Quantifying Streams of Thought during Cognitive Task Performance using Sequence Analysis

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Abstract

Streams of thoughts vary in content from one moment to the next, and these temporal patterns have been argued to be critical to understanding the wandering mind. But few analytic methods have been proposed that can account for both the content and temporal ordering of thoughts over time. In the present study, I apply sequence analysis and related methods to quantify the dynamics of thought from time series sequences of categorical experience sampling thought probes delivered across five different cognitive tasks in the same individuals ($N = 545$). Sequence analysis revealed a modicum of order and consistency in streams of thought within-individuals, but also demonstrated considerable variability within and between task sessions. Hierarchical clustering of sequence dissimilarities further revealed common typologies of mind wandering across individuals. These findings demonstrate the application of sequence analytic methods for quantifying the dynamics of thought over the course of task performance and show that contextual task constraints are associated with how streams of thought unfold over time. More broadly, sequence analysis provides a valuable framework for investigation of time ordered cognitive and behavioral processes across psychological domains.

Keywords: dynamics; Markov chain modeling; mind wandering; sequence analysis; task-unrelated thought

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Thoughts alight from one topic to another in a seemingly unconstrained manner likened famously to the many flights and perchings of a bird (James, 1890). As noted by Christoff and colleagues (2016), contemporary psychological research on mind wandering has focused almost entirely on understanding the many perchings of thought—the content of thoughts (e.g., about the past or future, negative or positive) and how they might be defined with respect to one’s current goals or activities (e.g., whether they are task-related or unrelated, deliberate or spontaneous). But comprehensive investigations of its flights have been largely neglected. This is perhaps expected as experience sampling methods rely on capturing random moments of cognition in situ with no clear methods for characterizing their continuous temporal dynamics. Nevertheless, the meandering and unconstrained nature of thought has been argued to be fundamental to definitions of mind wandering (Christoff et al., 2016, 2018; Irving, 2016; Irving & Thompson, 2018; but see Seli et al., 2018b).

From this “dynamic” perspective, mind wandering is distinguished from other episodes of thought based on the constraints imposed on how thought streams unfold over time (Christoff et al., 2016, 2018; Smith, Mills, Paxton, & Christoff, 2018). Some thought streams vary freely in their content from moment to moment with few constraints imposed on their dynamics. Mind wandering is argued to uniquely reflect those moments when thoughts occur more spontaneously and flow unconstrained between different kinds of content (Christoff et al., 2016, 2018). In contrast, thoughts are often bound in their content by contextual factors, habitual tendencies, or deliberate goal-directed constraints. For example, when cognition is successfully directed towards the accomplishment of some goal, thoughts should be coerced in content towards relevant topic domains while the occurrence of goal-unrelated thoughts are reduced.

The occurrence of task-unrelated thought has been demonstrated to be constrained in the cognitive task context and depend in part on how attention is regulated over time in

the service of task performance. Individuals strategically regulate instances of task-unrelated thought in response to momentary situational demands (Seli et al., 2018), and more gradual increases in the frequency of task-unrelated thought systematically occurs with time on task (e.g., Krinsky, Forster, Llabre, & Jha, 2017; Thomson, Seli, Besner, & Smilek, 2014). Furthermore, the content of thoughts are also contextually constrained, in which individuals, unsurprisingly, are more likely to experience thoughts relating to their performance and the parameters of their current task (i.e., task-related interference; McVay & Kane, 2012; Robison & Unsworth, 2018; Welhaf et al., 2019). Relatedly, individuals have also been shown to report task-unrelated thoughts in some contexts more than others (Kane et al., 2007, 2017; McVay, Kane, & Kwapil, 2009; but see Killingsworth & Gilbert, 2010).

Consistent tendencies to engage in task-unrelated thought are also moderately correlated within-persons across sessions of different cognitive tasks (Kane et al., 2016; Welhaf et al., 2019) and between laboratory situations and daily life (McVay et al., 2009). These findings suggest some stability in individuals' trait tendency to experience task-unrelated thoughts, which support the notion that other more habitual and automatic constraints influence individual's streams of thought. Individual difference studies of mind wandering have also provided support for this supposition, as the frequency and content of task-unrelated thought measured across different task contexts is reliably associated with individuals' cognitive abilities (e.g., Kane & McVay, 2012; Kane et al., 2016; Unsworth & McMillan, 2014; Welhaf et al., 2019). That the frequency and content of task-unrelated thought displays these many contextual constraints and stable individual tendencies nevertheless appears hard to reconcile with the common experience of its unbidden occurrence.

