Dynamics of Spontaneous Thought:
Insights from an Accumulation-to-Threshold Model

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Data and analysis code repository: https://osf.io/qc5fj/

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Abstract

The dynamics of the stream of spontaneous thoughts has been the object of increasing research in recent years. Here, we study the timing of transitions from one coherent thought episode to the next as one aspect of such dynamics. Participants were asked to either perform spontaneous word production or to let their mind wander during runs of 2 to 3 minutes, and were instructed to report thought transitions with a key press. We first validate this subjective mental event segmentation, which enables us to measure the duration of coherent thought episodes. We then show that the timing of thought transitions is best explained by an accumulation-to-threshold mechanism. We further find that the threshold of this accumulation – but not the drift rate – negatively correlates with participants' trait tendency for mind-wandering, highlighting the role of mental impulsivity in thought transitions.

Keywords: stream of thought, spontaneous thought, attention, accumulation models, metacognition, ADHD

Research Transparency Statement

General Disclosures

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Study One

Preregistration: This study was not preregistered. Materials: Instructions and stimuli are publicly available (https://osf.io/qc5fj/). Data: Data are publicly available (https://osf.io/qc5fj/). Analysis scripts: All analysis scripts are publicly available (https://osf.io/qc5fj/).

1. Introduction

The unfolding of subjective experience in time represents one of the enigmas of consciousness research. In modern psychological science, its investigation can be traced back to James' famous description of the *stream of thought* (James, 1890). He emphasized its dynamic aspect: thought content evolves in time at a variable pace, alternating between stable and unstable phases. This aspect is particularly salient in *spontaneous thought*, that is to say, thought processes that occur when one's mind is unoccupied or disengaged from the task at hand. Such a state has been estimated to represent between 30% and 50% of our waking hours (Kane et al., 2007; Killingsworth & Gilbert, 2010), making it an important object of study. In addition, abnormal spontaneous thought patterns seem to be at the core of some psychiatric conditions (e.g. racing thought in ADHD), some of which actually extend as a continuum in the general population (Asherson & Trzaskowski, 2015; Larsson et al., 2012; McLennan, 2016).

In the last few years, methodological advances led to the development of quantitative investigations of spontaneous thought, aiming at characterizing its dynamics. Experimental protocols typically require participants to report the unfolding of their thought in time, either in a free format, or using more constrained word association tasks (Andrews-Hanna et al., 2021; Sripada & Taxali, 2020). Two broad findings have already emerged using such protocols. First, the stream of thought consists of a succession of coherent thought segments, punctuated by various kinds of transitions. In particular, Sripada and Taxali (2020) argued for a "clump-and-jump" structure of the stream of thought, where thoughts about a similar topic cluster and are delimited by abrupt transitions to other topics, and Kérébel et al. (2024) found evidence for the existence of buffer unfocused thinking in some transitions. These findings reinforce earlier research about the structure of the stream of thought (e.g. Klinger, 1978). Second, the dynamics of spontaneous thought differ between individuals in the general population (Diaz et al., 2013), and can be traced to broad personality traits such as, rumination (Andrews-Hanna et al., 2021), creativity (Raffaelli et al., 2023), and inattention (Kérébel et al., 2024).

In the present study, we focused on the durations of coherent thought segments as one aspect of thought dynamics. We sought to characterize their distribution, beyond their overall mean frequency. We reasoned that this could give us insights into the cognitive mechanisms underpinning thought transitions, as classical computational modeling has repeatedly shown that the timing of events provides information on the underlying processes (Luce, 1991; Posner, 1986; Schurger et al., 2012). To do so, we used a procedure of *online thought segmentation* (Li et al., 2021; Pope, 1978) that enabled us to study the dynamics of spontaneous thought without interfering with its content.

