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“Sticky” Thinking Disrupts Decision Making for Individuals With a Tendency Toward Worry and Depression

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Depressed individuals are commonly known to suffer from low mood. Less attention is paid to their decision-making deficiencies, consisting of indecisiveness and biased judgments. Many theories attempt to explain these impairments by focusing on reduced sensitivity to reward and punishment or biased information processing. Beyond these accounts, the present study explores another scenario, namely, whether the occurrence of sticky thinking—the occurrence of thoughts that are difficult to disengage from—could be a cause for the disruption of the decision-making process in individuals with depression. To test this hypothesis, we utilized the drift-diffusion model to investigate the influence of sticky thinking on the accumulation of evidence during a task commonly used to measure spontaneous thinking—the Sustained Attention to Response Task. Results showed that the more vulnerable group—specifically those with higher levels of repetitive negative thinking and depressive symptoms, including rumination—performed less accurately than the less vulnerable group. The more vulnerable group also showed a lower speed of evidence accumulation as evidenced by a decrease in the drift rate according to the drift-diffusion model. Moreover, the more vulnerable group exhibited prolonged nondecision time when more sticky thoughts occurred. At the neural level, we found that stronger alpha-band power marked more sticky thinking. We also demonstrated that the lower drift rate in the more vulnerable group, compared to the less vulnerable group, was exclusive to moments when the alpha-band power was higher than average. In summary, the study supported the idea that sticky thinking could explain the decision-making impairment among individuals who are more vulnerable to depression and worry.

Keywords: decision making, depression, sticking thinking, drift-diffusion model, alpha-band oscillations

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Individuals who suffer from major depressive disorder (MDD) have been shown to have neuropsychological impairments including deficiencies in executive function and decision making (Lawlor et al., 2020; Pitliya et al., 2023; Richard-Devantoy et al., 2012). Indeed, the *Diagnostic and Statistical Manual of Mental Disorders* (American Psychiatric Association, 2013) lists indecisiveness as a prevalent symptom of MDD. In addition, depressed individuals tend to make biased judgments that lead to less than ideal choices (Leykin et al., 2011).

There are several theories explaining decision-making deficiencies among depressed individuals including the reduced sensitivity to reward and punishment (Dillon et al., 2022; Eshel & Roiser, 2010; Forbes et al., 2007; Harlé et al., 2010) or biased information processing (Gotlib & Joormann, 2010). The former account considers depression to be due to impairments in reinforcement processing and the inability to exploit affective information to guide behavior (Eshel & Roiser, 2010). A number of studies suggested that depressed patients show dysfunctional responses to feedback (especially when it is negative) and indifference to rewards compared to the healthy controls (Cléry-Melin et al., 2019; Eshel & Roiser, 2010; Horne et al., 2021). This could explain why depressed individuals demonstrate diminished motivation in response to the given reward—the reward just does not feel so rewarding to them. Consistent with this, it has been found that participants with more severe depression tend to have a greater reduction in motivation than healthy individuals (Bari et al., 2010; Beats et al., 1996; Halahakoon et al., 2020; Steffens et al., 2001).

An alternative account of decision deficiencies focuses on biases toward emotional information, which interfere with making judgments about negative stimuli including negative life events (Gotlib & Joormann, 2010; Huys et al., 2015). More specifically, participants with a history of depression show an advantage in processing negative information compared to healthy controls (Hindash & Amir, 2012). These heightened responses toward negative information may potentially distort the decision-making process among depressed individuals by perceiving previous mistakes as catastrophic events, therefore, making individuals more wary to respond.

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Beyond these accounts, another theory that could explain depressed people's difficulty in making rational judgments is that rumination—that is, excessive thoughts that focus on the causes and consequences of negative feelings and events (Nolen-Hoeksema & Morrow, 1991)— impairs the decision-making process. A growing amount of evidence points to dysfunctions such as impaired concentration provoked by rumination (repetitive negative thinking) among depressed individuals (Grol et al., 2015; Whitmer & Gotlib, 2013). These thoughts can potentially disengage one from the ongoing task and thereby impair the collection and evaluation of evidence needed for making decisions. This impairment arises because weighing judgments requires concentration; hence, interference by ruminative thoughts impairs such judgments. This interference is unlikely to be explained by the theory of diminished motivation toward the reward because no prominent rewards are present when ruminative thoughts occur. It also could not be explained by the theory of processing advantages over negative information since the spontaneous thoughts can arise endogenously even without exogenous negative stimuli.

Indeed, rumination has been shown to affect the decision-making process among individuals with depressive symptoms. Using self-report questionnaires, studies demonstrated that rumination could be both a cause and a risk factor for indecision among depressed individuals (Watkins & Baracaia, 2002). In another study (van Randenborgh et al., 2010), a mediation model was used to demonstrate that ruminative thought content is related to both the difficulty of decision making and the level of dysphoria among ruminators. These lines of evidence indicate that ruminative thoughts might play an important role in the decision-making deficiency associated with MDD (Joormann & Tanovic, 2015), but little is known about whether rumination is directly related to impairment in decision making. To gain access to the impairment in decision making among depressed individuals, clinical studies typically evaluate the symptoms of indecisiveness or decision-making deficiency using self-report questionnaires (Franken et al., 2008; Leykin et al., 2011) or clinical interviews (Paykel, 1985). These approaches are subjective and may be biased (Baer, 2019) because the outcomes are highly dependent on the way that the questions are framed and structured. Additionally, they rely on integrating information over long periods of time and, therefore, are distorted by memory biases, which can be avoided by thought probes that ask only the present moment. In the case of clinical interviews, the lack of expertise of the interviewers or evaluators can affect the objectivity and reproducibility of the results. This raises challenges in obtaining reproducible decision-making deficiencies.

A better alternative for mapping out decision-making deficits are behavioral tests that are an objective quantification of decision making. For example, the decision-making deficiency can be explored through behavioral tasks such as the Iowa Gambling Task (Must et al., 2013), which presents participants with a card game where they must balance short-term gains and long-term losses to maximize overall rewards, or the Balloon Analogue Risk Task (Saloner et al., 2022) which simulates the inflation of virtual balloons with potential monetary rewards but increasing risk of bursting as monetary rewards rise. These tasks generally measure risk-taking behaviors, and depression is associated with reduced sensitivity to reward and punishment, which might contribute to depressive symptoms (Hevey et al., 2017; Must et al., 2013). The Balloon Analogue Risk Task has achieved high test–retest reliability in both nonclinical and clinical populations such as bipolar disorder, obsessive compulsive disorder, and attention-deficit/hyperactivity disorder (Buelow & Barnhart, 2018). They demonstrated advantages over questionnaires and interviews because they provide objective response time and accuracy, making them less prone to biases.