How then do we understand the purposeful wandering of the mind (Irving, 2016), in which thoughts often appear aimless but also seem guided by our goals and current concerns? The utility of the dynamic framework for mind wandering (Christoff et al., 2016, 2018) rests on its ability to demonstrate that constraints placed on the content of thought influence how streams of thought unfold over time, and that the temporal dynamics of thought are critical to understanding human cognition and behavior. Regardless, few empirical studies have directly characterized the ongoing dynamics of thought or the actual extent to which it is spontaneous or unconstrained under different circumstances, and methods have yet to be identified that prove effective in characterizing the temporal ordering of experience sampling thought probes over time. Whereas increasing numbers of researchers have applied functional neuroimaging and electroencephalography techniques towards understanding brain dynamics and their links to spontaneous thought

(Christoff et al., 2016, 2018; Wang et al., 2018), other analytic and behavioral methods that are effective in characterizing the dynamics of thought are under specified.

One limitation of past research is that studies of mind wandering have primarily characterized the frequency and content of task-unrelated thought as a sum or average of experience sampling thought reports across whole task sessions. Although this focus on characterizing the frequency of task-unrelated thought in cognitive tasks and daily life has proven fruitful (Seli et al., 2018c; Smallwood & Schooler, 2006, 2015), this approach ignores intra-individual variability in the content of thought and the dependence between thoughts from one moment to the next. More than the frequency of thought, its within-person dynamics are critically important for characterizing the extent to which patterns of thought display systematic tendencies and situational constraints. Nevertheless, few studies have directly examined the extent to which different thoughts occur over time and from which thoughts they are likely to follow, or the role attention plays in mediating these temporal dynamics during cognitive task performance.

Recently, Welhaf and colleagues (2019) conducted secondary analyses of a large multi-measure dataset originally reported by Kane et al. (2016), in order to more directly quantify the temporal dynamics of thought content over successive experience sampling probes embedded in five cognitive tasks. Specifically, they explored whether systematic patterns of switching and stability between kinds of thought content might predict individual differences in cognitive ability. For example, individuals reported switches in task-unrelated thought content on roughly 40% of successive thought probe reports, which demonstrates both a considerable amount of consistency in the kinds of thoughts occurring from one probe to the next as well as a great deal of variability in thought content over successive probes. This measure of thought switching, however, did not account for the specific content of thoughts across successive thought probes. That is, switches were assessed regardless of the kind of task-unrelated thought that followed particular thought probes. This is perhaps consequential as it implicitly assumes that thoughts and their transitions do not depend on what thoughts occurred previously or that they have no bearing on what thoughts might follow.

Instead, it appears critical that researchers consider both the temporal ordering of thoughts and the kinds of thoughts that arise in sequence. One type of thought (e.g., thoughts about everyday things) repeatedly followed by the occurrence of another type of thought (e.g., personal worries) is a kind of temporal consistency that might be contrasted with more randomly occurring thought content. In this way, the content of thought does not appear independent of its dynamics. Any

comprehensive characterization of the extent to which the temporal dynamics of thought are spontaneous or contextually constrained must therefore also consider measures that can account for differences and similarities of entire sets of successive thought probes across contexts or individuals.

One approach that lends itself well to the analysis of successive thought probes is the application of sequence analysis and related methods (Abbott & Tsay, 2000; Ritschard & Studer, 2018). Sequence analysis can be broadly defined as a set of techniques that take as their input entire sets of sequences of categorical data rather than individual data points (Abbott & Tsay, 2000). This provides for comparison of entire time series of thought probes as whole units, accounting for both their content and dynamics over successive probes. Sequence analytic methods were originally applied in the domains of computer science and biology (e.g., Sankoff & Kruskal, 1999), but have also been continually developed for application in the social sciences (e.g., Abbott & Tsay, 2000; Ritschard & Studer, 2018). Most commonly, sequence analysis involves defining the dissimilarity between symbolic sequences using an edit distance based on the number of edit operations required to transform one sequence into another. The pairwise dissimilarities of entire streams of thought can be defined in this way, allowing for tests of differences between sequences or the identification of clusters of similar sequences (Studer, Ritschard, Gabadinho, & Müller, 2011). In addition to analysis of sequence dissimilarity, information theoretic measures that quantify the randomness of thought content and the temporal variability of thought probe sequences can be calculated from the categorical sequences (i.e., Elzinga & Liefbroer, 2007; Elzinga, 2010; Shannon, 1948). Finally, Markov chain modeling of transitions can be used to quantify the systematic tendencies of thought content to occur in sequence. Together, these measures may prove useful for characterizing the dynamics of thought probe sequences.

