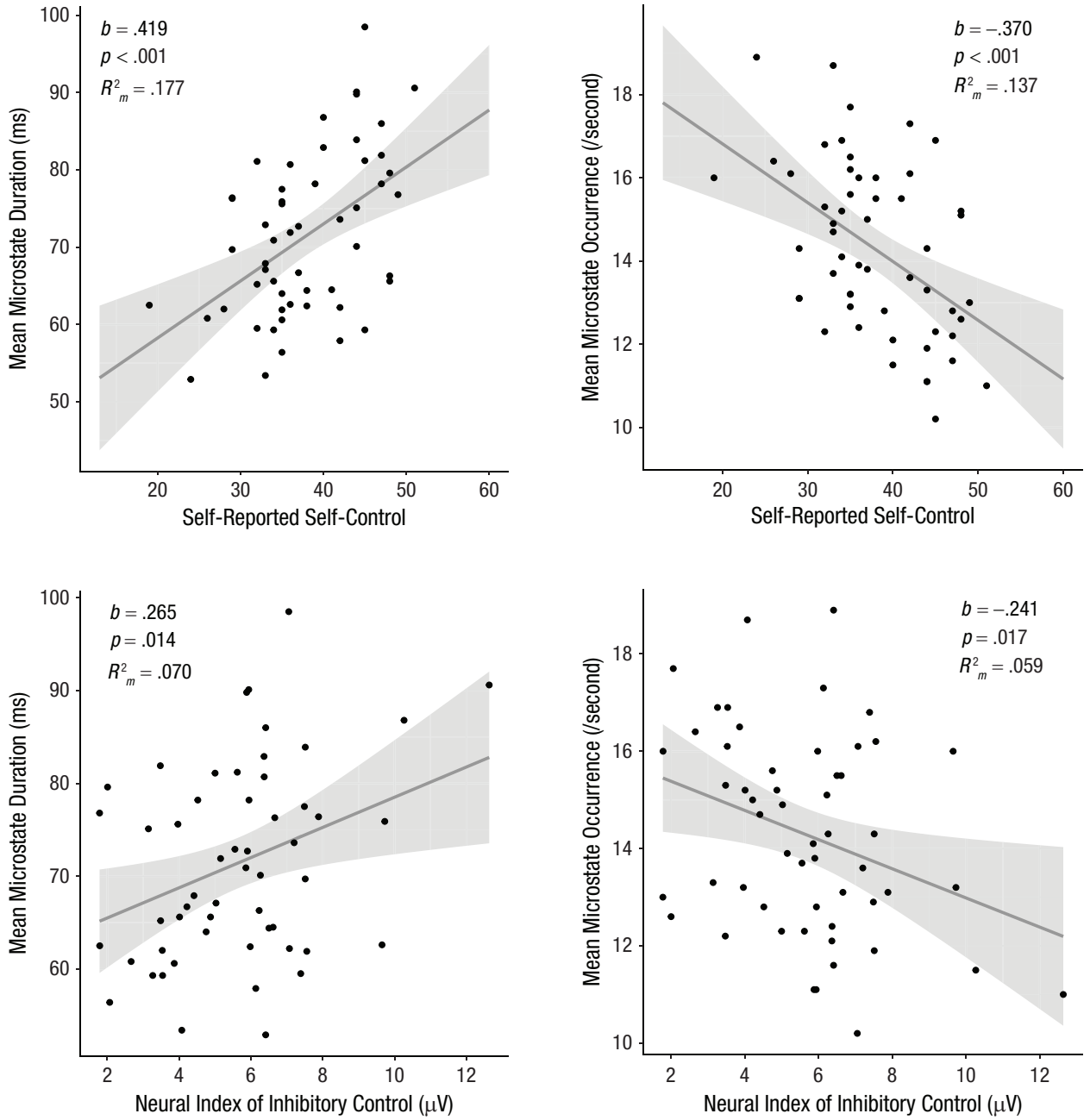

Fig. 2. Associations of stable mental processing with self-reported self-control and a neural index of inhibitory control. The scatterplot at the top left illustrates the association of the mean microstate duration across types A through D with self-reported self-control (Brief Self-Control Scale; Tangney et al., 2004). The scatterplot at the top right illustrates the association of the mean microstate occurrence across types A through D with self-reported self-control. The scatterplot at the bottom left illustrates the association of the mean microstate duration with the neural index of inhibitory control as measured by the amount of electrical activity in the time frame of the P300 (GFP averaged over 300–423 ms after stimulus onset) in the no-go condition of the Continuous Performance Test (Fallgatter et al., 1997). The scatterplot at the bottom right illustrates the association of the mean microstate occurrence with the neural index of inhibitory control. All plots include 95% confidence intervals and coefficients resulting from mixed model analyses.