We present a gradient of four tasks ranging from spoken aloud spontaneous word production (*Words* condition) to inner thought segmentation (*Inner Thoughts+Online Segmentation* condition). The latter was our condition of main interest: participants let their minds wander and pressed a key whenever they noticed a change in the topic of their thought. The task gradient allowed us to ensure the validity of online reports of thought transitions. In particular, it is believed that spontaneous thought is constrained and structured by semantic relations (Bar et al., 2007; Mildner & Tamir, 2019), so we predicted that thought transitions and semantic metrics would align when both are collected. It also allowed us to measure the duration of thought segments with minimal interference. We show that the durations of coherent thought segments are best modeled with Wald distributions, suggesting an underlying accumulation-to-bound mechanism. In addition, we relate the parameters of this mechanism to questionnaire measures of participants' tendency for excessive mind-wandering and non-clinical ADHD-like symptomatology. We find that the threshold of accumulation – but not the accumulation speed – negatively correlates with trait tendency for mind-wandering.

2. Methods

2.1. Participants

61 people from the general population participated in this study (age = 25.3 +/- 6.7, 20 men, 41 women). They responded to a recruitment announcement sent through a dedicated mailing list. The inclusion criteria were the following: having normal or corrected to normal vision, being a native French speaker, and being 18 years old or older. This study received approval by the ethics committee of Université Paris Cité (CER-U-Paris Cité). All participants received a compensation of 15€ for 1h30 of participation. The sample size was chosen so as to match the one of a previous experiment that used a comparable paradigm (Kérébel et al., 2024).

The post-experiment debriefing session revealed that two participants had misunderstood the instructions in one or all conditions. The data of the corresponding trials was removed prior to the analyses. One participant who indicated only one thought transition in the whole experiment was excluded for the modeling analyses.

In addition, some of the audio data went missing due to a technical problem (two participants for the control task, one for most of the main experiment).

2.2. Materials and procedure

2.2.1. Tasks and design

2.2.1.1 Main tasks

Participants completed 3 blocks of 4 tasks forming a gradient towards probing pure thought segmentation: 1) *Words*, 2) *Words+Online Segmentation*, 3) *Inner Words+Online Segmentation*, 4) *Inner Thought+Online Segmentation*.

In the *Words* condition they were instructed to say aloud the words that came spontaneously to their mind, at a rhythm that "felt natural to them". In the *Words+Online Segmentation (OS)* condition they had to produce words exactly like in *Words* but also to press the space bar whenever they realized they had just changed thought topic. In the *Inner Words+OS* condition, the instructions were to do the same thing as in *Words+OS* without vocalizing the word – but saying them internally and performing the online thought segmentation with keypresses. Finally, in the *Inner Thoughts+OS* condition, participants just had to let their thoughts wander freely and to press the spacebar when they noticed a thought transition. This *Inner Thoughts+OS* condition is the one that most directly measured what we were interested in, that is, the segmentation of spontaneous thought in time. Importantly, since there was no constraint on the kind of words to produce, the spontaneous word generation conditions are better thought of as indirect approximations of participants' streams of thought rather than as a semantic fluency task.

In the first block, participants read the instructions of each condition before doing the corresponding task. The experimenter was present during training and made sure that the instructions were well understood. In the two following blocks, they completed the four tasks in a row. At the beginning of each trial, a seed word (see supplementary materials) was displayed on the screen, that participants had to read aloud. It was made clear that the goal of the task was not to keep revolving around those seed words. After 3 seconds, this word was replaced by a fixation cross that remained until the end of the task. Each trial lasted 120, 150 or 180 seconds, with the order shuffled within conditions. At the end of each trial, participants answered two questions about the intensity of their thought on a continuous scale (see supplementary materials).

2.2.1.2. Subjective annotation and control tasks

After the three main blocks, participants did two trials of an *Online Segmentation Control task*: we presented on the screen words produced by a previous participant in a pilot experiment (see supplementary materials) one by one, at the pace they were produced, and they had to press the spacebar to indicate the groups of words that seemed to belong together. At the end of the experiment, participants were presented with a printed transcription of the words they produced in the task (conditions *Words* and *Words+OS*). They were instructed to indicate the groups of consecutive words that corresponded to a same thought. This subjective annotation procedure provided us with a retrospective offline segmentation of the series of words. They also did a similar exercise on two series of words that they had not produced, as a control (*Offline Segmentation Control*). The series of words used in the control tasks were the same for all participants (see supplementary materials).