In the present study, I conducted secondary analyses of data originally reported by Kane et al. (2016) and Welhaf et al. (2019), with the goal of demonstrating the utility of sequence analysis and related methods for quantifying the dynamics of thought. Secondarily, I had the aim of examining variability and consistency in streams of thought across successive thought probe reports and between cognitive task contexts. I had several specific research questions which guided my investigation. Specifically, I sought to examine whether systematic similarities and differences could be identified in the frequency of and transitions between kinds of reported thought content between cognitive tasks. To this end, I characterized sources of variability in thought probes both within and between cognitive task contexts, and directly compared temporal sequences and thought probe transitions

between tasks. Finally, to the degree that some amount of systematicity in thought probe sequences might be observed within or between individuals, I had the exploratory goal of identifying data-driven typologies of mind wandering through clustering of sequence dissimilarities to evaluate common thought streams across individuals or cognitive tasks.

Methods

Deidentified participant data was acquired from an online data-sharing repository via the Open Science Framework (<https://osf.io/guhw7/>) provided by Welhaf et al. (2019). Secondary analyses of these data used the same participant exclusions and outlier treatment as reported in Kane et al. (2016) and Welhaf et al. (2019).

Participants

Kane et al. (2016) recruited and assessed 545 undergraduates at the University of North Carolina at Greensboro (UNCG). Complete details regarding participant recruitment and demographic characteristics are reported in Kane et al. (2016). 545 participants completed the first of three assessments, 492 returned to complete the second assessment, and 472 completed all three assessments. All participants gave informed consent and the study was approved by the Institutional Review Board of UNCG.

Procedure

Participants completed a battery of cognitive-behavioral tasks during three separate assessment sessions. The complete description of tasks and their order over assessments is described by Kane et al. (2016). Importantly, five tasks included experience sampling thought probes presented randomly during task performance. At the first assessment, a semantic version of the Sustained Attention to Response Task (SART) and a Letter Flanker task were administered. An Arrow Flanker task and a Number Stroop task were administered at the second assessment. Finally, a 2-Back working memory task was administered at the third assessment.

Experience Sampling of Thought Content

45 thought probes occurred randomly during the SART, whereas 20 occurred in the Arrow Flanker, 12 in the Letter Flanker, 20 in the Number Stroop, and 15 in the 2-Back task. At the presentation of each probe, participants selected among 8 possible options to describe whether their attention was currently focused “on-task” (option 1) or whether their thoughts were directed towards “task performance and evaluation” (option 2); thoughts about normal life concerns

Figure 1: Sequences of 45 experience sampling thought probe responses (rated according to 8 content categories) during the SART are depicted on rows for three individuals. Pairwise dissimilarities between sequences are calculated based on optimal matching (OM) with substitution costs derived from transition probabilities of the entire set of SART sequences ($n = 526$) and insertion / deletion (indel) costs set as half the maximum substitution cost. Sequences 1 and 2 are more alike (dissimilarity = 37.9) than they are to sequence 3 (dissimilarities > 60.4). Sequence 1 has more entropy (0.75) and is more complex (0.65) and turbulent (0.58) than sequences 2 (entropy = 0.54, complexity = 0.44, turbulence = 0.36) and 3 (entropy = 0.60, complexity = 0.55, turbulence = 0.48).

and “everyday things” (option 3); thoughts about one’s current physical, cognitive or emotional “state of being” (option 4); thoughts about “personal worries” (option 5); fantastical thoughts and “daydreams” (option 6); thoughts about stimuli in the “external environment” (option 7); and “other” thoughts that were not described by other categories (option 8).

Sequence Analyses of Thought Probes

Sequence analysis of participants’ thought content considered each response to thought probes as a discrete categorical state that occurred in sequence across the duration of cognitive tasks. The entire range of categorical responses were considered (i.e., from 1 “on-task” to 8 “other”) for all analyses and calculation of measures of sequence dynamics. Successive categorical responses to thought probes were concatenated into sequences of thought content separately for each individual and cognitive task. Thought probe sequences were manipulated and visualized in *R* using package *TraMineR* (Gabadinho, Ritschard, Müller, & Studer, 2011) and *seqHMM* (Helske & Helske, 2017).

Information theoretic analyses of entropy, complexity, and turbulence. Several dependent measures were calculated from the categorical thought probe sequences using package *TraMiner* (Gabadinho et al., 2011) to quantify variability in the temporal ordering and content of sequences of thought probe reports. I calculated the average number of unique kinds of thought probe categories reported, and the proportion of transitions between content categories out of the total possible transitions (i.e., length of sequence - 1). Three information theoretic measures were also calculated: sequence entropy (Shannon, 1948), complexity (Elzinga, 2010), and turbulence (Elzinga & Liefbroer, 2007).

Entropy in this context reflects how unpredictable one’s thought probe responses are based on the size of the

“alphabet” of content categories (i.e., the range of possible thought probe responses) and their proportion of occurrence. Entropy was standardized to range from 0 to 1. Entropy is 0 when the same thought content occurs for all experience sampling probes. In contrast, the maximum entropy would be reached when the occurrence of each content category was equiprobable. Low entropy (close to 0) therefore indicates that thought probe responses display some systematic tendencies, whereas high entropy (close to 1) suggests that probe responses are unpredictable in their occurrence. Entropy is calculated from the distribution of thought content occurrences only and does not depend on the length of the sequence or the sequential ordering of content.