Associations of control-related brain areas and stable mental processing. We used sLORETA (Pascual-Marqui, 2002) to identify neural sources of inhibitory control during the CPT (i.e., voxels that were more active during the P300 in the no-go condition compared to the P300 in the go condition) that were associated with task-independent stable mental processing. We identified a significant positive correlation of current source density

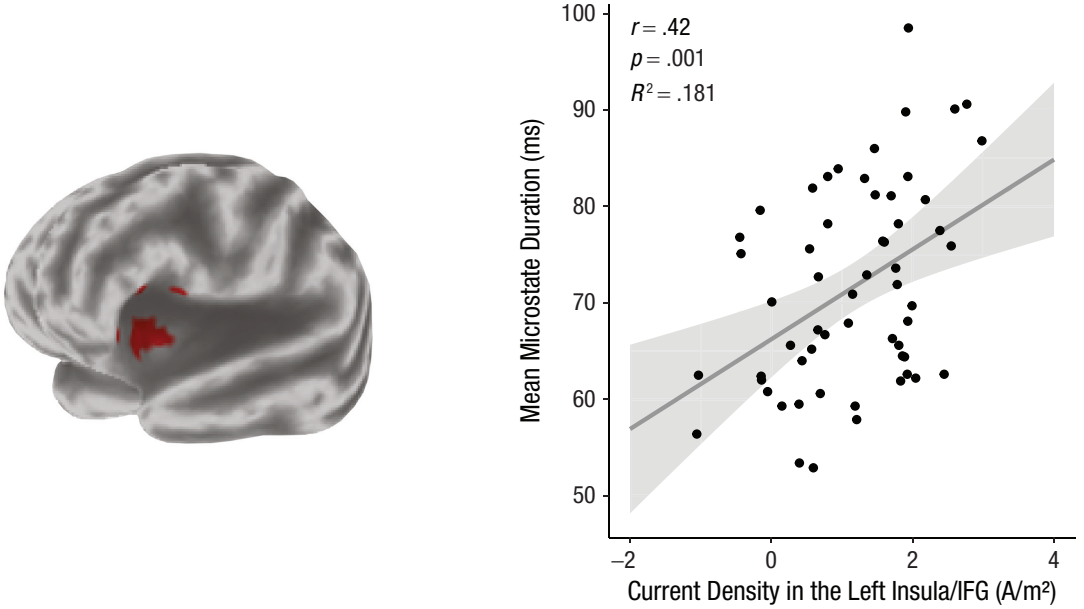

Fig. 3. Association of mean microstate duration with source-localized brain activity. On the left, locations of the 14 voxels that showed significant correlations are indicated in red (corrected at $p < .05$; ten of these voxels were located in the left insula, Brodmann's area [BA] 13; peak voxel at Montreal Neurological Institute [MNI] coordinates $x = -40$, $y = 15$, $z = 5$; four voxels were located in the left inferior frontal gyrus (IFG), BAs 44, 45, and 47; peak voxel at MNI coordinates $x = -40$, $y = 20$, $z = 5$). On the right, the scatterplot illustrates the association between mean microstate duration and current density (global field power [GFP] channel) in these 14 voxels during the no-go condition of the Continuous Performance Test (demonstrating the average correlation across all voxels that exceeded the corrected p threshold in the same cluster; the plot includes a 95% confidence interval and coefficients resulting from a Pearson's correlation analysis).

estimates originating from the left insula and inferior frontal gyrus (14 voxels, $p < .05$, corrected; see Fig. 3; see also Table S5 in the Supplemental Material) and the mean duration of microstates ($r = .42$, 95% CI = [.187, .616], $p < .001$), indicating that people with stronger activity in these regions during response inhibition show more stable mental processing at rest (there were no significant associations with the mean occurrence of microstates).