2.2.2. Set up

Participants were seated in front of a computer screen (52.3 cm * 29.5 cm), at a 70 cm distance. Their head was stabilized by a forehead-rest and a chin rest. Text and stimuli were displayed in white on a gray background. Participants were instructed to avoid moving or blinking and to keep fixing the center of the screen as much as possible during the task.

Pupillometric data was recorded with an EyeLink 2000 eye-tracker (SR Research). This data was not used in the current study. Audio data was captured using the Audacity software, transcribed and timestamped using the Vosk Speech Recognition Toolkit (Shmyrev & Alpha Cephei, 2020) in Python. We used *fastText* embedding model (Grave et al., 2018) to compute semantic distances between the words (see Supplementary materials).

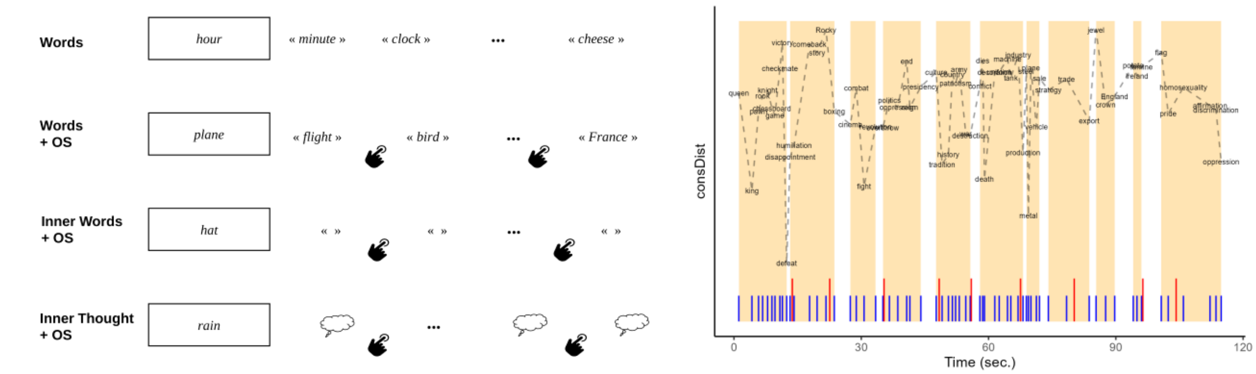

Figure 1. Illustration of the task. *Left.* Schematic representation of trials in the four conditions. After the presentation of a seed word on the screen, participants produced words at their own pace (vocally or internally) or thought freely, for 2 to 3 minutes. They also reported thought transitions by means of keypresses (3 bottom conditions). *Right.* Example trial of the *Words+OS* condition. Red bar: keypress. Blue bar: word onset. Orange rectangle: retrospective subjective cluster (offline segmentation). Y axis: semantic distance with the previous word (angular distance in the *fastText* embedding model).

2.2.3. Questionnaires

Participants filled two questionnaires between the main task and the subjective annotation procedure. First, they completed the ADHD Self-Report Scale (ASRS, Kessler et al., 2005, French translation by Caci et al., 2014), a clinical questionnaire used by psychiatrists to help diagnose ADHD (see supplementary materials). Since we tested participants from the general population, we take the score of this questionnaire to reflect their "attentional profile", *i.e.* trait tendency for inattention and impulsivity. We used the short version of this questionnaire (ASRS-A) that has been shown to be a better diagnostic tool than the full one (Kessler et al., 2005). Second, they completed the Mind Excessively Wandering Scale (MEWS, Mowlem et al., 2019, the French translation we used is reported in the supplementary materials). This recent questionnaire more specifically concerns the construct that our task was targeting, namely the tendency for disorganized thought.

3. Results

We proceeded in two steps for analyzing the data. In a first part, we validated the online segmentation as a measure of thought transitions. In order to do that, we compared behavior between conditions, and we tested the coherence of self-reported thought segmentations with questionnaire scores and objective measures. In a second part, we set to identify a potential cognitive mechanism underlying thought transitions, moving from a descriptive to a process account of individual differences.