In contrast, the measure of complexity considers both the ordering of thought probes in sequence as well as their frequency distribution. Complexity is determined based on both the frequency of transitions between different thought probe contents in the sequence as well as the sequence entropy. Complexity is standardized (from 0 to 1) with respect to the sequence length. Complexity is 0 when a sequence contains only a single content category for all probes (i.e., 0 transitions and 0 sequence entropy), and 1 when the maximum number of transitions occurs (i.e., length - 1) and the durations of each content occurrence across probes are uniform. Finally, turbulence is calculated based on the number of distinct subsequences found in each sequence and the variance of the duration of each subsequence. Turbulence is also standardized to range from 0 to 1 based on the maximum possible turbulence for a sequence of the same length. When turbulence is low, few unique kinds of thought content categories occur in a sequence, and when they do occur, the same category occurs many times in succession. In contrast, when turbulence is high, different thought content frequently occurs but rarely lasts across subsequent thought probes, instead transitioning to the occurrence of a different kind of content category.

Figure 2: Sequences of experience sampling thought probe responses (rated according to 8 categories) during cognitive tasks are depicted (left) on rows for each individual. The distribution of thought probe responses for each thought probe are also shown (right). 45 thought probes occurred during the SART ($n = 526$), whereas 20 occurred in the Arrow Flanker ($n = 479$), 12 in the Letter Flanker ($n = 462$), 20 in the Number Stroop ($n = 478$), and 15 in the 2-Back task ($n = 461$).

These five dependent measures were compared between tasks using mixed effects models in *R* with package *lme4* (Bates, Mächler, Bolker, & Walker, 2015). Model parameters were estimated using restricted maximum likelihood and degrees of freedom were calculated by Satterthwaite

approximation. Type III tests of fixed effects are reported for omnibus tests, and parameter estimates are given for models. The proportion of variance explained (R^2) by the fixed effects was also calculated (Nakagawa, Johnson, & Schielzeth, 2017). Random subject intercepts were included to allow for within-person dependencies.

Table 1: Sample size and the proportion of thought probes for each task

	<i>N</i>	1	2	3	4	5	6	7	8
SART	526	0.216	0.274	0.051	0.232	0.047	0.096	0.036	0.047
Arrow Flanker	479	0.340	0.170	0.067	0.207	0.064	0.098	0.022	0.031
Letter Flanker	462	0.283	0.131	0.076	0.268	0.064	0.095	0.045	0.038
Number Stroop	478	0.332	0.217	0.063	0.213	0.053	0.071	0.022	0.027
2-Back	461	0.369	0.207	0.045	0.200	0.054	0.084	0.019	0.021

Note: The sample size (*N*) and the proportion of all probes classified as each thought probe response (1 “on-task” to 8 “other”) are provided for each cognitive task.

To evaluate the consistency of these measures between- and within-participants, I also calculated the intraclass correlation (ICC) on null (i.e., unconditional means) models using the *R* package *sjstats* (Lüdtke, 2019). For repeated measures data, the ICC describes the proportion of variance attributable to differences in the means of individuals versus the share of variance attributable to within-person variation and measurement error. Often, ICC is used as an index of consistency and measurement reliability over multiple measurements. This is because the ICC will be large for highly reliable measures that are stable over repeated assessments when within-person variation and measurement error is low. ICC above 0.75 is commonly interpreted as a good level of reliability, whereas from 0.50 to 0.75 is moderate, and 0.50 and below is poor (Koo & Li, 2016).

Markov-chain transition analyses. Markov-chain transition probabilities were calculated based on the entire sample of thought probe sequences for each task using package *seqHMM* (Helske & Helske, 2017). Transition probabilities reflect the probability of thought probes transitioning from each particular response option to each other option. Each row of the transition probability matrix reflects the total probability (i.e., each row sums to 1) of thought probes transitioning to other probes. Transition probabilities were compared to a null distribution of probabilities occurring by chance using non-parametric permutation-based statistical comparisons. Thought probe sequences were shuffled randomly in their ordering for each individual for 5000 iterations and an empirical null distribution of transition probabilities occurring by chance were calculated. The actual transition probabilities were compared to the distribution of permutations to identify whether the observed probability was sufficiently extreme (i.e., permutations greater than or less than 99.5% of all permutations) with respect to the null distribution of probabilities occurring by chance.