Study 2

Method

Participants. For a preregistered replication analysis in Study 2, we used an already collected, substantially larger sample of 110 first-year psychology students recruited at the University of Alberta, Canada. Nine participants were excluded because of poor-quality resting EEG recordings, resulting in a final sample size of 101 for all analyses (58 females, 43 males). The mean age was 19.76 years ($SD = 1.62$, range = 17–26). Gender differences were not further considered in Study 2, as females and males did not show any significant differences (see Table S8 in the Supplemental Material).

Procedure. Participants were equipped with a 64-channel EEG system (Brain Products, Munich, Germany). All tasks were completed in an electrically shielded and noise-shielded cabin on a computer using *Presentation* (Version 18.0, Neurobehavioral Systems, Berkeley, CA). First, demographic information and several questionnaires were collected, including the BSCS. Second, a 4-min resting EEG was recorded (a 60-s eyes-open period followed by a 60-s eyes-closed period, repeated two times in total). Again, only eyes-closed periods were used for further EEG analysis (2 min). Participants were then randomly assigned to one of two experimental conditions that are unrelated to the current study (anxiety or control). Note that controlling for experimental conditions had no impact on the main results of this study (see Table S9 in the Supplemental Material). Afterward, participants completed two tasks that will be evaluated elsewhere, followed by the BART for the measurement of risk-taking behavior. Finally, participants were thanked for their time and compensated with class credit. The average duration of the experiment was 110 min.

Measurement of self-reported self-control and risk-taking behavior. Self-reported self-control was measured

with the BSCS that we used in Study 1 (Tangney et al., 2004). Risk-taking behavior was measured with the BART, which is associated with self-control deficiencies, impulsivity, and sensation seeking, as well as addictive, risky, and unhealthy behaviors (Lejuez et al., 2002). In the BART, participants were informed that they could increase their number of ballots in a lottery (price of $100) by performing well in a balloon-pumping game. The task was to press a button to pump up balloons (20 in total) that would explode after an unknown and variable number of pumps (explosion threshold; 15 pumps on average). Balloons were inflated more and more with every pump; each pump earned one ballot but also brought the balloon closer to the explosion threshold. Participants earned no ballots for exploded balloons. In each trial, they could stop pumping at any time in order to retain the earned ballots and continue with the next trial. An individual score of risk-taking behavior (RT) was computed as (RT = average pumps × (explosions + 1)/total number of trials). Thus, RT increases with a higher average number of pumps and explosions, making it a more sensitive and valid measure of risk-taking compared with traditional measures that focus on the number of either pumps or explosions (also see Leota et al., 2021). Following a reviewer's suggestion, we also checked whether our findings remained robust when using an alternative risk-taking score, as originally proposed by Lejuez et al., 2002. All reported associations remained significant—association of the alternative risk-taking measure with microstate duration: $b = -0.215$, 95% CI = [−0.388, −0.042], $SE = 0.088$, $t(99) = -2.45$, $p = .016$, $R^2_m = .047$; association of the alternative risk-taking measure with microstate occurrence: $b = 0.198$, 95% CI = [0.026, 0.370], $SE = 0.087$, $t(99) = 2.28$, $p = .025$, $R^2_m = .040$.

EEG recording, preprocessing, and resting-state microstate analysis. In our Canadian sample, continuous resting-state EEG was recorded in an electrically shielded cabin with a sampling rate of 500 Hz and an online band-pass filter between 0.1 and 100 Hz using 64 Ag-AgCI active electrodes (actiCHamp; Brain Products, Munich, Germany) arranged in the 10-10 system on the scalp. The signal was referenced online to an electrode on site TP9 over the left mastoid. EEG preprocessing steps and the resting-state microstate analysis were conducted in the same way as in Study 1.

Statistical analysis. Again, we calculated linear mixed models with microstate characteristics (i.e., duration, occurrence) as dependent variables, self-control and/or risk-taking behavior as independent variables (all variables *z*-standardized), and a random intercept across participants (no random slope used). Again, we added interaction terms with dummy variables of microstate types to the respective model in a next step, allowing for a direct comparison of effects between microstate types. First, we aimed to replicate a positive association of self-reported self-control with microstate duration and a negative association with microstate occurrence. Second, we applied a conceptual extension by testing for a negative association of risk-taking behavior with microstate duration and a positive association with microstate occurrence. Finally, we added both self-reported self-control and risk-taking behavior as joint predictors in multiple predictor linear mixed models to test whether a higher percentage of variance in the duration and occurrence of resting-state microstates can be explained by combining self-report and behavioral measures of self-control.