3.1. Online segmentation reflects thought transitions

3.1.1. Descriptive statistics

Summary statistics of behavior in the four conditions are presented in Table 1 and Supp. Tables 1 and 2. We first compared behavior across conditions by means of paired t-tests. We considered the time intervals between consecutive words (thereafter Word Onset Asynchrony, WOA) and the time durations between consecutive keypresses, i.e. the Thought Segment Durations (TSD). The pace of word production did not differ between the *Words* and *Words+OS* conditions ($t(58) = -0.69$, 95% CI [-0.21; 0.1], $p = .49$, $d = -0.09$). Participants indicated longer thought segment durations (TSD) in the *InnerThought+OS* condition compared to *Words+OS* and *Inner Words+OS* ($t(54) = 2.59$, 95% CI [0.68; 5.31], $p = 0.037$, $d = 0.35$, and $t(54) = 4.53$, 95% CI [2.46; 6.37], $p < 0.001$, $d = 0.61$ respectively). Offline, they identified more segments in the *Words* than in the *Words+OS* condition ($t(58) = 3.5$, 95% CI [0.17; 0.64], $p < 0.001$, $d = 0.46$). Correlation tables of segmentation metrics across conditions are reported in the Supplementary materials (Supp. Table 5).

	WOA (sec.)	**TSD (sec.)**	**nb. online segments/min.**	**nb. offline segments/min.**
Words	2.64 (1.16)			4.06 (1.73)
WordsOS	2.7 (0.92)	17.47 (7.82)	4.11 (2.15)	3.66 (1.41)
InnerWordsOS		15.91 (7.56)	4.62 (3.04)	
InnerThoughtOS		20.33 (10.16)	3.83 (3.01)	

Table 1. Summary statistics of word production and thought segmentation. Format: mean (sd). WOA: Word Onset Asynchrony, TSD: Thought Segment Duration.

3.1.2. Keypresses reflect thought transitions

We then assessed the validity of the keypresses as a measure of thought segmentation, using *Words+OS* condition in which we had both the thought segmentation and a proxy for the stream of thought.

We started by quantifying the correspondence between online and offline segmentation. First, we used a linear mixed effect model (Bates et al., 2015) to predict the number of keypresses in each trial based on the number of retrospectively identified segments, with the number of words as a control. We observed a positive relationship between the number of segment boundaries identified online and offline (est. = 0.91, $p < 0.001$, see Supp. Table 14). Second, we used permutations to verify that the online and offline segment boundaries aligned (mean divergence = 1.66 +/- 0.71 words, mean chance level at 2.65 +/- 1.08, see Supp. Analysis 1).

We then investigated whether the keypresses reflected meaningful transition points in mental content. We predicted whether each word was immediately following a keypress or not in a hierarchical logistic regression, with the consecutive semantic distance (thereafter *consDist*), the Word Onset Asynchrony (WOA) and word onset time in the trials as predictors (see Supp. Table 15). We observed a positive effect of the WOA (est. = 0.37, $p < 0.001$) and of the *consDist* (est. = 1.23, $p = 0.015$), but no effect of word onset time ($p = 0.24$).

These elements suggest that participants reported meaningful transitions, as the online segmentation corresponded to semantic and dynamic boundaries and mirrored retrospective judgments.

3.1.3. Correlations between thought durations and tendency for mind-wandering

Then, we tested whether the online segmentation aligned with the self-reported tendency for mind-wandering. In the *InnerThought+OS* condition we observed a negative correlation between the mean TSD and the MEWS score ($r = -0.36$, $p = 0.005$, BF = 10.51), and a trend between mean TSD and ASRS score ($r = -0.26$, $p = 0.05$, BF = 1.68). In the *InnerWords+OS* condition there was a trend of correlation with both questionnaires (respectively, $r = -0.24$, $p = 0.06$, BF = 1.48, and $r = -0.25$, $p = 0.05$, BF = 1.63), but no significant correlation in the *Words+OS* condition ($p = 0.41$, BF = 0.40; $p = 0.52$, BF = 0.35). See Supp. Analysis 4 for details.