Observed differences in transition probabilities between cognitive tasks were also compared to a null distribution of differences occurring by chance using non-parametric permutation-based statistical comparisons. Sequences were shuffled randomly between pairs of cognitive tasks for 5000

iterations and an empirical null distribution of transitions probabilities were calculated. The actual difference in transition probabilities for each transition-pair were compared to the empirical null-distribution to identify whether the observed probability was sufficiently extreme (greater than or less than 99.5% of all permutations) with respect to the null distribution of differences occurring by chance.

Optimal matching and analyses of sequence dissimilarities. Pairwise sequence dissimilarities were calculated for thought probe sequences in *R* using package *TraMineR*. Dissimilarities were based on optimal matching (OM) with substitution costs derived from transition probabilities and insertion / deletion (indel) costs set as half the maximum substitution cost. OM algorithms function by defining an edit distance based on the number of substitutions, insertions, and deletions required to transform one sequence of categorical states into another with corresponding costs associated with these different operations (Abbot & Tsay, 2000; Studer & Ritschard, 2016). Figure 1 depicts a schematic showing three sequences of thought probes and their corresponding sequence dissimilarities.

Importantly, a number of statistical tests can be conducted based on generalization of partitions of sum of squares ($SS_{total} = \frac{1}{2n} \times \sum d_{ij}$) from the matrices of pairwise dissimilarities (d_{ij}) calculated through OM (see Studer et al., 2011, for extensive discussion). Discrepancy analysis can be used to quantify partitions of the total dissimilarity accounted for by participant level categorical covariates. Significance is evaluated based on permutation testing (5000 permutations were used here) of a pseudo-*F* statistic in which categorical covariate labels are shuffled randomly between sequences to generate a distribution of *F* statistics under the null hypothesis. Importantly, the pseudo-*F* statistic does not follow the Fisher-Snedecor *F* distribution, and instead, significance is determined based on whether the observed pseudo-*F* statistic is sufficiently extreme with respect to the

Table 2: Descriptive statistics of dependent measures of thought probe sequences

Task	Length	Num. Reported	Prop. Transitions	Entropy	Complexity	Turbulence
SART	45	5.529 (1.641)	0.499 (0.212)	0.610 (0.191)	0.546 (0.198)	0.492 (0.193)
Arrow Flanker	20	4.090 (1.600)	0.468 (0.253)	0.494 (0.234)	0.476 (0.237)	0.491 (0.230)
Letter Flanker	12	4.242 (1.481)	0.598 (0.257)	0.559 (0.217)	0.574 (0.228)	0.613 (0.223)
Number Stroop	20	3.994 (1.538)	0.471 (0.241)	0.484 (0.218)	0.473 (0.221)	0.488 (0.218)
2-Back	15	3.683 (1.524)	0.476 (0.261)	0.463 (0.224)	0.464 (0.235)	0.494 (0.233)

Note: Means and standard deviations are given for the number of unique thought content categories reported, the proportion of total transitions, and thought probe sequence entropy, complexity, and turbulence for each of the five cognitive tasks. The length of thought probe sequences is also provided.

null distribution of permuted values. A pseudo- R^2 can also be defined as the sum of squares between groups (SS_{between}) over SS_{total} and represents the proportion of discrepancy among sequences accounted for by categorical covariates.

Ward hierarchical agglomerative clustering of sequence dissimilarities was used to identify unique clusters of individuals' thought probe sequences for each task, and for all individuals' sequences combined across tasks. Clustering was conducted using the *WeightedCluster* package in *R* (Studer, 2013). The optimal number of clusters were chosen based on examination of three cluster selection criterion (see Studer, 2013, for further discussion): including the Point Biserial Correlation, Huberts Gamma, and the weighted Average Silhouette Width (AWS). The lowest number of clusters was chosen as optimal for the cluster selection identified by the local maxima of all three criteria. The weighted AWS reflects the homogeneity of the cluster and can be interpreted as a measure of similarity between the sequences comprising a cluster. Clusters with very similar sequences will have a high AWS, whereas clusters of more heterogeneous sequences will have a lower AWS. Kaufman and Rousseeuw (1990) suggested that AWS lower < 0.25 reflected little cluster homogeneity, whereas 0.26 to 0.50 suggests weak homogeneity, and AWS > 0.51 reasonable homogeneity. The proportion of discrepancy explained (pseudo- R^2) in sequences was also examined for each cluster solution based on partitions of dissimilarities according to cluster assignment as a categorical covariate. It is important to note that more clusters will necessarily explain more discrepancy until pseudo- R^2 approaches 1 with a cluster for each individual sequence. Finally, to evaluate whether participants were organized into the same clusters together across tasks, individuals' cluster assignment identified from one cognitive task was used as a categorical predictor of the pairwise sequence dissimilarities of each other task.