Results

Descriptive statistics. Again, we found high heterogeneity of self-control across different measurement domains. Self-reported self-control as measured with the BSCS amounted to an average of 39.12 points ($SD = 6.90$, range = 18–59), and risk-taking behavior as measured by the BART amounted to an average of 3.91 points ($SD = 2.73$, range = 0.13–12.68). Self-reported self-control was not significantly associated with risk-taking behavior ($r = -.001$, 95% CI = [−.196, .195], $p = .996$).

On average, there were 105.64 s of artifact-free resting-state EEG data available for microstate analyses ($SD = 9.30$, range = 50.94–112.70), and the four prototypical microstate types accounted for an average of 74.71% of EEG signals ($SD = 4.78$, range = 55.93–84.43; see Tables S10 and S11 in the Supplemental Material for grand-mean microstate maps and detailed descriptive statistics of Study 2).

Replication analysis: associations of self-reported self-control and stable mental processing. As hypothesized via our preregistered analysis plan, a positive association of self-reported self-control with microstate duration was replicated, albeit with a more modest effect size than in Study 1, $b = 0.179$, 95% CI = [.003, .354], $SE = .089$, $t(99) = 2.02$, $p = .046$, $R^2_m = .032$ (see Fig. 4). To test whether this effect was driven by specific microstate types, we tested for an interaction of self-reported self-control with microstate types. We did not find a significantly higher model fit after including interactions with microstate types in the model ($p = .090$), illustrating that all microstate types contributed to the effect (see Table S12 in the Supplemental Material for correlations). In an analogous analysis, a negative association of self-reported self-control with microstate occurrence was not replicated, $b = -0.140$, 95% CI = [−0.315, 0.035], $SE = 0.088$, $t(99) = 1.59$, $p = .116$, $R^2_m = .020$ (see Fig. 4). Critically, this association was significant, $b = -0.171$, 95% CI = [−0.302, −0.039], $SE = 0.066$, $t(95) = -2.57$, $p = .012$, $R^2_m = .052$, after removing outliers with regard to microstate characteristics (see Table S4 in

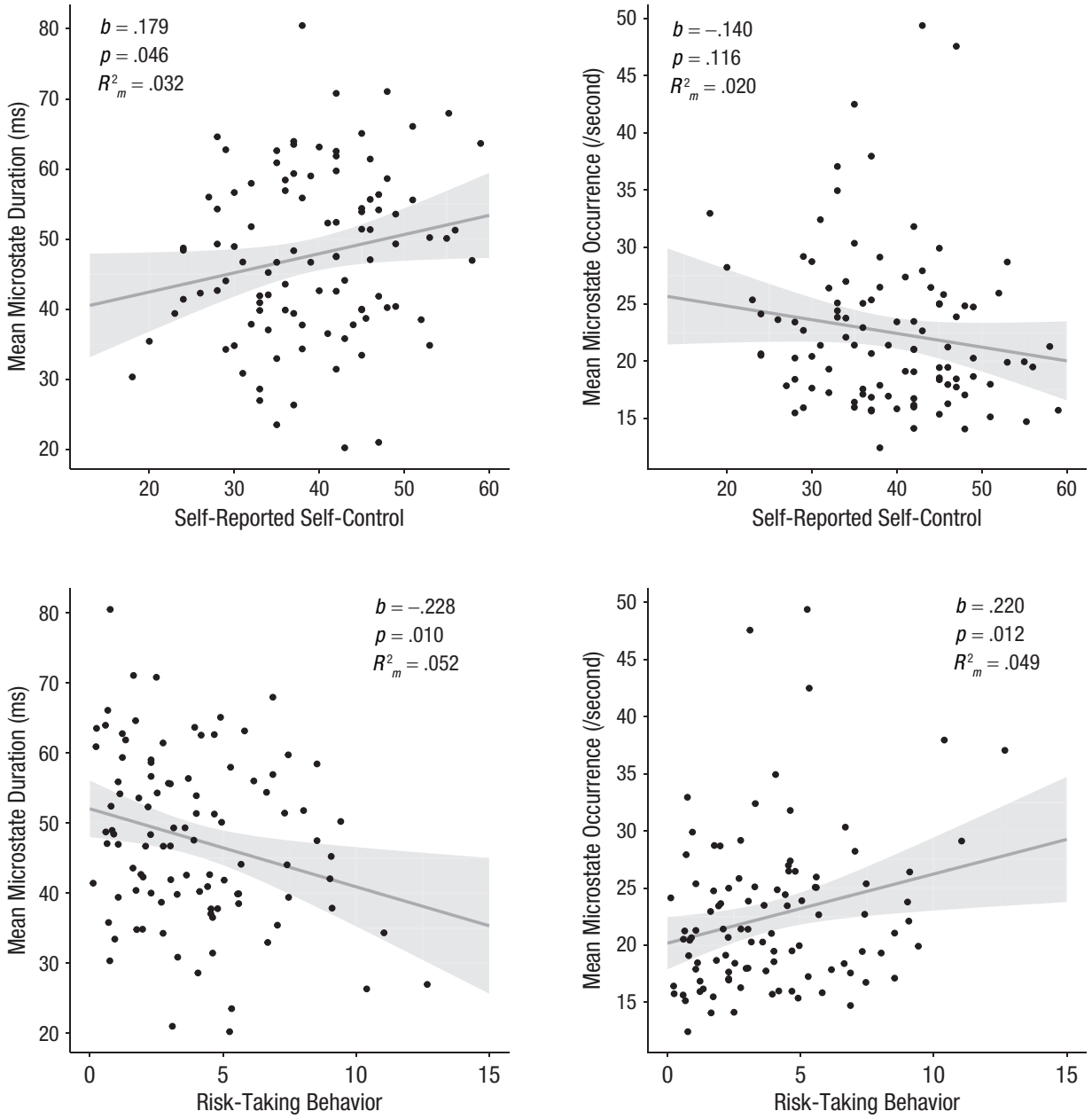

Fig. 4. Associations of stable mental processing with self-reported self-control and risk-taking behavior. The scatterplot at the top left illustrates the association of the mean microstate duration across types A through D with self-reported self-control (Brief Self-Control Scale; Tangney et al., 2004). The scatterplot at the top right illustrates the association of the mean microstate occurrence across types A through D with self-reported self-control. The scatterplot at the bottom left illustrates the association of the mean microstate duration with risk-taking behavior as measured in the Balloon Analogue Risk Task (Lejuez et al., 2002). The scatterplot at the bottom right illustrates the association of the mean microstate occurrence with risk-taking behavior. All plots include 95% confidence intervals and coefficients resulting from mixed model analyses.

the Supplemental Material). Adding interactions with microstate types to the model did not result in a higher model fit ($p = .290$). Overall, Study 2 provided somewhat mixed evidence regarding the association of self-reported self-control and stable mental processing compared with Study 1. However, outlier analyses support a replication of Study 1's findings.

Conceptual extension: associations of risk-taking behavior and stable mental processing. As a conceptual extension, we tested for associations of stable mental processing with risk-taking behavior. As hypothesized, risk-taking behavior was negatively related to microstate duration, $b = -0.228$, 95% CI = [–0.400, –0.055], $SE = 0.087$, $t(99) = -2.61$, $p = .010$, $R^2_m = .052$ (see Fig. 4).

There was no higher model fit after including interactions with microstate types to the model (p = .389). Furthermore, risk-taking behavior was positively associated with microstate occurrence, b = 0.220, 95% CI = [0.049, 0.391], SE = 0.086, $t(99)$ = 2.55, p = .012, R^2_m = .049 (see Fig. 4), indicating that the positive association of the temporal stability of resting EEG networks with risk-taking behavior is driven by both the duration and the occurrence of microstates (see Table S12 for correlations; see Table S4 for outlier analyses demonstrating the robustness of these associations). Adding interactions with microstate types to the model did not result in a higher model fit (p = .156).

Next, we used self-reported self-control and risk-taking behavior as joint predictors for the duration and occurrence of resting-state microstates in multiple predictor linear mixed models. Both predictors showed incremental validity on top of each other for the prediction of microstate duration—self-reported self-control: b = 0.179, 95% CI = [0.009, 0.348], SE = 0.086, $t(98)$ = 2.08, p = .040; risk-taking behavior: b = −0.228, 95% CI = [−0.397, −0.059], SE = 0.085, $t(98)$ = −2.67, p = .009, R^2_m = .084. Risk-taking behavior showed incremental validity on top of self-reported self-control for the prediction of microstate occurrence—self-reported self-control: b = −0.140, 95% CI = [−0.309, 0.029], SE = 0.086, $t(98)$ = −1.64, p = .105; risk-taking behavior: b = 0.220, 95% CI = [0.051, 0.388], SE = 0.085, $t(98)$ = 2.58, p = .012, R^2_m = .068. Compared with single-predictor models using only self-reported self-control as a predictor, adding risk-taking behavior increased the amount of variance explained in microstate duration by 5.2% (from 3.2% to 8.4%) and in microstate occurrence by 4.9% (from 1.9% to 6.8%). These results illustrate independent associations of stable mental processing with both perceptions and behavioral preferences related to self-control.

Association of self-reported self-control and stable mental processing across both studies. In a final set of analyses, we combined the samples of Study 1 and Study 2 (N = 159) to identify the overall association of stable mental processing with self-reported self-control. Across samples, self-reported self-control was positively related to microstate duration, b = 0.266, 95% CI = [0.135, 0.398], $t(157)$ = 3.99, p < .001, R^2_m = .071, and negatively related to microstate occurrence, b = −0.224, 95% CI = [−0.353, −0.094], $t(157)$ = 3.40, p < .001, R^2_m = .050 (see Table S4 for outlier analyses demonstrating the robustness of these associations). There were no interactions with microstate types (prediction of microstate duration: p = .975; prediction of microstate occurrence: p = .774), indicating that all four types—A, B, C, and D—contributed equally to both effects (correlations of self-reported self-control with the duration of type A: r = .265, 95% CI = [.114, .404], p < .001; type B: r = .283, 95% CI = [.133, .420], p < .001; type C: r = .256, 95% CI = [.104, .396], p = .001; and type D: r = .261, 95% CI = [.110, .400], p = .001; correlations of self-control with the occurrence of type A: r = −.266, 95% CI = [−.405, −.115], p < .001; type B: r = −.204, 95% CI = [−.349, −.050], p = .010; type C: r = −.208, 95% CI = [−.352, −.054], p = .009; and type D: r = −.216, 95% CI = [−.360, −.062], p = .006).

Controlling for the frequency content of the EEG data. Following a reviewer's suggestion, we analyzed associations of the mean spectral EEG power of the delta, theta, alpha, and beta frequency bands with microstate duration and the three indices of self-control. As several EEG power values were associated with microstate duration and self-control indices (see Table S3 in the Supplemental Material for details), we recalculated our main analyses including EEG power values as additional predictors. Across samples, the association of self-reported self-control with microstate duration remained significant, b = 0.227, 95% CI = [0.099, 0.355], SE = 0.065, $t(153)$ = 3.47, p < .001. In Study 1, the association of the neural index of inhibitory control with microstate duration remained significant, b = 0.225, 95% CI = [0.052, 0.397], SE = 0.087, $t(52)$ = 2.57, p = .013. In Study 2, the association of risk-taking behavior with microstate duration remained significant, b = −0.215, 95% CI = [−0.385, −0.044], SE = 0.086, $t(95)$ = −2.48, p = .015.

Discussion

Self-control is commonly defined as the ability to inhibit impulses in order to achieve long-term goals. However, recent research has challenged the assumption that self-control is all about inhibition. On the basis of both a theoretical account of self-control and recent research, we hypothesized that self-control is associated with stable mental processing as indicated by fewer but longer-lasting mental-processing steps. To test this hypothesis, we assessed mental-processing stability by means of resting EEG microstates analysis, which allowed us to determine individual durations and occurrences of mental-processing steps when no task is at hand. Across two laboratories and two independent samples, we found that stable mental processing was associated with self-report, neural, and behavioral measures of self-control.

Our first exploratory study demonstrated strong associations of stable mental processing with self-reported self-control and a neural measure of inhibitory control (Study 1: N = 58 males). Following a preregistered analysis plan, our second study (Study 2: N = 101;

58 females) replicated associations of stable mental processing with self-reported self-control, albeit the effect sizes were more modest than in Study 1, and the association of microstate occurrence and self-reported self-control was significant only after removing outliers. As a conceptual extension, Study 2 revealed inverse associations of stable mental processing with risk-taking behavior. These analyses added to the robustness of our findings yet also suggested that the first study may have somewhat overestimated the true effect size in the general population.

Our findings resonate with recent expansions of the concept of self-control beyond the inhibition of impulses (Fujita, 2011; Inzlicht et al., 2021). Self-control has been defined more broadly as the process of advancing abstract, distal motives (e.g., the desire to lose weight) over conflicting, concrete, and proximal motives (e.g., eating high-calorie foods). Though impulse inhibition is one important means used to solve this conflict, there might be other effective ways to do so. For example, one can proactively regulate the availability of temptations or cognitively reappraise the experience of temptations. One could speculate that individuals with stable mental processing are more efficient in achieving long-term goals because they have more stable mental processes with fewer interruptions by distracting impulses (see also research on an "implemental mindset," which promotes goal achievement by reducing attention to task-irrelevant stimuli without the need for conscious monitoring; Fujita, 2011). This idea fits with recent work suggesting that the biggest problem in goal achievement is not lacking control to resolve conflict but rather the presence of conflicting motives to begin with (Inzlicht et al., 2021). Thus, people high in self-control may simply experience fewer interrupting impulses rather than only being better at inhibiting them. Indeed, recent research has observed less real-time conflict in individuals who are more successful at self-control (Stillman et al., 2017).

Alongside the conceptual debate on the nature of self-control, there is an ongoing discussion on how to best measure this construct. Recent meta-analytic evidence demonstrates that different self-control measures often fail to correlate with each other (Wennerhold & Friese, 2020). In line with this, self-reported self-control was not significantly correlated with neural or behavioral self-control measures in our study. Conversely, the temporal stability of resting EEG microstates was significantly associated with self-report, neural, and behavioral self-control measures. Thus, stable mental processing might represent a domain-general feature of self-control, capturing common variance of existing self-control measures. Note that the low convergent validity of existing self-control measures has been attributed to its task- and domain-specific measurement approach (Wennerhold & Friese, 2020). In contrast, stable mental processing as identified by resting EEG microstate analysis constitutes a task- and domain-independent measure, possibly contributing to its robust associations with various (domain-specific) self-control measures.

In sum, relying on EEG microstate analysis, we provide evidence that self-control is characterized by stable mental processing as indicated by fewer but longer-lasting mental-processing steps at rest. This study demonstrates that analyzing the temporal dynamics of task-independent brain activity can inform behavioral and cognitive sciences on the nature of the human mind. It also raises questions ripe for future research. Do our findings hold in larger sample sizes with distinct characteristics, or are they limited to college students? Do individuals notice their degree of stable mental processing? Can we learn to engage in stable mental processing? Do stable mental processes at rest relate to stable mental processes while executing self-control? Following up on these questions has the potential to shed light on why some are better than others in implementing self-control and living a healthier and happier life.

Transparency

Action Editor: Daniela Schiller
Editor: Patricia J. Bauer

Author Contributions

T. Kleinert, K. Nash, M. Heinrichs, and B. Schiller conceptualized the study. T. Kleinert, J. Leota, and T. Koenig provided the methodology and software for the study. T. Kleinert, K. Nash, T. Koenig, and B. Schiller did the formal analysis. T. Kleinert, J. Leota, and B. Schiller collected the data for the study. T. Kleinert, K. Nash, and B. Schiller wrote the original draft. All authors reviewed and edited the draft. K. Nash and M. Heinrichs provided the resources for the study. K. Nash, M. Heinrichs, and B. Schiller supervised the study. B. Schiller received the funding for the study.

Declaration of Conflicting Interests

The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

Funding

This research was supported by the Wissenschaftliche Gesellschaft Freiburg (Project grant "The role of self-control and individual values in social decisions," awarded to Bastian Schiller).

Open Practices

All data and analysis scripts have been made publicly available via OSF and can be accessed at https://osf.io/sk3pw/. The design and analysis plans for Study 2 were preregistered at https://osf.io/sajxv/. This article has

received the badges for Open Data, Open Materials, and Preregistration. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

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Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/09567976221110136

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