3.1.4. Thought transitions are driven both by semantics and elapsed time

Finally, we aimed at better understanding why and when participants reported thought transitions, again using the *Words+OS* condition.

First, we ran logistic regression models predicting whether each word was immediately *preceding* a keypress or not, considering temporal and semantic predictors. We found that a model including the consecutive semantic distance with the previous word (*consDist*), the semantic distance with the word following the last keypress (*lastKPDist*), and the time elapsed since the last keypress (*nSec*) was the best fit to our data (respectively est. = 2.69, $p < 0.001$, CI = [1.62; 3.75]; est. = 2.95, $p < 0.001$, CI = [1.66; 4.25]; est. = 0.02, $p < 0.001$, CI = [0.02; 0.03], see Supp. Table 16). Notably, it was better than an equivalent model where *nSec* was replaced by the accumulated semantic distance since the last keypress.

Then, we investigated whether the effects of *lastKPDist* and *consDist* increased progressively along the coherent thought episode or whether they appeared abruptly at the end of the episode, using linear models. Comparing the slopes between last and before-last pairs of words, we found evidence for abrupt increases right before the transitions for both metrics (p*s* < 0.001), along with a progressive semantic drift throughout the thought segment for the lastKPDist (see Supp. details on section 3.1.4 and Supp. Tables 7 to 10).

Taken together, these analyses suggest that thought transitions are driven both by semantic content and some non-semantic variable that reflects the effect of the pure passage of time.

3.2. Thought segment durations follow a Wald distribution

3.2.1.1. Model Space

Next, we set to identify the cognitive mechanism driving thought segmentation, even in our target condition (*InnerThought+OS*) where, by construction, no semantic data was available. We used the distribution of Thought Segment Durations (TSD, see Fig. 2) to constrain the possible underlying mechanisms. We identified three plausible candidate mechanisms and corresponding models. In model *exp*, the probability to press the key is the same at every time point (a Poisson process). In model *norm*, the duration between key presses is roughly constant as if an inner metronome regulated the timings of thought transitions, with Gaussian noise. In models *W* and *sW*, keypresses are driven by an accumulation-to-threshold mechanism (respectively a Wald and shifted-Wald model). The four models are recapitulated in Supp. Table 12, and illustrated on Fig. 2.

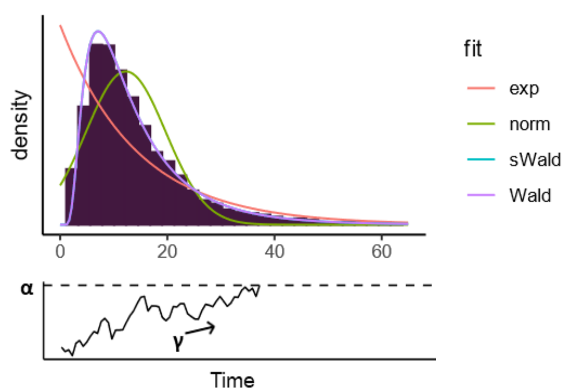

Figure 2. Model fits to Thought Segment Durations. *Top*: Distribution of thought segment durations (TSD), normalized to the mean for each participant, and density probability functions of the candidate models. Note that the fitted probability functions presented here are mainly illustrative, since the analyses we report were done on a participant basis. *Bottom*: illustration of a single trial of the accumulation process in a Wald model: signal is accumulated at rate γ until a threshold α is reached.

3.2.1.2. Model comparison

The four candidate models were fitted on the data of each participant individually (*Words+OS*, *InnerWords+OS*, and *InnerThought+OS* conditions pooled), using minimum likelihood estimation (Delignette-Muller & Dutang, 2015; R Core Team, 2024). We compared model fits on the basis of the Bayesian Information Criterion (BIC, Schwarz, 1978). Results are summarized on Table 2. The accumulation model without non-decision time parameter was the best for most of the participants.

model	**nb. best**	**BIC pooled data**
W	46	68576.97
norm	10	81839.49
sW	2	68586.99
exp	2	87430.48

Table 2. **Results of the model comparison.** Models fitted on thought segment durations (TSD). *Words+OS*, *InnerWords+OS*, and *InnerThought+OS* conditions pooled. For each line, "nb. best" indicated the number of participants whose data was best fitted by the corresponding model, and "BIC pooled data" indicates the Bayesian Information Criterion when fitting the model on the pooled data of all subjects (see Fig. 2).