Results

Sequences of thought probe responses are depicted in Figure 2 for all individuals in each of five cognitive tasks. There were 526 thought probe sequences in total for SART, 479 for Arrow Flanker, 462 for Letter Flanker, 478 for Number Stroop, and 461 for 2-Back tasks. The proportion of thought probes categorized according to on-task focus or categories

of task-related interference or task-unrelated thoughts are provided in Table 1 for each task.

Kolmogorov–Smirnov tests demonstrated that the response distributions of thought probes significantly differed between tasks (all $ps < .001$). Most notably, proportions of on-task reports appeared lower in the SART, whereas reports of task-related interference appeared greater in the SART, compared to other tasks. Despite these differences, proportions of thought probes were highly similar. Across all tasks, reports of being on-task, experiencing task-related interference, or thoughts about one's current state were the most prevalent. Daydreams, worries, and thoughts about everyday things were the next most frequent categories.

Dependent Measures of Thought Probe Sequence Dynamics

Descriptive statistics are provided in Table 2 for dependent measures of thought probe sequence dynamics for each of the five cognitive tasks. Comparisons between tasks are provided below for each measure, and parameter estimates from mixed effects models are given in Table 3.

Number of unique thought content categories reported.

Individuals reported between 3.7 to 5.5 unique kinds of thought content categories on average during task performance for each of the five cognitive tasks (see Table 2). The number of thought contents reported significantly differed between cognitive tasks in a systematic manner, $F(4, 1901) = 175.00, p < .001$. The number of content categories was significantly lower in the Arrow Flanker ($b = -1.443, p < .001, 95\% \text{ CI } [-1.593, -1.293]$), the Letter Flanker ($b = -1.278, p < .001, 95\% \text{ CI } [-1.429, -1.126]$), the Number Stroop ($b = -1.535, p < .001, 95\% \text{ CI } [-1.685, -1.384]$), and the 2-Back ($b = -1.848, p < .001, 95\% \text{ CI } [-1.999, -1.696]$), compared to the SART (intercept $b = 5.523, 95\% \text{ CI } [5.390, 5.656]$). Individuals therefore reported more kinds of thought content categories in the SART compared to other tasks. The intra-class correlation (ICC) for the number of reported thought contents was 0.311, suggesting that 31.1% of variance was attributable to differences between individuals, but that the majority of variance (~69%) was attributable to within-person variation and measurement error. Task context

Figure 3: Model estimated means and 95% confidence intervals are provided from mixed effects models for sequence entropy, complexity, and turbulence derived from thought probe sequences from the SART ($n = 526$), the Arrow Flanker ($n = 479$), the Letter Flanker ($n = 462$), the Number Stroop ($n = 478$), and the 2-Back ($n = 461$). Observed subject data are plotted from individuals' sequences as dots in grey.

explained 15% of the observed variance ($R^2 = .150$) in the number of unique categories reported.

Proportion of total transitions. Participants reported different thought content on subsequent probes for 47% to 60% of all possible transitions on average for each of the different cognitive tasks (see Table 2). The proportion of transitions significantly differed between cognitive tasks, $F(4, 1896.5) = 43.94, p < .001$. Transitions were significantly lower in the Arrow Flanker ($b = -0.032, p = .006, 95\% \text{ CI } [-0.054, -0.009]$), the Number Stroop ($b = -0.028, p = .013, 95\% \text{ CI } [-0.051, -0.006]$), and the 2-Back ($b = -0.025, p = .029, 95\% \text{ CI } [-0.048, -0.003]$), compared to the SART (intercept $b = 5.523, 95\% \text{ CI } [0.477, 0.519]$). In contrast, transitions were more prevalent in the Letter Flanker ($b = 0.101, p < .001, 95\% \text{ CI } [0.079, 0.124]$), compared to the SART. Individuals therefore had more transitions between different thought content categories in the SART and Letter Flanker compared to other tasks. The ICC was .469 and task context explained 4% of the observed variance ($R^2 = .039$) in the proportion of transitions.

Sequence entropy. Mean thought probe sequence entropy ranged from 0.46 to 0.61 among tasks, which indicated that individuals' sequences demonstrated a fair amount of systematicity in their responding (see Table 2). Entropy significantly differed between cognitive tasks, $F(4, 1900.7) = 68.12, p < .001$. Entropy was significantly lower in the Arrow Flanker ($b = -0.117, p < .001, 95\% \text{ CI } [-0.137, -0.097]$), the Letter Flanker ($b = -0.048, p < .001, 95\% \text{ CI } [-0.069, -0.028]$), the Number Stroop ($b = -0.126, p < .001, 95\% \text{ CI } [-0.146, -0.106]$), and the 2-Back ($b = -0.147, p < .001, 95\% \text{ CI } [-0.168, -0.127]$), compared to the SART (intercept $b = 0.609, 95\% \text{ CI } [0.591, 0.628]$). Individuals' sequences had greater entropy in the SART compared to other tasks. Figure 3 shows individual participant data for these comparisons, along with the model estimated means for each task. The ICC was 0.437 and task context explained 6% of the observed variance ($R^2 = .062$) in entropy.

Sequence complexity. Mean sequence complexity ranged from 0.46 to 0.57 among tasks (see Table 2). Complexity significantly differed between cognitive tasks, $F(4, 1896.3) = 44.89, p < .001$. Complexity was significantly lower in the Arrow Flanker ($b = -0.070, p < .001, 95\% \text{ CI } [-0.091, -0.050]$), the Number Stroop ($b = -0.073, p < .001, 95\% \text{ CI } [-0.093, -0.053]$), and the 2-Back ($b = -0.083, p < .001, 95\% \text{ CI } [-0.103, -0.062]$), compared to the SART (intercept $b = 0.545, 95\% \text{ CI } [0.526, 0.564]$). But complexity was greater in the Letter Flanker ($b = 0.031, p = .003, 95\% \text{ CI } [0.010, 0.051]$), compared to the SART. Individuals' sequences were therefore more complex in the SART and Letter Flanker compared to other tasks (see Figure 3). The ICC was 0.478

Table 3: Parameter estimates from mixed effects models of dependent measures of thought probe sequences

Measure	Num. Reported	Prop. Transitions	Entropy	Complexity	Turbulence
Fixed Effects					
SART (Intercept)	5.523 (0.068)***	0.498 (0.011)***	0.609 (0.009)***	0.545 (0.010)***	0.491 (0.010)***
Arrow Flanker	-1.443 (0.077)***	-0.032 (0.011)**	-0.117 (0.010)***	-0.070 (0.010)***	-0.002 (0.010)
Letter Flanker	-1.277 (0.077)***	0.101 (0.011)***	-0.048 (0.011)***	0.031 (0.010)**	0.123 (0.010)***
Number Stroop	-1.535 (0.077)***	-0.028 (0.011)*	-0.126 (0.010)***	-0.073 (0.010)***	-0.004 (0.010)
2-Back	-1.848 (0.077)***	-0.025 (0.012)*	-0.147 (0.011)***	-0.083 (0.010)***	0.001 (0.010)
Random Effects					
Intercept variance	0.995 (0.997)	0.028 (0.168)	0.021 (0.143)	0.024 (0.155)	0.023 (0.151)
Residual variance	1.444 (1.202)	0.032 (0.178)	0.027 (0.163)	0.026 (0.162)	0.025 (0.159)
Subjects	537	537	537	537	537
Observations	2406	2406	2406	2406	2406

Note: Restricted maximum likelihood estimates are given from mixed effects models of the number of unique thought content categories reported, the proportion of total transitions, and thought probe sequence entropy, complexity, and turbulence for fixed effects of cognitive task. The SART serves as the reference condition. The number of subjects (N) and observations contributing to the analyses are provided. Standard errors are reported in parentheses for fixed effects and standard deviations for random effects. * $p < .05$, ** $p < .01$, *** $p < .001$.

and task context explained 4% of the observed variance ($R^2 = .039$) in complexity.

Sequence turbulence. Mean sequence turbulence ranged from 0.49 to 0.61 (see Table 2). Turbulence significantly differed between cognitive tasks, $F(4, 1895.6) = 54.84$, $p < .001$. Turbulence was significantly higher in the Letter Flanker ($b = 0.123$, $p < .001$, 95% CI [0.103, 0.143]), but did not differ for the Arrow Flanker ($b = -0.002$, $p = .853$, 95% CI [-0.022, 0.018]), the Number Stroop ($b = -0.004$, $p = .696$, 95% CI [-0.024, 0.016]), and the 2-Back ($b = 0.001$, $p = .901$, 95% CI [-0.019, 0.021]), compared to the SART (intercept $b = 0.491$, 95% CI [0.472, 0.509]). Turbulence was therefore higher in the Letter Flanker than other tasks (see Figure 3). The ICC was 0.473 and task context explained 5% of the observed variance ($R^2 = .048$) in turbulence.

Transition Probabilities of Experience Sampling Thought Probes

An examination of the Markov-chain transition probabilities for thought probe sequences revealed similar patterns of transitions for tasks overall. Indeed, bivariate correlations between sets of transition probabilities were highly correlated among tasks (r range = .926 – .983). Figure 4 depicts the transition probability matrices of thought probes.

Overall, individuals were highly likely to report the same thought content that they last reported. This was indicated by strong transition probabilities along the diagonal of matrices. Accordingly, patterns of transitions appeared more ordered than random, and fluctuations in thought content over the tasks behaved with some amount of systematicity. This was reflected in a number of transition probabilities that were more or less likely to occur than if they had been ordered at random according to 5000 random permutations of thought probes in sequence for individuals (i.e., transition probabilities more extreme than 99.5% of 5000 random

permutations of thought probes). Figure 5 depicts transitions that were significantly different from those expected by chance.