Another prevalent approach to understanding the impaired decision-making process among individuals with depression that is gradually being paid attention to is through the computational models of decision making (Huys et al., 2015; White et al., 2010). Examples of these models include but are not limited to reinforcement learning models, which consider decision making as a process in which an agent learns optimal actions through trial and error, receiving rewards or penalties for its choices (Lee et al., 2012); connectionist models that stimulate decision making by modeling the information flow and the activation of artificial neurons (Yeung et al., 2004); and sequential sampling models that assume decisions are made when evidence that is accumulated over time reaches a decision boundary (Forstmann et al., 2016; Ratcliff, 1978). Among these models of decision making, the drift-diffusion model (DDM) is a sequential sampling model that is well-suited for modeling accuracy and response time in typical behavioral tasks measuring decision making, even in decisions in which reward does not play a role. The DDM assumes accumulation is a noisy process that takes some time to reach the decision threshold—which determines the response time. The accumulation process has a speed determined by a parameter referred to as "drift rate" (Evans & Wagenmakers, 2020; Ratcliff et al., 2016). Another parameter of the model is nondecision time, which accounts for aspects of the reaction time (RT) that are theoretically independent of the evidence accumulation process such as stimulus processing and motor preparation (Cochrane et al., 2023). The third major parameter is the decision threshold that reflects speech–accuracy trade-off, such that higher thresholds indicate slower but typically more accurate decisions. A number of studies that applied the DDM found a generally slower drift rate among the depressed (Pe et al., 2013; Pitliya et al., 2023). This suggests the more sluggish evidence accumulation process among the depressed, but it does not yet explain why this occurs.

A possible explanation for this reduced speed of evidence accumulation could be an extra distraction caused by spontaneous thoughts, especially when the thoughts are ruminative, that is, negative, repetitive, and "sticky," which means they are difficult to disengage from (Huijser et al., 2020; Van Vugt & Broers, 2016). In this study, we refer to these ruminative thoughts that are difficult to disengage from as "sticky thinking" (Joormann et al., 2011). Studies using the DDM suggested that the drift rate decreases during episodes of mind wandering—a type of spontaneous thoughts (Mittner et al., 2014). Similarly, we have found a greater reduction in pupil size and decreased behavioral accuracy when sticky thinking is present compared to nonsticky thinking (Huijser et al., 2018, 2020). This suggests that especially sticky thoughts could have a strong effect on decision making. We expect that sticky thinking decelerates the evidence accumulation process, especially for individuals who are more vulnerable to depression. To test this hypothesis, the DDM is applied to fit the behavior during the Sustained Attention to Response Task (SART), a classic task designed to explore the nature of spontaneous thoughts via thought probes embedded within a Go/No-go paradigm. Compared to the self-report questionnaires, the thought probes can help to better reflect the moment-to-moment fluctuations of the thoughts since they are less susceptible to memory biases such as the primacy or the recency effect. If stickiness is a process that affects decision making, then incorporating a parameter reflecting the stickiness of thoughts into the model fitting should improve the fit of the model.

Furthermore, neural correlates of sticky thinking could provide additional information in understanding how this thought process affects the evidence accumulation process. The advantage of such an objective measure of sticky thinking is that it is potentially more reliable, but also, that it can be obtained for every trial, unlike subjective measures such as thought probes. We will further test whether this biomarker of sticky thinking provides information that improves the fitting of the DDM, which would be direct evidence for the interference of sticky thoughts in decision making. A good candidate for such a marker of sticky thinking is alpha-band power in electroencephalogram (EEG) since numerous studies have shown mind wandering to be related to alpha-band power at posterior sites (Arnau et al., 2020; Jann et al., 2010; Jin et al., 2019; Mo et al., 2013). Given that sticky thinking is also a type of mind wandering, but of a more disruptive kind, we hypothesized that sticky thinking may also be associated with alpha power in EEG.

Method

Transparency and Openness

We report how we determine our sample size, all data exclusions, and all measurements in the study. All data, data analysis code, and research materials are available on the Open Science Framework at https://osf.io/32467/. The data preprocessing, linear mixed-effect models, paired t tests, Bayes factor (BF), and data visualization were all implemented in R, Version 4.1.2 (R Core Team, 2021) and MATLAB (MathWorks, 2019). The data analysis plan was not preregistered.

Design

To explore how sticky thinking affects decision making and how the degree of depression modulates this impact, we used a 2 × 2 mixed design with groups (more vulnerable and less vulnerable) interacting with the stickiness of spontaneous thought (less sticky and more sticky). To measure spontaneous thoughts, participants were instructed to complete a SART with thought probes embedded to obtain the subjective stickiness of thoughts. Part of this data set has previously been published (40 participants) in a report focusing on how the steady-state visual evoked potential tracks sticky thinking (Yang et al., 2022) and in a report that classifies the degree of depression with machine-learning approaches (Kaushik et al., 2023). Compared to the prior publication (Yang et al., 2022), we have added an additional 10 participants. In this publication, we are exploring the impact of rumination on decision making among two groups with differing degrees of worry and depression. More specifically, we investigated how the evidence accumulation process varied with self-reported sticky thinking and examined how this effect of sticky thinking differed between those less and more vulnerable to worry and depression. If sticky thinking disrupts decision making, we expect that the behavioral performance and drift rates will be lower for trials in which the participant engages in more sticky thinking, and this is even more true for individuals with more depression and worries. In addition, we examined whether there was increased alpha-band power when more sticky thinking occurs, just like it does in the case of mind wandering as has been shown previously (Arnau et al., 2020; Compton et al., 2019).

Questionnaires

To measure individual differences in the degree of ruminative thought and depression, 124 candidate participants were asked to complete several questionnaires including the Perseverative Thinking Questionnaire (PTQ) measuring repetitive negative thinking (Ehring et al., 2011), Rumination Response Scale (RRS) for accessing depressive rumination (Nolen-Hoeksema & Morrow, 1991), and the Center for Epidemiologic Studies Depression Scale (CES-D) indicating the severity of depression (Radloff, 1977). High correlations between the CES-D score and scores of other two questionnaires were found among all 124 candidate participants. Specifically, the correlation between the CES-D score and the PTQ score was $r(122) = 0.70$, $p < 2.2 \times 10^{-16}$, while the correlation between the CES-D score and the RRS score was $r(122) = 0.75$, $p < 2.2 \times 10^{-16}$. Additionally, the PTQ score and the RRS score also showed a strong correlation with each other: $r(122) = 0.73$, $p < 2.2 \times 10^{-16}$. Due to the high correlations between the three questionnaires, a total score was calculated as the sum of the scaled score of these three questionnaires: $X = \sum \frac{(x_i - \bar{x}_i)}{\sigma_i}$, where x_i was the raw score on questionnaire i, σ was the standard deviation, and i ranged from 1 to 3. Utilizing the total score ($M = 0$, $SD = 2.71$) from the aforementioned questionnaires, participants scoring below −0.57 were invited for lab experiment and categorized into the less vulnerable group (24 participants) while those scoring above 0.53 were categorized into the more vulnerable group (26 participants). Individuals who scored from −0.57 to 0.53 were not invited to the laboratory experiment. In this study, the more vulnerable group and less vulnerable group do have active depression symptomatology and differ in the scores of all three questionnaires, PTQ: $t(48) = 10.80$, $p < .001$, $BF_{10} = 2.23 \times 10^{11}$; RRS: $t(48) = 10.69$, $p < .001$, $BF_{10} = 1.58 \times 10^{11}$; CES-D: $t(48) = 11.1$, $p < .001$, $BF_{10} = 5.46 \times 10^{11}$. The average and standard deviation of the PTQ, RRS, and CES-D scores for the more and less vulnerable groups are shown in Table 1. According to the CES-D scale, participants who score less than 15 can be considered as having no depression symptoms while a score above 21 can be considered as possibly suffering from major depression (Radloff, 1977). However, it should be kept in mind that the CES-D scale is a self-report scale; therefore, it is not equivalent to a clinical diagnosis of MDD.

Participants

We targeted a sample size of 40 participants who reported both more sticky and less sticky moments (nine participants were excluded due to not using the full scale of stickiness rating; this exclusion criterion is described in more detail in the Procedure section). The sample size was estimated using the software G*Power 3.1.9.7 by assuming a large effect size of 0.4 (Cohen's f) according to the criterion defined by Cohen (2013), α of .05, power of 0.8 in an analysis of variance with two groups and two within-subject measurements, given that we do not find any existing study exploring the group effect of sticky thinking. To reach the expected sample size (40), 10 additional participants were recruited *based on* the previous study (31 participants with the full scale of stickiness rating; Yang et al., 2022). In summary, among a total of 50 participants who joined this study, 40 participants reported both

Table 1
The Average (and Standard Deviation) of the Scores Across Groups That Are More and Less Vulnerable to Depression

Group	Questionnaire		
	PTQ score	RRS score	CES-D score
More vulnerable	45.08 (4.68)	66.58 (6.85)	31.50 (7.33)
Less vulnerable	25.12 (7.86)	42.69 (8.75)	10.73 (5.87)
Group comparison	$t(48) = 10.80$, $p < .001$	$t(48) = 10.69$, $p < .001$	$t(48) = 11.1$, $p < .001$
Bayes factor	2.23×10^{11}	1.58×10^{11}	5.46×10^{11}

Note. PTQ = Perseverative Thinking Questionnaire; RRS = Rumination Response Scale; CES-D = Center for Epidemiologic Studies Depression Scale.

more sticky thinking and less sticky thinking during the experiment and were kept in the behavioral analysis, EEG analysis, and model fitting.

There were 21 participants in the more vulnerable group (17 females, four males) and 19 in the less vulnerable group (eight females, 10 males, one prefer not to say). The imbalance in gender across groups, $\chi^2(2) = 6.73$, $p = .035$, $BF_{10} = 5.90$, was expected given that there is a generally high prevalence of depression among the female population (Gao et al., 2020; Hyde & Mezulis, 2020). Participants were all proficient English speakers with normal or corrected-to-normal vision. The data were too uncertain to tell whether there was a group difference in handedness, more vulnerable: one left-handed, 20 right-handed; less vulnerable: 0 left-handed, 19 right-handed; $\chi^2(1) = 2.14 \times 10^{-31}$, $p = 1$, $BF_{10} = 0.34$, but the more vulnerable group was not significantly different in education, more vulnerable: seven high school, 12 bachelor, two master, zero PhD; less vulnerable: six high school, six bachelor, six master, one PhD; $\chi^2(3) = 4.99$, $p = .17$, $BF_{10} = 2.54$, according to a chi-square test and BF with the BFcontingencyTable function (BayesFactor package of R, Morey & Rouder, 2021). This study was reviewed and approved by the Research Ethics Review Committee, University of Groningen (proposal number: 68060221). All participants provided their written informed consent to participate in this study. The participants were mostly recruited from the university; therefore, they likely have a comparable age range, but the exact ages of the participants were not asked in the experiment since age was not the main interest of this study.

Procedure

A Writing Task

To evoke more ruminative thoughts during the experiment, all participants were asked to engage in a 10-min writing task immediately preceding the SART. The content of the writing task was limited to a negative topic that had been bothering them in their daily lives. No additional clues and prompts were provided during the writing task. The task has been utilized in other studies to increase the occurrence of mind wandering and ruminative thoughts for us to explore (Stawarczyk et al., 2011). After the writing task, participants were asked to rate to what degree (intensity) and how often (frequency) the event bothered the participant on a 6-point Likert scale (Table 2).

SART

The SART was designed to measure spontaneous thoughts and has been applied in numerous studies on mind wandering (Denkova et al., 2019; McVay & Kane, 2009; Mooneyham & Schooler, 2013). The SART task is a Go/No-Go task with occasional thought probes that ask a participant what they are thinking about right now. A trial in the SART started with a white cross centrally located in a black background lasting for a duration jittered from 1,480 to 2,120 ms (equally distributed between 1,480, 1,640, 1,800, 1,960, and 2,120 ms), followed by a word presented for 320 ms. The word list comprises various nouns (see Appendix for all words) that were derived from a prior study (McVay & Kane, 2013). Following that previous work, we sought to increase the chances of rumination by inserting four personalized sets of word triplets that were extracted from the Personal Concerns Inventory. The Personal Concerns Inventory asked participants about their worries and concerns, and this questionnaire was administered to participants before they joined the lab experiment (Cox & Klinger, 2004). Specifically, participants were requested to describe their worries and concerns across nine different aspects of daily life, such as household affairs, financial situation, family, and friendship. For example, if the participant was worried about disappointing his/her family for not completing her study in time, we converted the worries into word triplets: timely–graduation–disappointment. During the SART, each word among the word triplets was presented in sequence. The four most significant word triplets, based on ratings of importance and duration of these worries, were then integrated into the SART.

After the presentation of the word, a mask was presented for 880 ms followed by an intertrial interval for 3,020 ms before the next trial. Each trial had an average duration of 6,020 ms. Due to another

Table 2
The Subjective Ratings on the Intensity and Frequency of the Event That Participants Were Writing About, Indicating the Success of the Writing Manipulation Intervention

Group	Writing manipulation[a]	
	Intensity	Frequency
More vulnerable	4.71 (1.01)	4.43 (0.87)
Less vulnerable	3.84 (1.03)	3.68 (1.03)
t test across groups	$t(44) = 2.90$, $p = .0058$	$t(44) = 2.63$, $p = .01$
Bayes factor	7.49	4.35

Note. These ratings were done immediately following the writing task. Ratings are presented as the average (*M*) and standard deviation (*SD*) values in parentheses.
[a] Due to incomplete filling in the ratings after the writing manipulation, we are missing three data points in the group of more vulnerable individuals and two data points in the group of less vulnerable individuals.

design that aimed to provoke the steady-state visual evoked potential (Yang et al., 2022), the cross and words were kept flickering at a frequency of 12.5 Hz. For that purpose, the screen resolution was set to 50 Hz for more precise manipulation. The effects of the steady-state visual evoked potential were reported in the earlier study. Participants were required to press the "N" key on the keyboard for lowercase words (go trials, made up 88.89% of all the trials) as soon as possible while they were informed to withhold the button for uppercase words (no-go trials, made up 11.11% of all the trials). The SART was made up of eight blocks in total, each including 90 trials and six thought probes. The stimuli were presented with Psychopy software (Peirce et al., 2019) on a computer 65 cm away from the participant. The word was presented with an angle from 5.72° to 36.39° horizontally (depending on word length) and 5.55° vertically.

During the SART, the spontaneous thoughts were accessed through thought probes focusing on both the content and the stickiness of the thoughts. More specifically, self-reported thought content was measured with various questions. The first of these was "What were you thinking about just now?" Participants were asked to select among the options: (1) I was completely focused on the task, (2) I was evaluating aspects of the task (e.g., how I was doing or how long the task was taking), (3) I was thinking about personal things, (4) I was distracted by my environment (e.g., sound, temperature, my physical state), (5) I was daydreaming or thinking about task-irrelevant things, and (6) I was not paying attention and did not think about anything in particular. The five trials before the thought probes were classified as on task if participants indicated Options 1 (I was completely focused on the task) and 2 (I was evaluating aspects of the task) and mind wandering if they indicated options 3 (I was thinking about personal things) and 5 (I was daydreaming or thinking about task-irrelevant things). We chose to label five trials preceding the thought probes based on previous studies, in which it was found that this number provided the optimal assessment of mental state (Seli, Carriere, et al., 2013; Seli, Cheyne, & Smilek, 2013).

Of more relevance to the present study, we asked "How difficult was it to disengage from the thought?" which was scored on a Likert scale from 1 (*very easy*) to 9 (*very difficult*). The five trials before each thought probe were classified as "less sticky" if participants chose Options 1–4 (easy to disengage from the thought) and "more sticky" if participants chose Options 6–9 (very difficult to disengage from the thought). As a result, a total of 236 trials were marked with stickiness for each participant and entered the analysis. Among them, a proportion of 20.62% of trials (48.66 trials for each participant) were marked as "5" in stickiness and thus were excluded from further analysis because they are right in the middle between sticky and nonsticky and can thus not be classified in either of the two categories. There were 45.26% of trials (106.82 trials for each participant) marked as more sticky and 33.84% of trials (78.92 trials for each participant) marked as less sticky in the analysis of the present study. Ten participants had no trials in either the less sticky and more sticky condition and were therefore excluded from further analysis.

EEG Recording

During the SART, the EEG was recorded with a sampling rate of 512 Hz using a Biosemi 32-channel system (BioSemi, Amsterdam, Netherlands) with six individual electrodes to measure eye movements (two horizontal and two vertical electrooculography electrodes) and mastoid signals (one on the left and one on the right). An electrode near the vertex was used as the online reference. The impedances were kept below 20 kΩ for all participants.

EEG Analysis

EEG Preprocessing

The EEG signals were preprocessed with the EEGLAB toolbox (Delorme & Makeig, 2004) and MATLAB (The MathWorks, Inc.). Bad channels were detected via visual inspection and replaced through interpolation of adjacent electrodes. The continuous EEG was band-pass filtered from 0.5 to 40 Hz. An independent component analysis was performed to remove eye blinks, saccades, and muscular artifacts. Then the continuous data were segmented into trials from 500 ms before stimulus onset to 1,548 ms after stimulus onset time, and the baseline was corrected based on the periods before stimulus onset. EEG signals were rereferenced to the average signal of all EEG electrodes. After rereferencing, segmented epochs were excluded if the amplitudes of the trial went above 100 μV. After the preprocessing, the power spectrum was calculated for every single trial.

Frequency Analysis

Based on previous literature on mind wandering, we chose P7 and P8 as representative electrodes to track mind wandering (Jin et al., 2019). EEG epochs were filtered using a filter kernel constructed with firls in MATLAB (The MathWorks, Inc.) and separated into the alpha (8–12 Hz) band. After applying the filter with the filtfilt function, the EEG signal was then Hilbert transformed. To calculate the power spectral density estimate, the pwelch function was further applied to the resulting complex numbers of the Hilbert transform. The power value was calculated as 10 multiplied by the log10 transformation of the square of the absolute value of the power spectral density to obtain the appropriate scale for the power values.

Fitting Decision Behavior With the DDM Model

We applied the HDDM package to fit the behavioral data during the SART (Wiecki et al., 2013). As described above, the DDM describes decisions as a random walk process that drifts in the direction of a decision boundary. When the decision boundary is reached, the decision is made. In this specific case, a response is emitted when the participant reaches the "go" boundary, and no response is emitted when the "no-go" boundary is reached. Due to the nature of SART, which was a variant of Go/No-Go task and, therefore, has unobserved responses on the no-go trials, we assumed an implicit decision boundary for no-go trials as was described in the previous study (Zhang et al., 2016). This implicit boundary was implemented by setting the reaction time for no-go trials as 999 s while the reaction times for go trials remained at their original values. Besides the speed of drift (drift rate), the nondecision time is another process, independent of evidence accumulation, which captures perceptual and motor delays. The starting point describes the response bias toward one of the two alternatives; in the case of SART, this bias pertains to either making a response or withholding a response. We built various models with the HDDMStimCoding module of the HDDM package by fitting behavior only (Models 1–6) and a model that fit both behavior and alpha-band power (Model 7). In Model 1, we set the drift rate for go trials and no-go trials as the same absolute value but in opposite directions (Gomez et al., 2007). In Model 2, we allowed the starting point to vary across more sticky/less sticky thinking. In Model 3, the drift rate was allowed to vary between more sticky/less sticky thinking trials. In Model 4, the drift rate and starting point were allowed to vary across stickiness condition. In Model 5, the drift rate, starting point, and nondecision time were allowed to vary across stickiness condition. In Model 6, the drift rate and nondecision time were allowed to vary across stickiness condition.

To explore how the subjective stickiness and the neural marker of sticky thinking (alpha power) could jointly contribute to the model fit, the last Model 7 was built by allowing the drift rate to vary across four categories. These categories were (a) high alpha-band power and more sticky trials, (b) high alpha-band power but less sticky trials, (c) low alpha-band and more sticky trials, and (d) low alpha-band and less sticky trials. To fit each of these models, 50,000 samples were drawn from the posterior distribution while the first 1,000 samples were discarded. The traces of the posterior chains were visually inspected to confirm that the chains had reached a stable distribution and to access autocorrelation. Additionally, posterior predictive plots were generated and examined to ensure that they were smooth and unimodal. We used the deviance information criterion (DIC) value to compare the model fits where better models are associated with lower DIC values.

Statistics

We applied a linear mixed-effect (LME) model to examine the 2 × 2 design (stickiness condition and group). In this LME model, the participant number was set as random effects. Stickiness condition and group were set as fixed effects, and the interaction between them was also explored. If there was a significant interaction between stickiness and group, we used paired *t* tests (significance level $p < .05$, two-tailed) and BF (implemented by the BayesFactor package, Morey et al., 2011) for post hoc comparisons. Given that there were limited standardized approaches specified to evaluate the effect size for the LME model, we used the partial η^2 that has been applied to the LME model in a recent work (Correll et al., 2022). A partial η^2 value of .0099 corresponds to a small effect, .0588 to a medium effect, and .1379 to a large effect.

Results

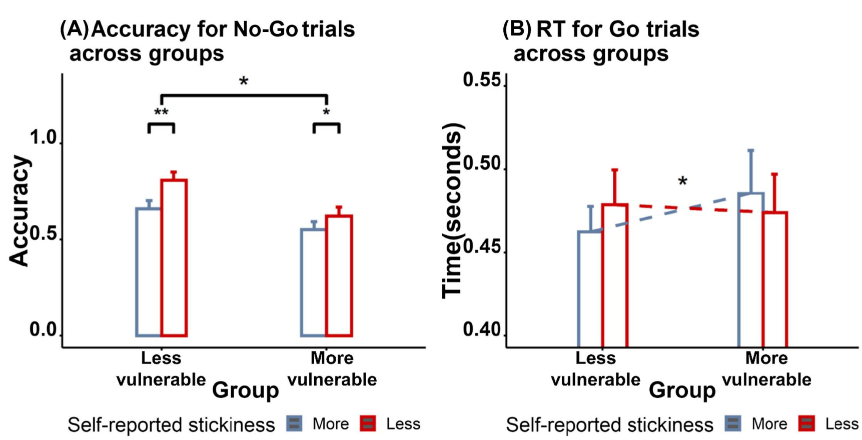
Behavioral Results

First, we evaluated the validity of the thought probe responses by investigating if there was a difference in the behavioral performance of subjectively less and more sticky trials (see Figure 1) as indicated by thought probe responses. An LME of the 2 × 2 design (Group × Stickiness) confirmed that there was a main effect of stickiness, $\chi^2(1) = 15.57$, $p < .001$, $\eta^2 = 0.28$, and group, $\chi^2(1) = 8.28$, $p = .004$, $\eta^2 = 0.17$, on no-go accuracy. However, there was no interaction between stickiness and group, $\chi^2(1) = 2.14$, $p = .14$, $\eta^2 = 0.05$.

We also analyzed the reaction time of go trials with the same test, but no significant main effect was found in any group according to an LME model, no main effect of stickiness, $\chi^2(1) = 0.05$, $p = .82$, $\eta^2 = 1.32 \times 10^{-3}$, or group, $\chi^2(1) = 0.10$, $p = .75$, $\eta^2 = 2.50 \times 10^{-3}$. Furthermore, we observed an interaction between stickiness and group, $\chi^2(1) = 4.34$, $p = .037$, $\eta^2 = 0.10$. However, further post hoc comparisons revealed uncertainty in determining the nature of this interaction: For the more vulnerable group, the mean reaction time for more sticky trials was $M = 0.49$ s ($SD = 0.12$ s), and for less sticky trials, it was $M = 0.47$ s ($SD = 0.10$ s), and the data were too uncertain to find an effect of stickiness, $t(20) = 1.45$, $p = .16$, 95% confidence interval (CI) [−0.0050, 0.028], $d = 0.32$, $BF_{10} = 0.57$. Also, for the less vulnerable group, the data were too uncertain to determine whether there was an effect of stickiness in reaction time, $t(18) = 1.42$, $p = .17$, 95% CI [−0.0077, 0.040], $d = 0.33$,

Figure 1

Bar Plot Comparing Behavioral Performance Between Trials That Were Less Sticky (Red) and Trials That Were More Sticky (Blue) for the Less and More Vulnerable Groups



Note. (A) Accuracy in no-go trials was significantly higher for less sticky trials in both less and more vulnerable groups. The more vulnerable group had lower accuracy compared to the less vulnerable group. (B) The interaction effect between stickiness of thoughts and group for reaction time in go trials. RT = reaction time. See the online article for the color version of this figure.
* $p < .05$. ** $p < .01$.

$BF_{10} = 0.57$; more sticky trials ($M = 0.46$ s, $SD = 0.06$ s), and less sticky trials ($M = 0.48$ s, $SD = 0.09$ s).

To test whether the more vulnerable group was experiencing more sticky thoughts, we compared the proportion of less sticky thinking and more sticky thinking between the groups. We found that an average of 33.84% of labeled trials were marked as less sticky while 45.26% of trials were marked as more sticky. On 20.62% of the trials, participants reported neutral stickiness, and on 0.28% of trials, responses were missing. We excluded neutral stickiness and missing responses from the analysis. Contrary to our hypothesis, the groups were equal in their tendency to report more sticky thinking, $t(48) = 0.63$, $p = .53$, 95% CI [−0.11, 0.21], $d = 0.18$, $BF_{10} = 0.33$, and the data were too uncertain to say whether there was a group difference in less sticky thinking, $t(48) = 1.38$, $p = .17$, 95% CI [−0.05, 0.28], $d = 0.39$, $BF_{10} = 0.61$.

EEG Results

Oscillatory Power

To begin with, we investigated whether increased alpha-band power would occur during sticky thinking, similar to what was observed in previous studies on mind wandering (Kam et al., 2022; Yang et al., 2022). We analyzed the alpha-band power of the selected representative electrodes derived from our previous work (Jin et al., 2019) including the P7 electrode and P8 electrode. There was a main effect of stickiness in the average power of the two electrodes, $\chi^2(1) = 5.34$, $p = .021$, $\eta^2 = 0.12$, which suggested more sticky thinking trials showed stronger alpha-band power compared to less sticky trials. However, there was neither a main effect of group, $\chi^2(1) = 1.85$, $p = .17$, $\eta^2 = 0.04$, nor an interaction between stickiness and group, $\chi^2(1) = 0.20$, $p = .65$, $\eta^2 = 4.98 \times 10^{-3}$ (Figure 2).

DDM Results

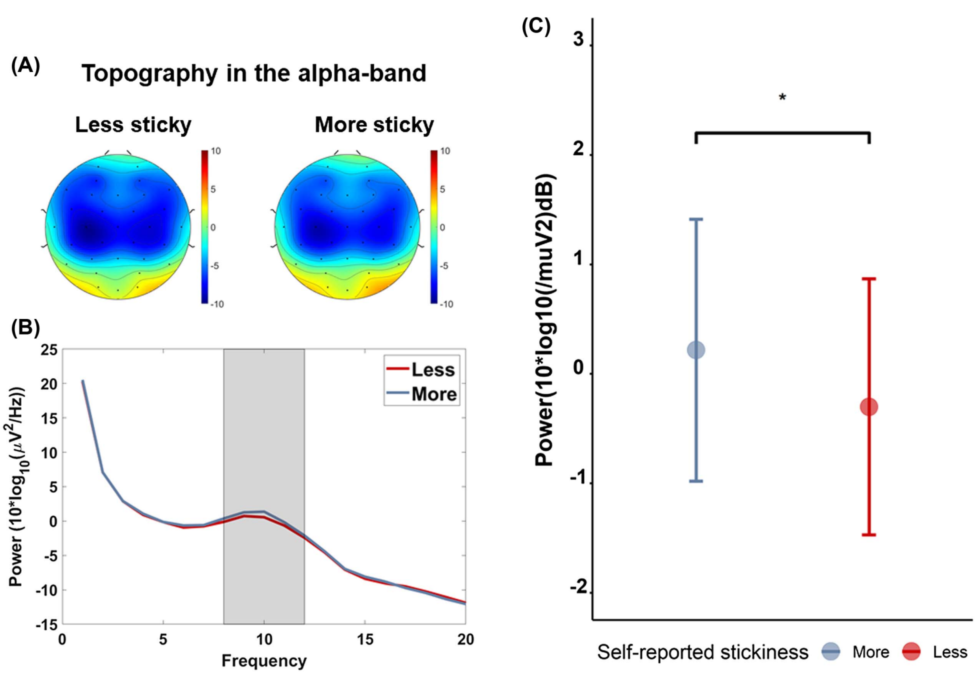
The previous section showed increased alpha-band power during episodes of more sticky thinking. To examine whether this also influenced decision behavior, we fit the DDM.

Fitting the DDM With Behavior Only

We started by fitting the model to behavior only, ignoring the EEG data, and compared models in which different decision parameters were allowed to vary across conditions. The model in which the drift rate and nondecision time varied across the stickiness condition (Model 6) showed the best fit according to the DIC, which had the lowest value (−2,610). This model was compared to the other models that showed a higher DIC value (Model 1 [DIC value: −2,555], which did not consider sticky thinking; Model 2 [DIC value: −2,596], which allowed the starting point to vary across stickiness; Model 3 [DIC value: −2,590], which allowed the drift rate to vary across stickiness condition; Model 4 [DIC value: −2,609], which allowed the drift rate

Figure 2

Conditional Difference of the Alpha-Band Power Between Less Sticky and More Sticky Trials



Note. (A) Topography in alpha-band for less sticky and more sticky trials. (B) The power spectrum across frequencies (average across P7 and P8 electrode) comparing less sticky trials (red line) to more sticky trials (blue line). The shading area represents the alpha-band frequency range (8–12 Hz). (C) Mean (dot) and standard error (error bar) of alpha power (log-transformed) between less sticky trials (red) and more sticky trials (blue). The linear mixed effect showed a main effect of stickiness in alpha-band power. See the online article for the color version of this figure.
* $p < .05$.

and starting point to vary across stickiness condition; Model 5 [DIC value: −2,584], which allowed the drift rate, starting point, and nondecision time to vary across stickiness condition).

An LME of the drift rates across groups and stickiness conditions in Model 6 showed main effects of both sticky thinking, $\chi^2(1) = 19.43$, $p = 1.05 \times 10^{-5}$, $\eta^2 = 0.33$ (see Figure 3), and group, $\chi^2(1) = 4.48$, $p = .034$, $\eta^2 = 0.10$, with a significantly higher drift rate for the less vulnerable group than the more vulnerable group. No significant interaction effect, $\chi^2(1) = 0.87$, $p = .35$, $\eta^2 = 0.02$, was found. This was consistent with the results of previous studies showing lower evidence accumulation for MDD individuals (Lawlor et al., 2020).

The other parameter that can vary in Model 6, the nondecision time, did not show a main effect of stickiness condition, $\chi^2(1) = 3.40$, $p = .065$, $\eta^2 = 0.08$, see Figure 3, nor group, $\chi^2(1) = 0.40$, $p = .52$, $\eta^2 = 0.01$. Similar to the reaction time for go trials, there was an interaction effect between stickiness and group in nondecision time, $\chi^2(1) = 15.93$, $p < .001$, $\eta^2 = 0.28$. Further comparisons showed that, for the more vulnerable group, the nondecision time was longer when the participant was engaged in more sticky thinking ($M = 0.2138$ s, $SD = 0.0090$) compared to less sticky thinking, $M = 0.2035$ s, $SD = 0.069$, $t(20) = 4.13$, $p < .001$, 95% CI [0.005, 0.015], $d = 0.9$, $BF_{10} = 63.64$. For the less vulnerable group, the data were too uncertain to say whether nondecision time was significantly different or not across stickiness conditions, more sticky: $M = 0.2077$ s, $SD = 0.0101$; less sticky: $M = 0.2119$ s, $SD = 0.0072$. $t(18) = 1.52$, $p = .15$, 95% CI [−0.001, 0.010], $d = 0.35$, $BF_{10} = 0.64$.

Including Alpha-Band Power in the DDM Fits

As we have found that alpha-band power can reflect momentary fluctuations in ongoing sticky thinking, we expected trials with high alpha power would be associated with impaired decision making and, therefore, be associated with a lower drift rate. For this reason, we added the category of high or low alpha power to the DDM and exported the drift rate from Model 7, which allowed the drift rate to vary across four categories: more sticky–low alpha (47.88 trials per participant), more sticky–high alpha (47.73 trials per participant), less sticky–low alpha (33.85 trials per participant), less sticky—high alpha (31.55 trials per participant). We decided against the common practice of adding single-trial alpha as a continuous regressor since the regressor model in the HDDM package did not support fitting a Go/No-Go task.

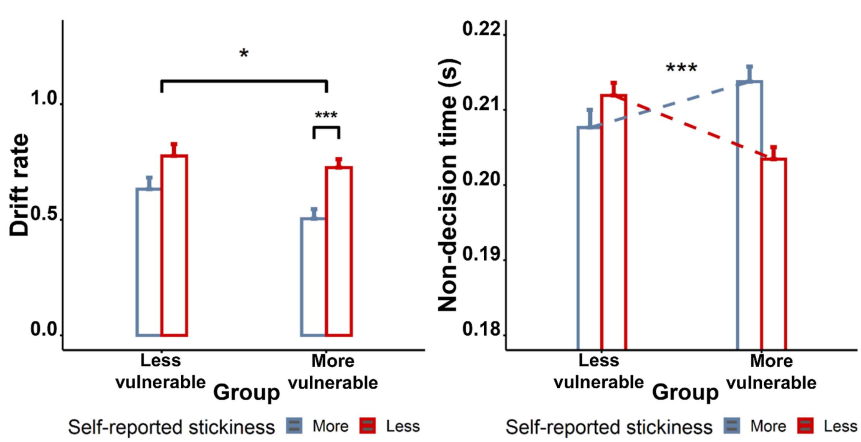
Compared to the aforementioned model with behavior only, the model fit improved as was indexed by the decreased DIC value (−2,664) in contrast with Model 6 (DIC value = −2,610), which allowed the drift rate and nondecision time to vary across the stickiness condition.

The LME model suggested a main effect of sticky thinking, $\chi^2(1) = 27.78$, $p = 1.36 \times 10^{-7}$, $\eta^2 = 0.19$; alpha-band power, $\chi^2(1) = 56.03$, $p = 7.16 \times 10^{-14}$, $\eta^2 = 0.32$; and group, $\chi^2(1) = 4.57$, $p = .033$, $\eta^2 = 0.10$. The main effect of stickiness conditions reflected a lower drift rate when sticky thinking occurred compared to nonsticky thinking. The main effect of alpha-band power showed that the drift rate was higher in trials with lower alpha-band power than trials with high alpha-band power. Furthermore, a significant interaction between group and alpha-band power has been found, $\chi^2(1) = 6.27$, $p = .012$, $\eta^2 = 0.05$. To further explore this interaction, we did post hoc comparisons. Among trials with low alpha power, there was no difference in drift rate between the more vulnerable group ($M = 0.74$, $SD = 0.13$) and the less vulnerable group, $M = 0.74$, $SD = 0.16$; $t(78) = 0.23$, $p = .82$, 95% CI [−0.057, 0.072], $d = 0.05$, $BF_{10} = 0.24$. However, when the trials were higher in alpha power, which is usually a marker of mind wandering and could therefore reflect sticky thinking, the more vulnerable group showed a significantly lower drift rate than the less vulnerable group: $t(78) = 3.12$, $p = .003$, 95% CI [0.03, 0.15], $d = 0.7$, $BF_{10} = 13.91$ (more vulnerable group: $M = 0.55$, $SD = 0.14$; less vulnerable group: $M = 0.64$, $SD = 0.13$, see Figure 4). There was no three-way interaction between stickiness, alpha-band power, and group, $\chi^2(1) = 1.11$, $p = .29$, $\eta^2 = 9.19 \times 10^{-3}$.

To explore whether alpha-band power is uniquely associated with sticky thinking or also influences other types of spontaneous thoughts such as mind wandering and on-task thoughts, we tested

Figure 3

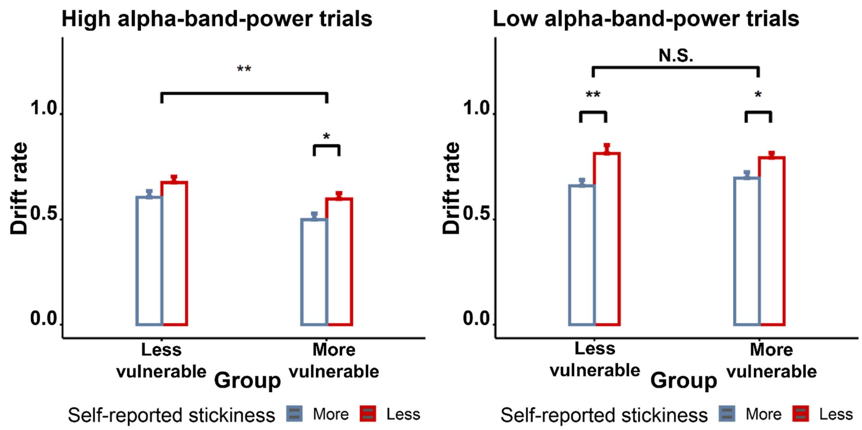
Bar Plot Comparing the Drift Rates Between More and Less Sticky Thoughts for the Less Vulnerable and More Vulnerable Groups



Note. See the online article for the color version of this figure.
$^{*} p < .05$. $^{***} p < .001$.

Figure 4

Posterior Drift Rates by Alpha-Band Power and Stickiness of the Thought Across Groups



Note. Bar plot of posterior estimates of the drift rates across four categories combining alpha-band power and stickiness of the thoughts (Left panel: high alpha-band power, right panel: low alpha-band power) for the more vulnerable group and less vulnerable group. The main effects of both sticky thinking and alpha-band power were observed while the group effect emerged only when alpha-band power was above average. N.S. indicates no significance between conditions. See the online article for the color version of this figure.
$^{*} p < .05.$ $^{**} p < .01.$

the DDM among four categories: mind wandering–low alpha, mind wandering–high alpha, on task–low alpha, and less sticky–high alpha (see Supplemental Results).

Discussion

In this study, we investigated whether the decision-making process was affected by the moment-to-moment fluctuations in sticky thinking and how it interplayed with the degree of worry and depression. In the SART, individuals who were more vulnerable to depression and worry were generally less accurate and had slower speed in the evidence accumulation process. This is consistent with decision-making impairments associated with depression symptomatology. Sticky thinking was found to impair the decision-making process and the underlying evidence accumulation rate. This impairment was evident in both the model that included alpha-band power and the model that did not. The alpha-band power acted as a modulator of the group differences in the evidence accumulation process between more vulnerable and less vulnerable individuals.

The stickiness of thoughts was found to be associated with alpha-band power in the posterior regions with higher alpha reflecting more sticky thoughts. Furthermore, the model fit improved after including the alpha-band power in the DDM compared to the model with only behavior. This suggested that alpha power captures trial-by-trial fluctuations in participants' ability to extract information from a stimulus, consistent with its known relevance for mind wandering (Jin et al., 2019). Since this effect varied between low and high stickiness trials, this suggests that the stickiness of thoughts is an additional dimension that affects decision making.

Moreover, we found that the alpha-band power modulated the evidence accumulation differently in individuals varying in worry and depression. During low-alpha power states, which are typically associated with alertness (Keefe & Störmer, 2021), on-task thoughts (Compton et al., 2019), and less sticky thinking in the present study, participants who are more vulnerable to depression demonstrated no difference in the drift rate compared to the less vulnerable group. A difference between the groups only appeared when alpha-band response was higher than average. In that situation, the more vulnerable group showed a slower drift process compared to the less vulnerable group, reflecting more difficulties in decision making. These results suggest that alpha-band power is a key modulator of the group differences in the evidence accumulation process although future studies need to replicate these post hoc findings. In the present study, the subjectively reported stickiness of the thoughts and their neural correlates (i.e., alpha-band power) affected the drift rates separately, and alpha-band power modulated the effect differently in the two groups.

Beyond the impact of depression on decision making, we added to literature by investigating how decision making was modulated by sticky thinking, a form of spontaneous thoughts that is difficult to disengage from by voluntarily shifting attention (Christoff et al., 2016). We found that sticky thinking was accompanied by increased alpha power, which has previously been found to be correlated with the activation of default-mode network in functional magnetic resonance imaging studies (Hlinka et al., 2010; Jann et al., 2010; Mantini et al., 2007) that was also consistent with the model proposed by Christoff et al. (2016), which suggests that the default mode network exerted automatic constraints on the sensorimotor areas without cognitive control to hold the attention, thus, making the spontaneous thoughts less flexible (Christoff et al., 2016; Kam et al., 2021).

We replicated reduced drift rates in the evidence accumulation among people who are more vulnerable, which likely reflects impaired decision making (Lawlor et al., 2020). This decreased drift rate could possibly be caused by various cognitive deficiencies such as diminished concentration (Mittner et al., 2014) and reduced motivation (Bottemanne & Dreher, 2019; Gesiarz et al., 2019) since it has been observed that depressed individuals suffer from difficulty concentrating (Keller et al., 2020) and a lack of motivation (Schulz, 2020; Smith, 2013). However, it remains to be verified which of these two explanations is more likely. Further empirical studies are needed to look deeper into the reason behind the decrease in drift rate among individuals more vulnerable to depression by manipulating the levels of motivation.

The impaired decision-making process might be distinct from, yet also tightly related to, the symptom of indecision derived from questionnaires. Indecision is characterized by an inability to make decisions when facing different choices. Interestingly, the nondecision time showed an increase when more sticky thinking occurred but only for the more vulnerable group. This result aligns well with existing studies illustrating that rumination provokes indecision among individuals with depression (Di Schiena et al., 2013). The result also aligns with previous work showing that depressed individuals suffer from psychomotor slowing (Wüthrich et al., 2022) since nondecision time is usually mapped to the speed of perceptual and motor processes (Evans, 2021). On the basis of our results, we speculate that perceptual and motor processes are delayed due to the occurrence of sticky thinking especially for more vulnerable individuals. Therefore, we further point out that the nondecision time could be an additional component giving rise to indecision problems associated with depression.

We did not find a difference in the occurrence of sticky thinking between groups; this is seemingly in lack of convergence with the group difference in the degrees of depression and ruminative thinking according to the questionnaire-based measures. It is worth noting that the self-report questionnaires for the group division on depression, preservative thinking, and rumination were explicit measures focusing on longer intervals in the past. In contrast, the SART generally requires participants to maintain focus with sticky thinking occurring in a relatively more implicit manner and restricted to shorter intervals during the task. These differences could potentially explain the seeming lack of convergence between questionnaire-based rumination and task-based sticky thinking. If the experiment were repeated over a longer time scale, then we could expect a higher correlation between these two measures.

We, however, have to point out a confounding factor in these group effects, namely, a gender imbalance, a trend also noted in other research on the prevalence of depression (Hyde & Mezulis, 2020). As such, the observed differences in decision making and sticky thinking between more and less vulnerable individuals could in fact be caused by the gender imbalance. Further studies on depression should take steps to minimize the influence of gender across groups to ensure robustness of the conclusions to such confounds. Additionally, the study depends on subjective reports of sticky thinking. People who are not strictly trained in scientific methods to quantify subjective experiences such as microphenomenology are generally not good at reporting their own mental states (Petitmengin et al., 2019; Sparby et al., 2023). It is worth exploring for future studies of ruminative thought to include a regime of training of the participants in introspection to verify these findings. Last, we evaluated the impact of sticky thinking on decision making in this study. However, spontaneous thoughts encompass diverse aspects that could be similar to sticky thinking, such as mind wandering, self-relatedness, and the valence (positive or negative, future-oriented or past-oriented) of thoughts. For example, according to the previous study, mind wandering has been shown to affect model-based decision making (Liu et al., 2023; Mittner et al., 2014). In a separate analysis, we demonstrated that the role of alpha-band power differed between the groups during episodes of mind wandering. Future research is needed to determine whether the effects of sticky thinking that we observed in this study after these variables were better controlled with sufficient trials.

Taken together, our study confirmed that a tendency to worry and depression resulted in a decrease in the speed of evidence accumulation in decision making. This deceleration gets even worse when sticky thinking occurs. By using behavioral testing, electrophysiological recording and computational modeling, our study supported the idea that sticky thinking, a thought process related to rumination, is a key factor in creating decision-making difficulties among individuals who are more vulnerable to depression and worries.

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(*Appendix follows*)

Appendix

Word List Presented in the Sustained Attention to Response Task

Words presented in the task							
Abbot	Carpenter	Dogsled	Heat	Lithium	Peat moss	Ruby	Sulphur
Aircraft carrier	Cello	Dove	Heron	Lobby	Peony	Rugby	Suspenders
Aluminum	Century	Drawing	Herring	Lynx	Persimmon	Run	Sweat shirt
Amy	Cereal box	Egypt	High heels	Magazine	Personal	Saint	Sweet pea
Animals	Charlottesville	Emerald	Hip	Magenta	Pharmacist	Sake	Tab
Aqua	Chartreuse	Entomology	Home	Mambo	Phenomenon	Sand	Tabernacle
Argentina	Checkers	Epilepsy	Honda	Men	Pineapple	Sandals	Tango
Aspen	Chemist	Evening	Horse racing	Mercury	Pink	Saxophone	Tape measure
Auburn	Chemistry	Father-in-law	Hot pad	Metaphor	Pipes	Scallop	Task
Avocado	Chess	Feeling	Houseboat	Millimeter	Planer	Scarlet	Theresa
Axe	Chicken	Field commander	Humid	Milwaukee	Play	Scow	Thurman
Bacteriology	China	Firefly	Hyena	Minister	Pledge trainer	Screwdriver	Traffic
Banjo	Chipmunk	First cousin	Ice pick	Minnesota	Poison	Screws	Tibia
Beets	Chives	First sergeant	Ice skating	Moment	Pornography	Scurvy	Tiger
Bethesda	Cider	Fitness	Idaho	Monkey	Portland	Seesaw	Travel
Billboard	Clarinet	Flagpole	Igloo	Monmouth	Potassium	Seltzer	Tree
Biochemistry	Cleveland	Flight	Impressionistic	Monorail	Potomac state	Shelf	Trumpet
Biophysics	Cloud burst	Flute	Indirect object	Mother	Preacher	Shelly	Tympani
Black bottom	Coconut	Fly	Inn	Mulberry	President	Shelter	Ugly
Black mollie	Cold	Foot	Interjection	Munich	Promise	Silver dollar	Venom
Blade	Conga	Forearm	Israel	Mushroom	Prose	Skip	Vulture
Blizzard	Congressman	Foundation	Jaguar	Narcotics	Proud	Skylight	Vise
Blowfish	Contemplation	Francium	Jeans	Naval	Psoriasis	Sleeping sickness	Wasp
Bolo	Cop	Fruit fly	Jeffrey	Nephew	Pull toy	Snow	Watermelon
Bomba	Copper	Futile	Harp	New hampshire	Quartz	Snow skis	Whiskey sour
Booze	Coral ebony	Gaberdine	Jigsaw	Nowhere	Rambler	Social worker	Windjammer
Bottle	Corkscrew	Gardenia	Jonquil	Notebook	Rattle	Socks	Wing
Boxing	Cornet	Gasoline	Kangaroo	Nurse	Ray	Solder	Wrench
Brass knuckles	Crest	Ginger	Killing	Officer	Recipe	Song	Wrist
Bread knife	Crystal	Gold piece	King	Oil	Recording	Span	Yellow fever
Bring	Cuba	Goldfinch	Ladle	Opal	Reference	Spear	Youngstown
Brooklyn	Cuff links	Good conduct	Lancaster	Oratorio	Remember	Speedball	Zebra
Brother	Dancer	Grandfather	Leaflet	Orchid	Reptile	Spinach	
Brown	Daughter	Grater	Legislature	Ottoman	Residence hall	Steam	
Bullion	Deerfly	Gum	Lemonade	Oven	Revivalist	Steam liner	
Cabin	Delegate	Hairband	Letter opener	Paperback	Rhode island	Stepbrother	
Cabinet member	Deputy	Hammer set	Lettuce	Parliament	Ribbon	Sterling	
Cable car	Desert	Handball	Lily	Parsley	Riddle	Stiletto	
Cadet	Discounting	Harbour	Liquor	Patricide	Rock	Stockings	
Car	Doctor	Harold	Liter	Peacock	Rocking chair	Storm	

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