We did the same comparison and model estimation on the online segmentation control task. The Wald distribution was once again the best fitting one (see Supp. Table 11).

Details on our fitting procedure, quality checks and additional analyses can be found in the supplementary materials.

3.3. Accumulation thresholds (but not rates) correlate with inattention and tendency for mind-wandering

We then turned to better characterize individual differences in thought segmentation by investigated whether the questionnaire scores were selectively predictive of one of the estimated parameters models of the TSD.

First, we looked at the parameters estimated for each participant on the three conditions providing online segmentation (*Words+OS*, *InnerWords+OS*, and *InnerThought+OS*). We observed negative correlations between the threshold and the questionnaire scores (ASRS: $r = -0.41$, $p = 0.002$, BF = 28.31; MEWS: $r = -0.31$, $p = 0.018$, BF = 3.8), but not with the accumulation rate (ASRS: $r = -0.2$, $p = 0.12$, BF = 0.87; MEWS: $r = 0.008$, $p = 0.95$, BF = 0.3).

Then, we focused on our condition of main interest. We fitted the accumulation model on the *InnerThought+OS* condition only and observed a similar pattern: negative relationship with the threshold (ASRS: $r = -0.32$, $p = 0.019$, BF = 3.8; MEWS: $r = -0.35$, $p = 0.011$, BF = 5.9), but not with the accumulation rate (ASRS: $r = -0.055$ $p = 0.7$, BF = 0.33; MEWS: $r = 0.133$, $p = 0.34$; BF = 0.47). For completeness, correlations with the other conditions fitted individually are reported in the Supplementary materials.

Crucially, the parameters fitted on the online segmentation control task did not correlate with the questionnaire scores (all p*s* > 0.25, all BF*s* between 0.3 and 0.6).

		ASRS score		MEWS score	
parameter	*data*	*r*	*p*	*r*	*p*
α	all	-0.41	**0.002***	-0.31	**.018***
γ	all	-0.20	.12	0.01	.95
α	*InnerThought+OS*	-0.32	**.019***	-0.35	**.011***
γ	*InnerThought+OS*	-0.05	.27	0.08	.53
α	*Online Segmentation Control task*	-0.16	.25	-0.06	.66
γ	*Online Segmentation Control task*	-0.04	.12	0.01	.95

Table 3. Correlations between model parameters and questionnaires. *all*: pooled data from the *Words+OS*, *InnerWords+OS* and *InnerThought+OS* conditions. r: Pearson's coefficient.

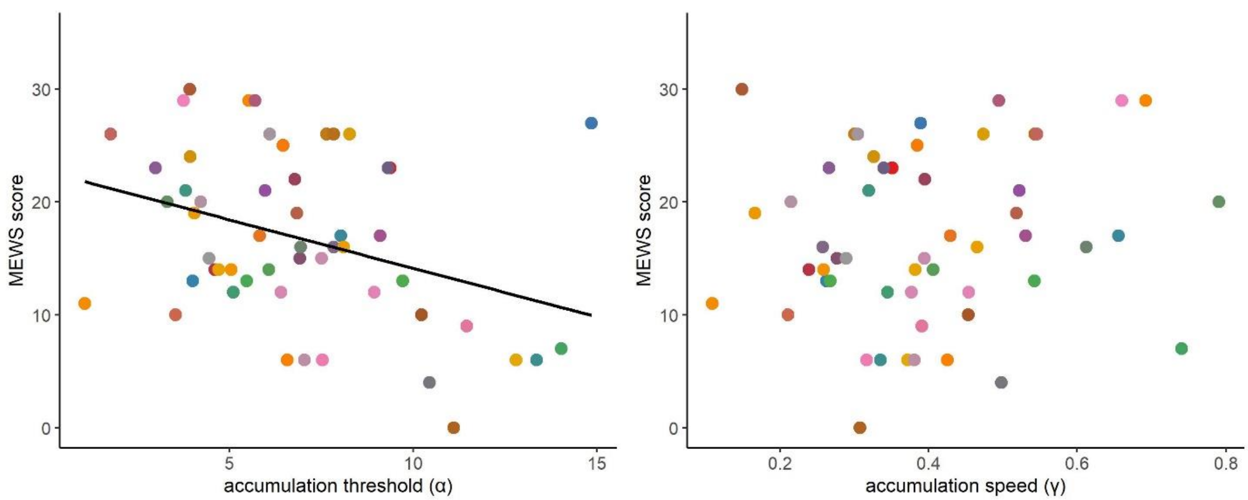

Figure 3. Relationships between MEWS questionnaire and the fitted accumulation parameters. *InnerThoughts+OS* condition. Left: r = -0.35, p = 0.011. Right: r = 0.13, p = 0.34.

4. Discussion

We studied the duration of coherent thought episodes by asking participants to report their thought transitions in real time. The distribution of thought segment durations (TSDs) revealed the signature of an accumulation-to-threshold process. We further found that individuals higher in trait inattention and with a greater tendency for mind-wandering had a lower threshold in this accumulation process.

4.1. *Interpretation of the results*

We observed a mean duration of coherent thought segments of 20.3 seconds. This can be directly compared to three previous results from tasks where participants had to indicate when their thoughts shifted to another topic. Pope (1978) observed thought segments of about 5 seconds (inner thinking) and 25 to 30 seconds (think-aloud), Sripada and Taxali (2020) reported a mean duration of 19.7 seconds and Li et al., (2021) found durations between 30 and 40 seconds, both with during inner thinking. Interestingly, Klinger (1978) found similar durations of about 9 to 15 seconds when probing individuals to report the length of their last thought segment. All these durations are comparable to indirect estimates of the duration of "mental states": Tseng & Poppenk (2020) derived durations of 9 seconds from neural data in resting state fMRI, Bastian & Sackur (2013) inferred durations of 10 to 20 seconds from behavioral data.

Beyond the overall frequency of transitions, our protocol provided us with the full distribution of TSDs, enabling us to try to identify the most likely mechanism from a set of plausible options. Our results suggest that, in a situation where external distractions and proximal goals are reduced to a minimum, the timing of thought transitions is driven by an accumulation-to-threshold mechanism. The data further reveal that participants higher in trait inattention or with more intrusive mind-wandering have more frequent thought transitions because of a lower threshold in this process.

Now, the questions of "what" is accumulated, and at which cognitive level, remain open. We approached it by considering that the spontaneous word production conditions provide an approximation of a participants' thought trajectory in a semantic space. We found a semantic drift preceding thought transitions: as participants got closer to a transition, the bird flight distance to the start of the episode progressively increased. However, the time duration since the last transition was a better predictor of the next transition than the accumulated semantic distance along the trajectory or the number of words produced. This suggests that the accumulated variable also integrates another component, potentially non-semantic in nature. This interpretation would be supported by the similarities between our online segmentation procedure and the Libet's task (Libet et al., 1983), where participants are required to press a key whenever they "feel the urge to move". It has been suggested that, in this paradigm, movement initiation results from an accumulation of neural noise that can be observed in the EEG signal (Schurger et al., 2012), resulting in a distribution of waiting durations with a shape similar to the one we observed. As participants in Libet-like tasks may feel the mounting pressure of an urge to move with the increase of accumulated neural noise until the reaching of a threshold, participants in our task may transition to a new thought episode as a result of a mounting pressure of an urge to explore new thoughts. Note that our *InnerThought+OC* condition still differs from Libet experiments in several important aspects. In particular, the mental events we asked participants to monitor exist outside of the context of the experiment, and are arguably easier to introspect and more familiar to them than an "urge" to press a key.

Our results suggest revisiting the classical notion of the train of thoughts as governed by associations of ideas (Hobbes, 1651 / 2008) and external distractions (Plimpton et al., 2015; Song & Wang, 2012). Indeed, these mechanisms alone should lead to a Poisson-like process if the probability of a concept being a pivot for a new chain of thoughts and the probability of an external distraction were constant. Our results suggest that underneath these mechanisms, there exists an accumulation process leading to thought transitions even without external or semantic distraction. Further work is needed to establish whether and how the two levels interact. For example, it could be that the distance to the accumulation threshold influences distractibility, i.e. the likelihood that a distractor would trigger a thought transition.

The link between ADHD traits and higher exploratory behaviors has recently been interpreted as a consequence of increased internal noise (Van den Driessche et al., 2019; Addicott et al., 2020; Dubois and Hauser, 2020). Our finding that trait inattention and intrusive mind-wandering is associated with lower transition thresholds rather than with higher accumulation rates offers another explanatory pathway for ADHD traits. Given that ADHD is associated with trait boredom (Hsu et al., 2020) and novelty seeking (Donfrancesco et al., 2015), we propose that the more frequent thought transitions observed in our study could result from lower thresholds in accumulation processes inducing a lower tolerance for boredom. It is worth noting that a low accumulation threshold is typically interpreted as a marker of impulsivity. Our results align with a previous study, where we found that both thought segmentation and tendency for impulsive exploration correlated with trait inattention (Kérébel et al., 2024).

4.2. *Alternative interpretations*

In principle, the distribution of thought segment durations (TSD) could exhibit the signature of an accumulation process in two different scenarios. One would be that there exist "true" thought transitions that participants noticed and reported, and that these are driven by a latent accumulation mechanism. Another one would be that mental content was drifting without clear boundaries, and that participants relied on an accumulation to segment it, as a result of task demands. Four elements suggest that the first scenario is more likely. First, several empirical studies found results supporting the view of a segmented – as opposed to continuous – stream of thoughts (Kérébel et al., 2024; Raffaelli et al., 2023; Sripada & Taxali, 2020). We can also make a parallel with research on memory, where recent results challenge the view of a continuous and passive drift of mental context (DuBrow et al., 2017). Second, in the condition with words pronounced aloud, we observed a transient increase in consecutive semantic distance prior to the keypresses, suggesting that the reported thought transitions were salient. Third, the online segmentation control task singles out the decision component (since participants are not producing the series of words they segment) and the fitted accumulation threshold did not correlate with the questionnaires. This suggests that the relationships we observed in the main task reflect intrinsic properties of the thought transitions, not of the detection. Fourth, if the second scenario were true, online and offline thought segmentations would be quite independent, especially between conditions where only one of the two was performed. Yet we found positive correlations between offline segmentation in the *Words* condition and online segmentation in the *Words+OS* and *InnerWords+OS* conditions, and Li et al. (2021) reported a similar observation.

There remains a possibility that the inter-individual segmentation differences we observed correspond to differences in introspection capacity. This would mean that some people experience more variable trains of thought not because their thought changes more, but because they are better at noticing when it changes. In a sense, this is as much a limitation of our design as a limitation of our current understanding of thought in general. At first glance, this seems counter-intuitive: if this was the case, we would expect participants with higher trait inattention to exhibit less detections. However, one could argue that these people appear inattentive to their environment precisely because they pay more attention to their thought process. In sum, this is a valid point that would require further investigation.

4.4 *Limitations*

We acknowledge several limitations in the present study. First, since we asked participants to report only punctual thought transitions, our experiment is by design blind to the potential presence of progressive transitions, blanks, or unfocused thought moments, that we had observed in a previous study (Kérébel et al., 2024). Second, we did not consider all possible sources of inter-individual variability. In particular, post-experiment debriefing revealed that for some participants word production stimulated thought processes, while for others it was inhibiting. Our conditions formed a gradient progressively guiding participants toward free thinking, but the cognitive demands of each condition did not necessarily follow the same gradient. Third, all the models we considered suppose that the duration of each thought segment is independent of the previous one, yet this is not the case since TSDs are partially autocorrelated (see Supp. Analysis 6).

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Statements and Declarations

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CRediT authorship contribution statement

Adrien Kérébel: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Software. Jérôme Sackur: Conceptualization, Methodology, Writing – review & editing, Funding acquisition.

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