Despite overall similarities, many transition probabilities significantly differed between cognitive tasks (differences between observed transition probabilities that were more extreme than 99.5% of permuted differences). Figure 6 depicts the observed difference for significant transition pairs. Of note, transitions from $1 \rightarrow 1$, $2 \rightarrow 1$, $4 \rightarrow 1$, and $8 \rightarrow 1$ were generally less likely to occur in the SART compared to other cognitive tasks. In contrast, transitions from $2 \rightarrow 2$, $4 \rightarrow 2$, and $6 \rightarrow 2$ were more likely to occur. These patterns of transitions suggest that during the SART, individuals were less likely to return to an on-task report after experiencing some amount of task-related interference or task-unrelated thoughts about their current state. Furthermore, they were more likely to continue experiencing task-related interference over time and report additional task-related interference after experiencing thoughts about their current state or daydreams. Another noteworthy pattern of transitions occurred for the Letter Flanker, in which individuals were less likely to remain in an on-task state (i.e., transitions from $1 \rightarrow 1$), and less likely to transition from $1 \rightarrow 2$, $2 \rightarrow 2$, and $3 \rightarrow 2$, compared to other tasks. This suggests that in the Letter Flanker, individuals had a harder time regulating their attention between successive thought probes and were less likely to experience recurrent task-related interference.

Sequence Analysis and Clustering of Experience Sampling Thought Probes

Sequence discrepancy analysis. Pairwise sequence dissimilarities based on OM were calculated for each participant between thought probe sequences of cognitive tasks. Discrepancy analysis of sequence dissimilarities for all 2406 sequences of all tasks combined demonstrated that

Figure 4: Transition probabilities indicate the total probability (rows sum to 1) of all transitions from each thought content category to each other category based on sequences for each cognitive task.

tasks significantly differentiated sequences, $F(4, 2401) = 55.154$, $p < .001$, and explained about 8% of total discrepancy (pseudo- $R^2 = .084$). Levene's test of homogeneity ($L = 2665.24$, $p < .001$) indicated that individuals' sequences were highly dissimilar within cognitive tasks. Tasks differentiated sequences to a smaller degree when considering only the first 12 thought probes in each sequence, $F(4, 2401) = 19.502$, $p < .001$, accounting for only 3% of discrepancy (pseudo- $R^2 = .031$). Finally, a generalization of the ICC from partitions of sums of squares of dissimilarities indicated that 31.6% of variance among sequences was attributable to variance between individuals, but that the majority of variance (68.4%) was attributable to intra-individual variation between and within-sessions. The ICC (0.343) was slightly larger when considering only the first 12 thought probes.

Clustering of sequences for cognitive tasks. Hierarchical agglomerative clustering of sequence dissimilarities revealed several typologies of thought probe sequences for each cognitive task. The optimal clusters were chosen based on the local maxima among three model assessment criteria with preference for the solution with the smallest number of clusters. The model selection criteria are shown in Figure 7

for cluster solutions 1 through 20, and the optimal clusters are depicted in Figure 8 for each task. Clusters of individuals derived from one cognitive task were then evaluated to see how well they explain discrepancy in other cognitive tasks. Table 4 provides the pseudo- R^2 for each cluster solution as a measure of discrepancy explained. Optimal clusters of sequences from each task explained between 17% to 32% of dissimilarity between the sequences of thought probes from that same task.

Four clusters were identified as optimal in the SART that explained 17.45% of discrepancy among individuals' sequences. Clusters were generally ill-defined as the weighted ASW ranged from -0.011 to 0.307, with sequences belonging to Cluster 1 being the most homogenous and sequences in Cluster 4 being the least homogenous. Nevertheless, cluster typologies were visually distinct and appeared to be differentiated based on different proportions of thought content (see Figure 8). Cluster 1 contained individuals who reported more on-task probes, whereas Cluster 2 contained individuals who reported more task-related interference. Cluster 3 contained individuals who reported more thoughts about their current state of being. Finally, Cluster 4 contained individuals whose sequences

Figure 5: Transition probabilities for each cognitive task are shown for pairs of transitions that were significantly extreme with respect to the null distribution of permuted transitions. Blue cells indicate transitions less likely to occur than if thought probes had been ordered at random, and red cells indicate transitions more likely than at random.

contained more daydreams but also appeared more heterogeneous overall. Individuals' cluster membership was then applied to other task sequences to examine whether thought probe sequence typologies from the SART consistently identified the same groupings of individuals' sequences from other tasks. The 4 clusters only explained between 3.6% to 5.4% of discrepancy in other tasks (see Table 4).

Six clusters were optimal in the Arrow Flanker that explained 29.5% of discrepancy. