

How to Catch a Blank Mind? Brain Similarities and Differences between Self- and Probe-Caught Mind Blanking

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Abstract

Mind Blanking (MB) is a mental state characterized by the experience of a seemingly empty mind. This apparent emptiness challenges the theoretical view of a continuous and content-full stream of thought, leading to the question of how it is possible to capture MB events in the first place. MB research has relied largely on probe-caught experience-sampling, during which participants are interrupted at random times to report their mental state. This approach risks missing some MB events as they may occur between probes. Self-caught paradigms, on the other hand, allow participants to report MB upon spontaneously realizing it, relying on meta-awareness. To date, it is not clear whether these two methods capture the same phenomenon neuronally. Here, we investigated whether probe-caught MB (pMB) and self-caught MB (sMB) converge on their behavioral properties and brain correlates. Twenty-two participants underwent 3T fMRI scanning while performing both a pMB and a sMB experience-sampling task. We compared the behavioral properties, BOLD activations and time-varying functional connectivity (FC) across the two approaches. We found that reporting frequencies of pMB and sMB were significantly correlated across individuals, and both MB reports were uniformly distributed over time, pointing towards a behavioral convergence across approaches. However, we observed a divergence in BOLD activations, as sMB recruited significantly greater activation in the dorsal anterior cingulate cortex (dACC) compared to pMB, likely reflecting the meta-awareness and metacognitive monitoring required for self-detecting a MB. Lastly, time-varying FC analysis revealed a convergence, with both pMB and sMB FC resembling a hyperconnectivity pattern compared to other content-full mental states, pointing towards low arousal FC. Together, our results show that sMB and pMB converge on overlapping neurobehavioral correlates. This positions the self-caught method as a complementary tool for studying MB without external interruption, while highlighting the role of meta-awareness in self-report detection.

Introduction

While wakefulness is typically characterized by a continuous stream of thought, individuals can experience periods of a seemingly empty mind. This experience is linked to a mental state known as Mind Blanking (MB), formally defined as a waking state in which individuals report no mental content or are unable to describe their immediate experience (Andrillon et al., 2025; Boulakis & Demertzi, 2025; Ward & Wegner, 2013). So far, research into MB has primarily relied on probe-caught methodologies, where participants are interrupted to report their immediate mental state at random moments (e.g., “What was on your mind just now?”). However, individuals can also spontaneously catch themselves in a blank state without an external prompt (i.e., self-caught). To the best of our knowledge, only one study so far has used the self-caught paradigm to characterize MB behaviorally (Ward & Wegner, 2013), while their brain correlates have not been explored. Consequently, it remains unknown whether these two reporting methodologies capture the same neurobiological phenomenon.

Probe-caught methods have been extensively used both during resting state (Boulakis et al., 2025; Koroma et al., 2023; Unsworth et al., 2021; Van Calster et al., 2017) and during cognitive tasks (Andrillon et al., 2021; Huijser et al., 2020; Robison et al., 2019, 2020; Unsworth et al., 2025). These studies have shown that probe-caught MB (pMB) events are reported sparsely (Boulakis et al., 2026), but uniformly across probes (Mortaheb et al., 2022). Converging evidence from neuroimaging studies points towards reduced cortical excitability and hyper-synchrony during pMB. First, the brain elicits parietal slow wave activity during pMB reports that, despite its localized nature, morphologically resembles the slow waves observed globally during deep sleep (Andrillon et al., 2021). Second, the brain shows widespread deactivations across cortical areas (Boulakis et al., 2023). Third, functional connectivity (FC) during pMB self-organizes in a hyperconnected pattern where all regions are synchronized together (Mortaheb et al., 2022) as also observed in unconscious states (Aedo-Jury et al., 2020; El-Baba et al., 2019). However, this relationship seems to be mediated by perceived arousal and task context. For instance, during a sustained attentional task, pMB has been associated with the typical anticorrelated FC pattern observed in wakefulness across vigilance levels, yet was associated with the hyperconnected pattern only during self-reported high vigilance levels, potentially due to hyperconnectivity being more dominant across mental states during sleepiness (Boulakis, Kusztor, et al., 2025). Lastly,

pMB reports increase in states of low arousal (Boulakis et al., 2025) and are characterized by higher fMRI global signal (GS) amplitude, a proxy of arousal level (Liu et al., 2017; Wong et al., 2013), compared to other mental states (Mortaheb et al., 2022).

Even though probe-caught methods are valuable, they possess an inherent limitation: they rely on externally timed cues and may miss episodes that occur between probes. Indeed, MB in probe-caught methodologies is typically captured by 10% of the probes (Boulakis et al., 2026), rendering it a highly time-consuming methodology. Approaches that do not depend on external sampling could therefore offer a more efficient alternative by capturing the entire sampling period and allowing for the unconstrained accumulation of reports. A promising alternative is the self-caught paradigm, which has been widely applied in mind wandering (MW) research (Chu et al., 2023) but rarely to MB (Ward & Wegner, 2013). In this method, participants are instructed to report whenever they notice or ‘catch’ themselves in a specific mental state. By design, this approach captures MB events with meta-awareness (Chu et al., 2023), meaning one must realize their mind feels empty in order to report it (i.e., awareness of absence) (Mazor & Fleming, 2020). Given that this introduces a distinct metacognitive demand, and because the paradigm has rarely been applied to MB, it remains unknown whether sMB shares the same behavioral properties and brain correlates as pMB or if the act of self-catching fundamentally alters its phenomenological and neurophysiological correlates.

The present study aims to compare self-caught and probe-caught methodologies and to investigate whether sMB shares the established behavioral properties and neural correlates of pMB. While we expect the core signature of this state to be similar, we hypothesize that sMB recruits additional brain regions related to meta-awareness and metacognitive monitoring.

Methods

Participants

Twenty-two individuals participated in the study (45% female; mean age = 29 ± 4 years). Participants were recruited via campus poster advertisements and intranet electronic invitations. All participants provided written informed consent in accordance with the Declaration of Helsinki. The study was approved by the Ethics Committee of the University Hospital of Liège (Nr:

B707201941887). Exclusion criteria involved MRI contraindications and history of neurological disorders. All participants were right-handed and french speakers with academic backgrounds.

Design & Tasks

The study employed a within-subject design, in which participants performed two experience-sampling tasks in a 3T MRI scanner (Magnetom Prisma, Siemens Medical Solutions, Erlangen, Germany): one with the self-caught, and the other with the probe-caught methodology. Tasks were performed in two sessions separated by a 15-minute break. The first session included the self-caught task, alongside other cognitive tasks outside the scope of the present study. The second session comprised the probe-caught task and diffusion-weighted imaging, which is also outside the scope of this study. In the self-caught task (approx. 8 min duration), participants were asked to press a button whenever they felt they had an MB event. In the probe-caught task (approx. 19 min duration), participants were interrupted at random times by auditory and visual probes (n=25, inter-probe interval: 30-60s), inviting them to use a button press to report their immediate mental state. Participants were asked to report if their thoughts were in the “past”, “future”, “present”, or simply “nowhere” (MB). When participants choose any of the first two options, they were presented with a second question asking if they were thinking of themselves or someone else (all coded as MW). When they selected “present” they were asked if their thought was stimulus dependent (Sensations, Sens) or independent (MW). This multi-step questioning tree was designed to mirror the specific dimensions of time, self-referentiality, and stimulus-dependence manipulated across the broader experimental protocol. However, because these granular distinctions are outside the scope of the present study, reports were collapsed into broader categories (MB, MW, and Sensations) for analysis. Frequency of other mental states aside from MB can be found in Supplementary 1. If a response took longer than 10 seconds, it was coded as an error and excluded from the analysis.

The tasks were implemented in MATLAB using the Psychophysics Toolbox (PTB) (Brainard, 1997) and are available at <https://gitlab.uliege.be/poc/self-caught-mb>. Experimental design and analysis are illustrated in Figure 1. During both tasks, participants were in a resting state, instructed to let their mind wander, with eyes open, fixating on a black screen. For each task, we defined rest and mental state periods. For the probe-caught task, mental states pMB, MW, and Sens) were defined as the 10s before the probe (Boulakis, Kusztor, et al., 2025; Mortaheb et al., 2022; Van Calster et al., 2017). For the self-caught task, sMB was defines as the 10s before the button press.

Regarding rest periods, they were defined as up to 30s in between probes in the probe-caught task. In the self-caught task, rest timepoints were defined as periods of uninterrupted resting state (i.e., no button press), with no specific length. To avoid signal contamination, timepoints surrounding each sMB report were excluded (buffer of 40s sMB report: 30s before and 10s following the button press).

fMRI

1. Functional Imaging parameters

FMRI data were acquired using a standard transmit–receive quadrature head coil and included T2*-weighted gradient-echo echo-planar imaging (EPI) sequence using the following parameters: repetition time (TR) = 1170 ms, echo time = 30 ms, field of view = $216 \times 216 \text{ mm}^2$, acquisition matrix = 72×72 ($3 \times 3 \text{ mm}^2$ in-plane resolution), and 36 axial slices of 3 mm thickness with a 25% interslice gap (0.75 mm), covering most of the brain. Slice acquisition was performed in an interleaved order, with phase encoding in the anterior-to-posterior direction. Multi-band acceleration factor of 2 was applied to reduce acquisition time. A total of 1000 volumes were acquired per run. A high-resolution T1-weighted magnetization prepared rapid gradient echo image (MPRAGE) was acquired for anatomical reference (TR = 1960 ms, echo time = 2.19 ms, inversion time = 900 ms, field of view = $256 \times 240 \text{ mm}^2$, matrix size = $256 \times 240 \times 176$, voxel size = $1 \times 1 \times 1 \text{ mm}^3$). Participants' heads were comfortably secured with a vacuum cushion to reduce movement during scanning. Visual stimuli were presented on a screen located at the back of the scanner, seen via a mirror attached to the head coil.

2. fMRI Preprocessing

FMRI data were preprocessed using fMRIPrep (version 24.1.1; (Esteban et al., 2018)), a standardized pipeline for robust fMRI preprocessing: for each participant, functional data were corrected for susceptibility distortion using dual-echo gradient-recalled echo (GRE) field maps, aligned to their native T1-weighted (T1w) anatomical space and spatially normalized to the MNI152NLin2009cAsym template at 2 mm isotropic resolution. Anatomical preprocessing, including brain extraction and normalization, was performed using ANTs (2.5.0; Avants et al., 2014). Tissue segmentation of cerebrospinal fluid, white matter, and gray matter was performed using FSL (version 6.0.4; Jenkinson et al., 2012). As surface-based analyses were not required

(parcellation was conducted in volumetric space using the predefined Schaefer atlas), full cortical surface reconstruction was skipped. Given the short TR (<2 seconds) and to avoid altering the temporal autocorrelation structure important for estimating time-varying FC, slice timing correction was not applied.

Analysis

Behavioral data

To assess the consistency of individual MB reports across conditions, we computed the Spearman correlation between the number of MB reports per subject for each task. Additionally, given our small sample size, we also computed the Kendall Rank coefficient for complementary robustness. This analysis aimed to evaluate whether MB occurrence reflects a stable individual characteristic, whereby participants who report more MB in one task also tend to report more in the other. Following previous studies (Mortaheb et al., 2022) we also examined the temporal distribution of MB reports within each task. Acquisition time was divided into 5 equal-duration bins, and the number of MB reports in each bin was counted. We then compared the resulting distribution against a uniform distribution using a χ^2 test, and calculated effect size using ϕ ($\phi = \sqrt{\chi^2/n}$). Additionally, to test for evidence in favor of the null hypothesis (uniformity), we computed a Bayes factor comparing a uniform distribution (all bins equally likely) against a non-uniform distribution multinomial model with a symmetric Dirichlet(1) prior, where $BF_{10} < 0.33$ indicates evidence for uniformity (null hypothesis), whereas values between 0.33 and 1 were considered inconclusive.

fMRI Analysis

Voxel-wise activation differences between MB report types

We employed a mass-univariate approach based on a General Linear Model to identify voxels exhibiting significant activation differences between MB types. A first-level analysis was performed independently for each subject. Because the probe-caught and self-caught events were recorded in separate sessions, we modeled them as two distinct runs within each subject-level GLM. The design matrix included the mental state reports (sMB, pMB, Sens, MW), task regressors (probe or button press) and rest periods, convolved with a canonical SPM hemodynamic response function. The nuisance regressors included six motion parameters and a binary motion outlier

regressor for volumes exceeding framewise displacement of 0.5 mm. A cosine-basis drift model was used to implement high-pass filtering (>0.008 Hz). Signal intensity was grand mean scaled to ensure that beta estimates the percentage of signal change. To account for temporal autocorrelation in the BOLD signal, we employed a first-order autoregressive model. Data were spatially smoothed using a Gaussian kernel of 8 mm FWHM. For each subject, we computed the contrast [sMB $>$ pMB] as the primary contrast of interest.

Group-level inference was performed using a one-sample t-test on the first-level contrast maps. To control for multiple comparison, we applied cluster-level Family-Wise Error (FWE) correction at $p < 0.05$ via non-parametric permutation testing (10,000 permutations, cluster-defining threshold $p < 0.001$). For transparency purposes (Taylor et al., 2023), results are visualized on a brain template using transparent thresholding, with the statistical map visualized at an uncorrected threshold of $p < 0.001$ ($z = 3.29$). Cluster-wise FWE-significant clusters are outlined with black contours.

Coupling between functional connectivity patterns and experience sampling

To estimate functional connectivity patterns, first preprocessed BOLD signals were denoised using junifer (version 0.0.7.dev47; (Mandal et al., 2023)). Confound regression included 24 motion parameters, white matter and CSF signals. Time series were detrended, z-scored, and bandpass filtered (0.008-0.09Hz). A gray matter mask was applied using a probabilistic threshold of 20%. The brain was parcellated according to the Schaefer-100 atlas (100 regions, 7-network version) (Schaefer et al., 2018), and instantaneous phase connectivity (IPC) was computed at each time point using a second-order Hilbert transform after re-filtering the data between 0.01 and 0.04 Hz. To normalize the distribution for statistical analysis, IPC values were Fisher z transformed.

Following previous studies (Boulakis, Kusztor, et al., 2025; Mortaheb et al., 2022), we identified recurring connectivity patterns by applying k-means clustering to resting state IPC matrices using cosine distance (n rest IPC = 17.687 matrices; 60% from probe-caught and 40% from self-caught task; additional analysis to guarantee same resting state baselines can be found in Supplementary 2). While internal validation metrics did not converge on a single optimal k (Supplementary 3), we selected $k=4$ based on established literature identifying four stable resting-state patterns (Demertzi et al., 2019; Mortaheb et al., 2022). We confirmed the stability of our findings by repeating the analysis for $k=3$ through $k=6$ (see Supplementary 4). Resulting centroids were ordered by their

spatial standard deviation (a proxy for pattern metastability) and visualized using PCA (Supplementary 4). We estimated the occurrence rate of each pattern counting the number of matrices assigned to each centroid for each participant. We compare occurrence rates with a paired t-test with $p\text{-FDR} < 0.05$ corrected for multiple comparisons.

To determine if the connectivity pattern of a mental state (sMB, pMB, MW and Sens) was associated with a specific baseline network configuration, we calculated the cosine distance at the single-timepoint level. Specifically, for a single sample (timepoint) of each report, we computed the cosine distance between that mental state's IPC matrix and each of the four canonical connectivity centroids derived from the resting state timepoints. Distances to each cluster were modeled using a Bayesian Generalized Linear Mixed Model. To account for the positive-bounded and negatively skewed nature of the distance metrics, we modeled the response variable using a Skew-normal likelihood. Population-level parameters were assigned weakly informative Skew-normal priors ($\xi=0$, $\omega=1$, $\alpha=-2$), while group-level standard deviations were modeled using a regularizing Half-Cauchy prior (scale = 0.5). The model included mental state reports as fixed effects and subject-specific random intercepts. Model fit was compared against a null model (containing only intercept and random effects) using Bayes Factors, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Supplementary 5). Bayes Factor favored the null model over the mental state model for each cluster, likely due to the inherent inter-subject variability of spontaneous cognition and the parsimony-based penalties applied by Bayes Factors. Nonetheless, AIC and BIC supported the response model. To explore even marginal effects of the mental states, we performed planned post-hoc comparisons using Estimated Marginal Means between the distances of each mental state to each pattern. To account for multiple comparisons across the six pairwise contrasts, we used a 98% credible interval criterion, which corresponds to a Bonferroni-corrected threshold relative to an uncorrected 89% interval (Makowski et al., 2019). A contrast was considered supported if its 98% credible interval excluded zero.

Global signal (GS) amplitude as a proxy for arousal fluctuations across mental states

We considered GS as the average BOLD activity across whole-brain voxels (Fox et al., 2009). As mentioned, GS amplitude serves as an indirect proxy for arousal levels, where higher amplitude typically indicates lower arousal and vice versa (Liu et al., 2017; Wong et al., 2013). Given that

MB is often associated with low arousal, we investigated whether GS magnitude (i.e., the L2 norm of the global signal time course during each mental state) differed between mental state reports.

The GS time series were extracted for each subject and task using the standard fMRIPrep pipeline. To account for potential baseline shifts between task sessions (self-caught vs probe-caught task), we performed a session-specific baseline normalization. For each task, the raw GS was divided by the mean GS during that session's rest periods. To account of the sensibility of the L2 norm (signal magnitude) to the number of data points, all events were truncated to a uniform distribution of 9 timepoints. We calculated the L2 norm for each event to obtain a single GS magnitude value per report.

GS magnitude was modeled using a Generalized Linear Mixed-Effects Model, including mental state reports (sMB, pMB, Sens, MW) as a fixed effect and a random intercept per subject. Given that GS magnitude values are strictly positive, we utilized a gamma distribution with a log link function. Post-hoc comparisons between mental states were performed using marginal means. All reported p-values were adjusted for multiple comparisons using the Tukey method. We additionally tested whether the global-signal effect could be explained by task duration by including total timepoints as a covariate (Supplementary 6).

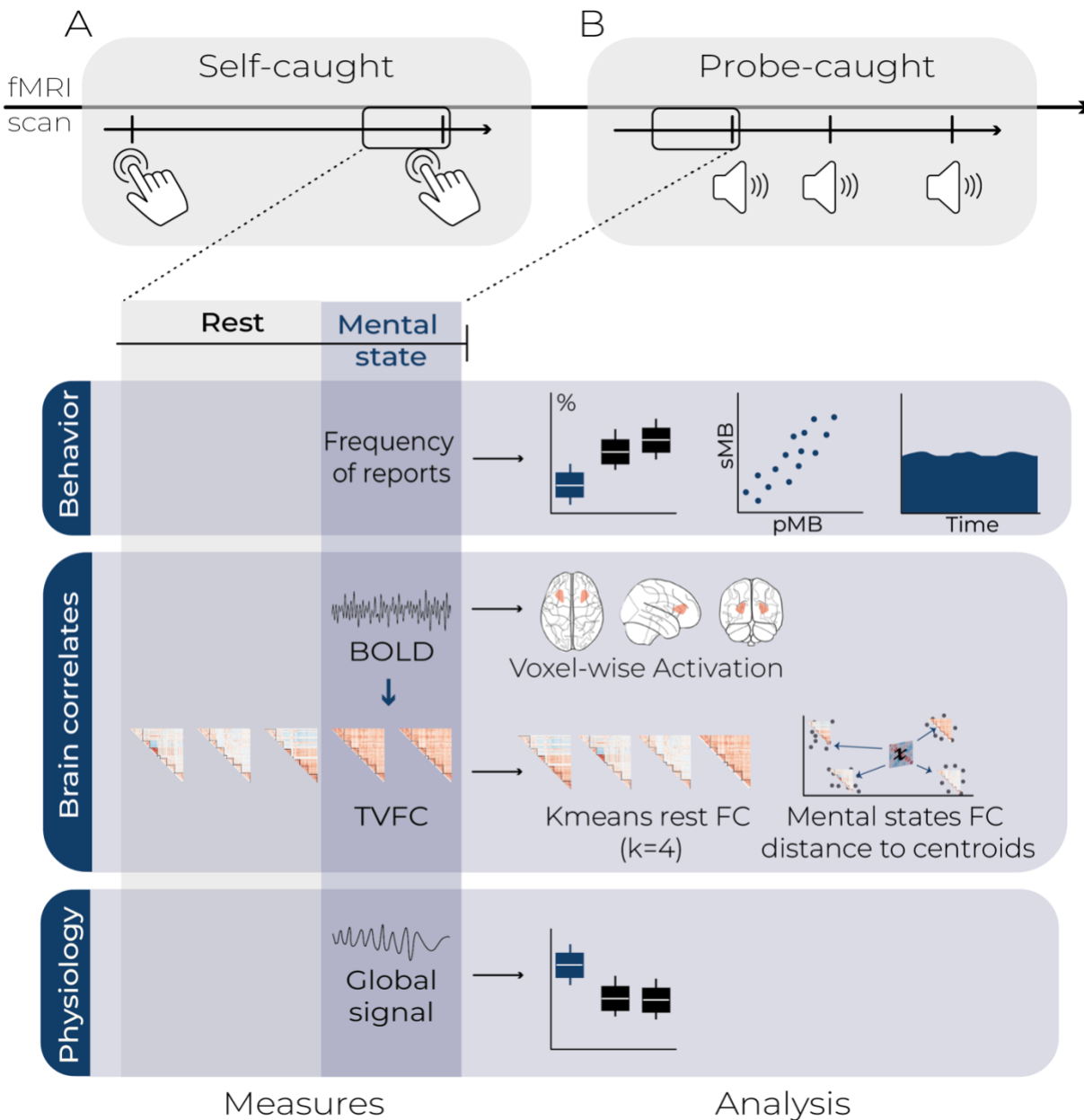


Figure 1. Experimental setup and analysis. Twenty-two participants performed A) self-caught and B) probe-caught experience-sampling tasks while lying down in a 3T MRI scanner. In both tasks, mental states epochs (in blue) were defined as the 10 s preceding the self-report button press (self-caught) or auditory and visual probe (probe-caught), and rest epochs as 30 s (in grey) of uninterrupted resting activity (which could be longer in the self-caught task if no button press occurred). Analysis spanned three domains: (1) Behavior: We analyzed report frequencies, cross-task correlations across individuals, and the temporal distribution of MB reports. (2) Brain correlates: We extracted BOLD timeseries for two distinct analyses. First, a voxel-wise activation analysis contrasted SMB versus pMB. Second, we computed time-varying functional connectivity (TVFC) across both tasks; we clustered rest timepoints to identify representative

connectomes (centroids) and calculated the distance of the TVFC patterns during each mental states deviated to these baseline rest clusters. (3) Physiology: We tested whether mental states differed in global signal (GS) magnitude. TVFC = time-varying functional connectivity; BOLD = blood oxygen level dependent; GS = global signal.

Results

MB reports converged on their behavioral properties across methods

To assess the reliability of MB across self-report methods, we compared the frequency of episodes captured via self-caught and probe-caught tasks. Participants reported on average 5 sMB (range = 0-31, N = 119) and 2 pMB episodes (range = 0-7, N = 55). In terms of method-specific relative frequency, pMB episodes were reported in 10.8% of total probes, while sMB reports occurred at a rate of approximately 1 episode per 2.54 minutes of acquisition. A significant positive correlation was observed between sMB and pMB frequencies ($r = .49, p = .019$; $\tau = .39, p = .019$, Figure 1A), suggesting MB reporting was consistent at the individual level.

The temporal distribution of MB reports was analyzed to determine if the occurrence of these episodes was influenced by time (Figure 2B). The distribution of MB reports across acquisition time did not significantly deviate from a uniform distribution in either task. Furthermore, Bayes factor analyses yielded evidence supporting the null hypothesis, supporting that the MB reports were uniformly distributed across both tasks.

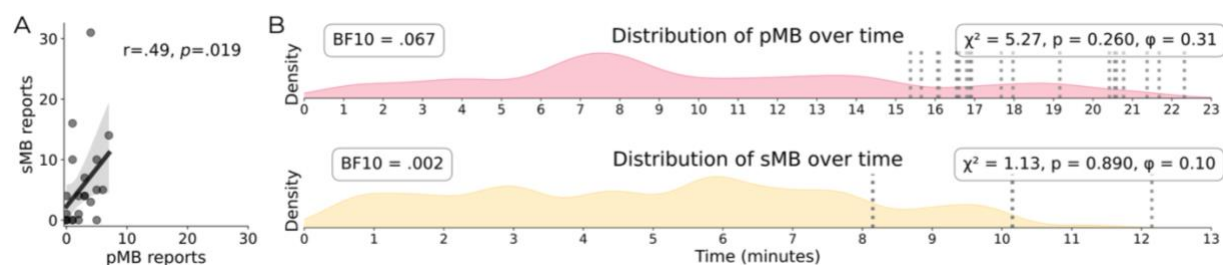


Figure 2. Consistent rate and uniform distribution of MB reports across tasks and time. A) The positive Spearman (r) and Kendall (τ) correlation between the number of sMB and pMB reports per subject indicate that the two report methods are reflecting similar content at the individual level. B) The temporal distribution of pMB (upper panel) and sMB (lower panel) reports during each task indicated that the MB reports were uniformly distributed across both tasks as evidenced by the Bayes factor supporting

the null hypothesis. Vertical dashed lines indicate each subject's task end time. sMB = self-caught mind blanking; pMB = probe-caught mind blanking.

Self-caught MB recruits greater dorsal anterior cingulate cortex activity than probe-caught MB

We compared the neural signature underlying to the two types of MB reports considering all the subjects that reported both types of MB ($n=13$). We found a main positive effect of sMB in the right dorsal anterior cingulate cortex (dACC/paracingulate gyrus; Harvard-Oxford atlas) within medial prefrontal cortex (mPFC) (Peak MNI: [17.5, 31.5, 13.5], cluster size = 2008 mm³, FWE $p < 0.05$; Figure 3A), compared to pMB.

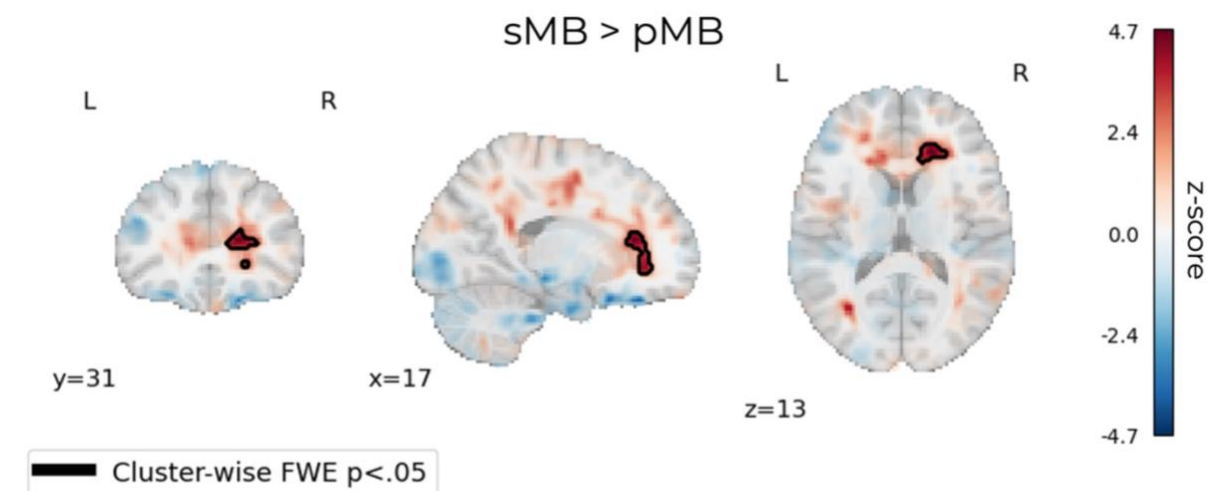


Figure 3. Self-caught MB recruits the activation of the dACC. Second level contrast between sMB>pMB of the voxel-wise activation analysis indicated the recruitment of the dorsal ACC, highlighting the involvement of metacognitive properties when self-evaluating content-free reports. The graph is thresholded at $p < 0.001$ uncorrected, with red-colored voxels imply activations and blue-colored imply deactivations of sMB compared to pMB. Black-contoured areas show FWE $p < 0.05$ surviving clusters.

MB reports share a connectome signature of global functional hyperconnectivity

To identify the primary brain states that emerge during rest, we applied k-means ($k=4$) clustering to the time-varying FC of the rest timepoints. Figure 4A and 4B show the occurrence rate and the four identified distinct FC patterns. Pattern 1 was characterized by anticorrelations between sensory/attentional networks and the default mode (DMN)/frontoparietal (Con) networks. Pattern 2 showed high within-network connectivity restricted to the somatosensory network, but low

connectivity both within and between all other networks. Pattern 3 showed a generalized low connectivity, characterized by reduced connectivity both within and between networks. Finally, Pattern 4 displayed an all-to-all positive connectivity (hyperconnectivity) within and between networks. The generalized low connectivity (Pattern 3) occurred significantly more often than all the other brain patterns (Pattern 1 – Pattern 3: $t = -5.62$, $FDR-p < .0001$; Pattern 2 – Pattern 3: $t = -191.68$, $FDR-p < .0001$; Pattern 3 – Pattern 4: $t = 4.14$, $FDR-p = .001$; all other comparisons $FDR-p < .05$, Figure 3A).

Having defined the FC self-organization during rest, we next tested whether the reported mental states showed greater proximity to any of these specific configurations. Across all mental states, the response model outperformed the null model when considering the AIC and BIC. Given that Pattern 4 has been previously associated with pMB during rest (Mortaheb et al., 2022), we focused our primary analysis on this hyperconnected state. Consistent with our hypothesis, sMB and pMB time-varying FC matrices showed significantly higher similarity to this hyperconnected state than content-full mental states (sMB-MW: $\Delta = -0.004$, 98% CI [-0.006 -0.001], $p < .0001$; sMB-Sens: $\Delta = -0.005$, 98% CI [-0.01 -0.001], $p < .0001$, pMB-MW: $\Delta = -0.004$, 98% CI [-0.008 -0.001], $p < .0001$, pMB-Sens: $\Delta = -0.006$, 98% CI [-0.01 -0.001], $p < .0001$). Overall, these findings suggest that both forms of MB episodes share a common FC signature characterized by global hyperconnectivity, regardless of the self-report detection method.

Further analysis revealed additional differences in the proximity of other mental states to other patterns (Figure 3C, Supplementary 7). For Pattern 1, Sensations were significantly further away from this FC configuration than all other mental states, followed by sMB, as both pMB and MW showed closer proximity than sMB. For Pattern 2, pMB was also significantly closer to this pattern compared to other mental states and sMB was also closer than MW. Regarding Pattern 3, MW was significantly further away compared to other mental states.

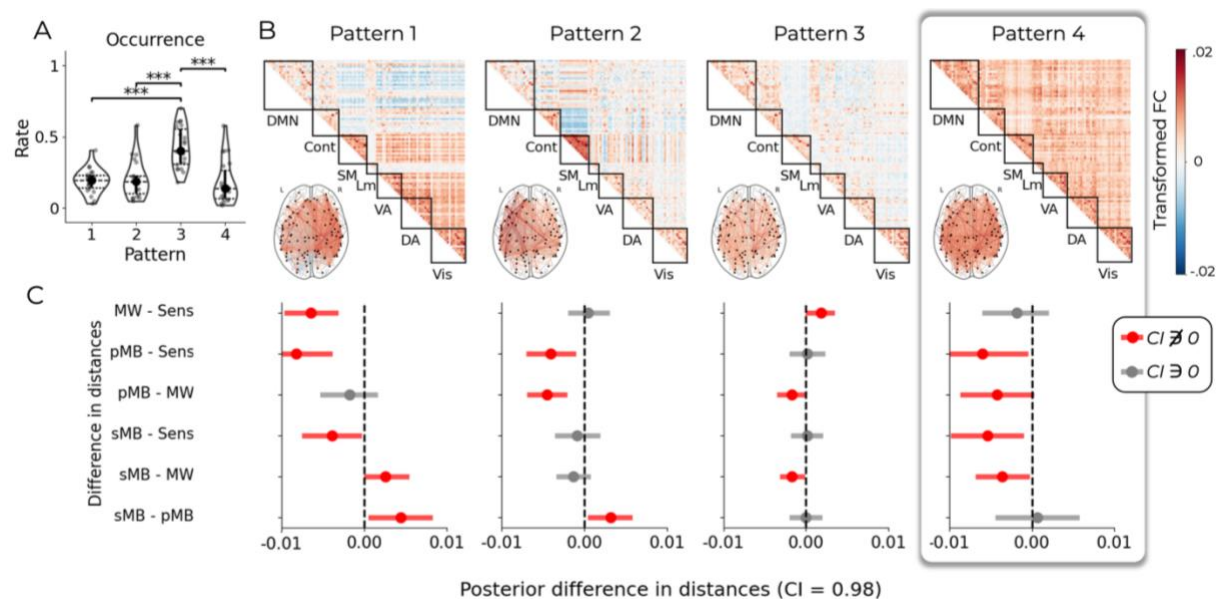


Figure 4. Mind Blanking reports show higher similarity to a hyperconnected pattern of functional connectivity both during the self-caught (sMB) and probe-caught (pMB) method. A) The occurrence rate of each connectivity pattern (normalized by subject) indicates that patterns occurred at different frequencies, with Pattern 3 occurring significantly more often than all other patterns. This replicates the findings of previous studies that applied the same methodology (Mortaheb et al., 2022). Each dot denotes one subject percentage occurrence rate. B) Data-driven k-means centroids of time-varying functional connectivity and connectome indicates that the brain self-organizes into a pattern of anticorrelations between the DMN and sensory networks (Pattern 1), a pattern of somatosensory integration (Pattern 2), a pattern of lower overall coherence pattern (Pattern 3) and a pattern of hyperconnectivity (Pattern 4). Scale shows Fisher Z and L2 normalized functional connectivity. Positive values indicate higher phase synchronization, while values close to zero indicate the absence of a systematic phase coherence. C) Estimated Marginal Means contrast between distances of each mental state functional connectivity matrices to each centroid. Contrast estimate on the right side means the first mental state of the contrast is closer to that pattern. When comparing contrasts across all patterns, both MB reports systematically had higher similarity (lower distance values) to the hyperconnected connectome (Pattern 4) compared to both mind-wandering and sensations. Significant contrasts are red-colored. DMN = default mode network; Cont = control network, SM = somatosensory network, Lm = limbic network, VA = ventral attentional network, DA = dorsal attentional network, Vos = visual network, MW = mind wandering, Sens = sensations, pMB = probe-caught mind blanking, sMB = self-caught mind blanking. *** $p < .001$.

Self-caught MB linked with lower physiological arousal compared to MW

To investigate physiological arousal across mental states, we analyzed the magnitude of the GS (Figure 4). We found that sMB presented a significantly higher GS magnitude than MW episodes (MW-sMB: $\Delta = -0.001$, 95% CI $[-0.002, -0.0001]$, $z = -2.82$, $p = .02$, Figure 5B), a marker of reduced vigilance (Liu et al., 2017; Wong et al., 2013). Thus, our findings suggest that sMB reports

occur during periods of lower physiological arousal relative to MW. No other significant differences were observed between the remaining mental states ($p > .05$). These results remained stable when adding the task length for each subject as a covariate (Supplementary 5).

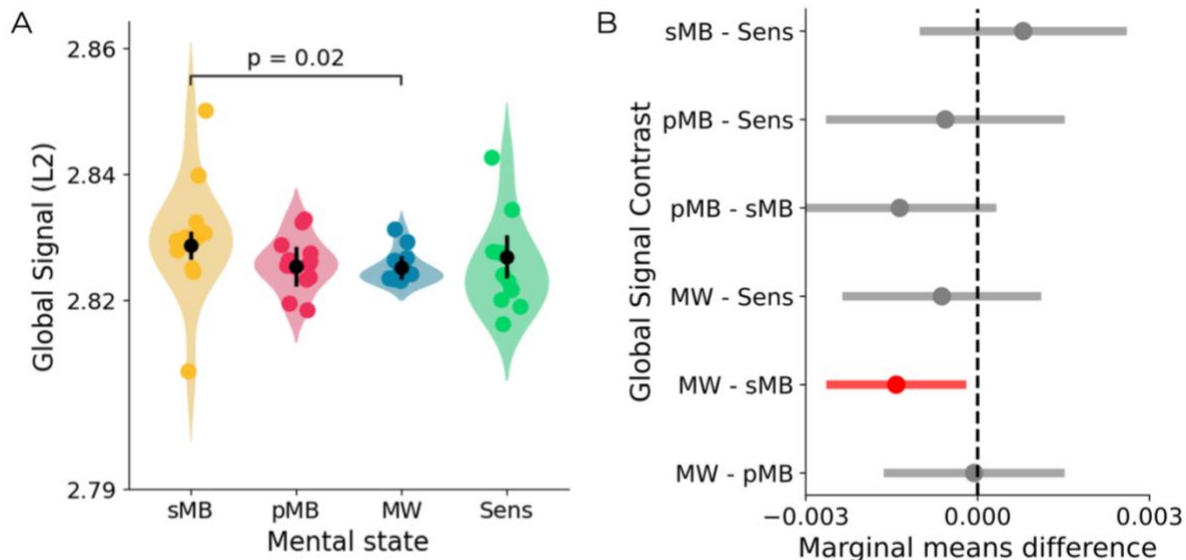


Figure 5. Self-caught MB reports showed higher fMRI global signal magnitude compared to MW, pointing to the potential implication of low cortical arousal when self-assessing the presence of content-less experience. A) Boxplot comparing global signal magnitude around mental states reports. Each dot represents an average of one subject's reports. B) Statistics from marginal means contrast between the global signal characterizing different mental states reports (adjusted for multiple comparison via Tukey method) indicates that sMB has a significantly higher fMRI global signal magnitude compared to MW. MW = mind wandering, pMB = probe-caught mind blanking, sMB = self-caught mind blanking, Sens = sensations.

Discussion

We here compared two self-report methodologies for capturing MB events during typical waking time, the widely-used probe-caught method (Boulakis et al., 2025; Koroma et al., 2023; Munoz-Musat et al., 2025; Robison et al., 2019; Unsworth et al., 2021; Van Calster et al., 2017), and the self-caught method (Ward & Wegner, 2013). Our results indicate that both methods successfully capture MB episodes, which share similar behavioral properties and are characterized by hyperconnectivity across the brain. Where these states diverged was in BOLD activation, with sMB recruiting greater dACC activation compared to pMB.

A primary contribution of this work is the exploration of sMB, demonstrating that sMB shares convergent neurobiological correlates with pMB. Unlike previous paradigms that required participants to intentionally “empty their minds” (Kawagoe et al., 2019), the current approach allows participants to report if they notice their mind went blank spontaneously. The significant correlation between sMB and pMB frequencies across individuals suggests high cross-method consistency, indicating that both detection methods track individual differences in the propensity to experience MB within the experimental environment. Furthermore, the uniform temporal distribution of reports in both tasks aligns with previous evidence suggesting that MB occurrence is not time-dependent, but a default mental state taking place in the stream of ongoing thinking (Mortaheb et al., 2022). While Ward and Wegner (2013) also proposed that overall MB reports appeared steadily over time, they observed a diverging trend over time where pMB reports increased while sMB decreased. It should be noted, though, that those findings were observed during a task condition (reading) and over a longer duration (20 min), which could have led to a lower capacity to monitor one’s stream of thought due to fatigue. In the present analysis, both tasks took place at a shorter resting-state context (8 min), which could have permitted the preservation of sufficient vigilance so that both detection methods led to capture the MB phenomenon stably across time.

Additionally, we show that with the probe-caught task, MB was reported in approximately 10% of probes, which is consistent with previous literature at large (for a meta-analysis on MB rates see Boulakis et al., 2026). However, given that the frequency of these reports is probe-dependent, episodes occurring between probes are inherently missed. While self-caught reports were more frequent in absolute count, the two methods differed in sampling rate and task duration, making a direct numerical comparison difficult: self-caught reports were collected continuously over acquisition time, whereas probe-caught reports were constrained to the probes. Nevertheless, this descriptive pattern aligns with Ward and Wegner (2013), who similarly observed that sMB events consistently outnumbered pMB episodes during a reading task. Our results point in a similar direction and extend this trend to a resting-state condition, notwithstanding the task instruction to self-detect and report these blank moments.

We consider that the higher absolute frequency of sMB relative to pMB suggests a critical methodological trade-off. While the self-caught method provides a continuous real-time reporting

that can capture events that would otherwise be missed between intermittent probes, the explicit requirement for metacognitive assessment of sMB may create a dual bias. On the one side, it might redirect the participant's focus to internal monitoring, thereby increasing false positive detection of MB (i.e., over-sensitivity). On the other side, it could as well paradoxically underestimate true frequency, because the continuous cognitive load of self-monitoring may actively prevent the mind from entering a blank state. Moreover, as self-caught methodologies by definition only capture mental states with meta-awareness (Chu et al., 2023), they necessarily exclude instances without meta-awareness. A possible alternative for future research to resolve this reporting paradox is to move towards report-independent decoding techniques. For instance, by using the neural signatures (i.e., hyperconnectivity, decrease in GS) as features in a decoder scheme, it may be possible to validate the occurrence of MB episodes independent of the participant's active report in a more representative way. Initial efforts to decode MB from brain markers (Munoz-Musat et al., 2025), as well as from body-brain signals (Boulakis et al., 2025), have already been proved successful. Indeed, these protocols involved training classification algorithms that relied on MB reports as the ground truth. While Boulakis et al. (2025) applied these models to predict other labeled MB reports, Munoz-Musat et al. (2025) took an initial step towards extrapolation by applying their trained classifier to unprobed, unlabeled data blocks during a cognitive task. By crossing these unlabeled predictions against behavioral performance (e.g., increased miss rates and prolonged reaction times), they provided an indirect behavioral validation of the decoded MB episodes. Ultimately, efforts to develop classification schemes free from reports could provide the ideal middle alternative: they do not confound MB with the detection itself (like self-caught methods) but also allow for a continuous tracking without being limited to discrete sampling windows (like probe-caught methods).

Regarding the activation analysis, we consider that the finding that sMB recruits the dACC compared to pMB likely reflects aspects of meta-awareness, meta-cognitive evaluation, and monitoring processing required for self-detection (Mazor & Fleming, 2020). Indeed, sMB requires active, continuous meta-awareness to detect a MB event where one must not only be in a MB state, but also become aware of being in that state, while pMB relies on a passive, reactive appraisal prompted by the external probe (Chu et al., 2023). As the ACC is tightly involved in metacognition (Vaccaro & Fleming, 2018) and self-referential processing (D'Argembeau et al., 2007), we propose

this activation reflects the internal evaluation of their ongoing cognition. Activity on the ACC has only been observed during MB when participants are asked to empty their minds intentionally (Kawagoe et al., 2019), but no such activity has been observed during spontaneous pMB (Boulakis et al., 2023). This could be tapping into distinct nuances of MB: with and without meta-awareness, as similarly observed for MW (Christoff et al., 2009; Chu et al., 2023; Seli et al., 2017).

Aside from BOLD divergences, both MB capturing methodologies converged on their connectome signature. Indeed, we found that both MB events were only consistently associated with the hyperconnected brain state (Pattern 4), which lacks the variability in connectivity linked to typical content-full cognition (Deco et al., 2017). It is important to mention that this hyperconnected brain pattern has also been observed in states of reduced consciousness, such as during sleep and under anesthesia (Aedo-Jury et al., 2020), which reinforces the hypothesis that MB is characterized by a physiological and neural profile of modified arousal. This point is here supported by the significantly higher GS magnitude during sMB compared to content-full states, such as MW. Given that high GS amplitude is a robust marker of low cortical arousal (Liu et al., 2017; Wong et al., 2013), these findings add to previous findings that MB's brain correlates resemble those of sleep-like activity, as previously supported by the detection of local slow wave activity during MB episodes (Andrillon et al., 2021; Munoz-Musat et al., 2025). Interestingly, the association with low arousal markers appeared more robust in the self-caught reports. This pattern may point toward two distinct mechanisms. On the one hand, it may stem from the nature of the task: as participants continuously monitor their cognition, they may more readily identify a MB episode whenever they perceive a relevant decrease in vigilance. On the other hand, the task itself may actively induce this state: the sustained cognitive effort of continuous monitoring could produce mental fatigue, hence leading to a reduction in overall arousal levels and thereby leading to reporting MB episodes. It is important to note, though, that sleep and MB are not the same state. Phenomenologically, individuals distinguish the feeling of an empty mind from the sensation of drowsiness, and reporting frequencies of MB and sleep do not correlate (Boulakis et al., 2025). As a limitation, in our protocol, while participants were explicitly instructed to report MB, they were not offered the choice of "Sleep", which could have facilitated a clearer interpretation of the underlying mechanism of the two MB capturing methods.

What we found, though, was that pMB reports did not significantly differ in their GS magnitude levels compared to other mental states and were also associated with a FC pattern characterized by anticorrelations between the DMN and sensory networks (Pattern 1), for which MW was also associated with. Furthermore, pMB also showed proximity to a pattern of increased somatosensory integration (Pattern 2), which was not observed in sMB. These findings, unique to pMB, may arise from the fact that probe-caught tasks may capture a boarder, more heterogeneous range of blanks (Chu et al., 2023). For instance, pMB often aggregates both the phenomenological feeling of an empty mind and the retrospective inability to retrieve previous thoughts (Boulakis et al., 2026). This aligns with our recent study in the context of an attention task, where pMB was associated not only with the hyperconnected brain FC pattern, but also with an anticorrelation FC pattern, and this effect was mediated by perceived levels of vigilance: when people reported being alert, the connectomes around MB reports resembled the hyperconnected pattern (Boulakis, Kusztor, et al., 2025). Overall, the broad associations between pMB with distinct FC configurations may reflect the different kinds of experience and psychological mechanisms that are grouped under the umbrella term MB (Boulakis et al., 2026; Boulakis & Demertzi, 2025).

This study presents some limitations. A primary drawback is our relatively small sample size ($n=22$), although this is comparable to other MB studies (Adam et al., 2020; Torres et al., 2024). Notably, the activation analysis could only be performed on a subset of participants who reported MB episodes in both tasks, effectively reducing the sample size to $n=13$, a challenge inherent to MB low report frequency. Furthermore, as an artifact of the different methodologies, the MB window of analysis differed slightly between tasks. For the self-caught task, MB was defined immediately preceding the button press, whereas for the probe-caught task, the mental state was defined prior to the probe appearance. This inevitably places sMB reports in closer temporal proximity to the motor response and its associated preparation of the movement process. Even though the motor response was regressed out from the BOLD time-series, this temporal proximity could potentially contribute to the observed activity in the dACC related to motor intention and decision-making. Lastly, we did not include “Sleep” among the probe-caught choices, an addition that could have aided the interpretation of our findings.

Conclusions

Our findings demonstrate that sMB resembles pMB in their behavioral properties and brain correlates of hyperconnectivity, although they diverge in the recruitment of the dACC, a difference we attribute to the meta-cognitive process involved inherent to the self-caught task. This positions the self-caught methodology as an adequate tool to detect MB episodes. Therefore, this work provides a new framework for studying MB, enabling new experimental protocols, where probe-caught approaches might be disrupting the stream of thought. Overall, our work advances our ability to investigate content-less experiences that are of both theoretical and clinical relevance.

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530 **Code**

531 All codes are available at <https://gitlab.uliege.be/poc/self-caught-mb>.

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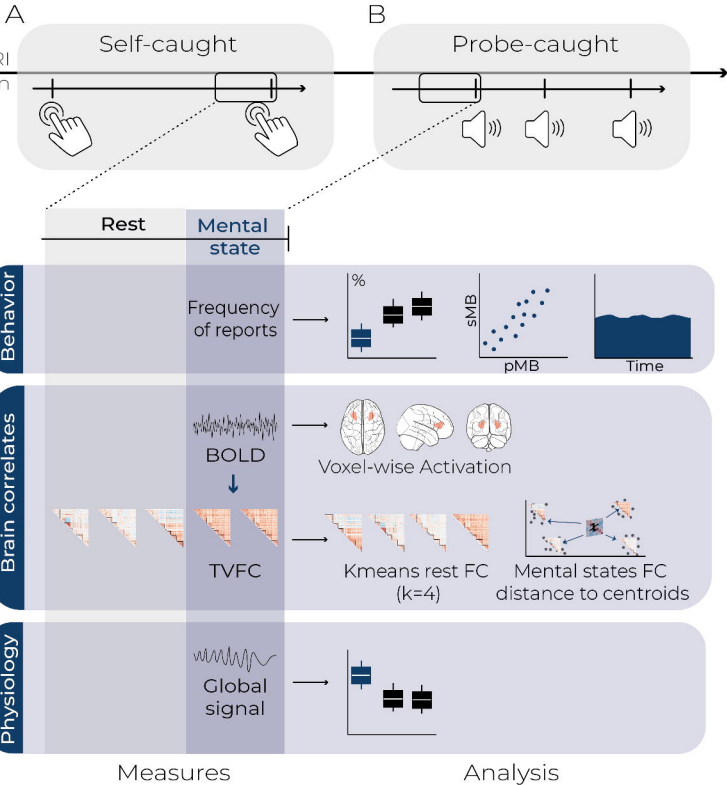
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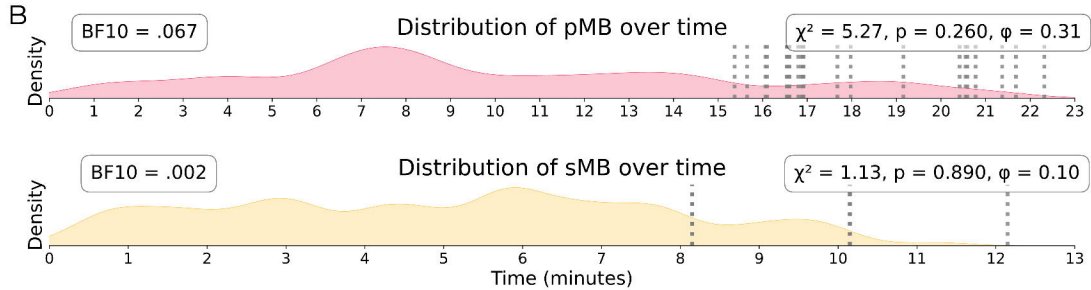
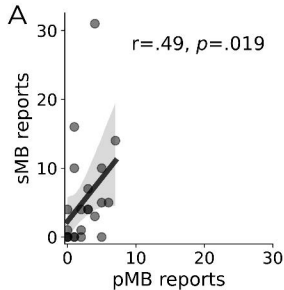
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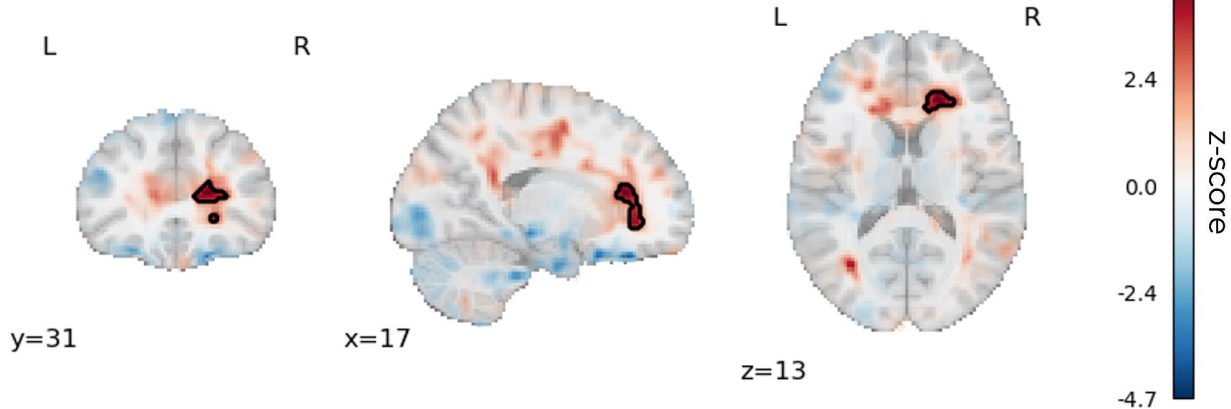
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sMB > pMB



Cluster-wise FWE $p < .05$

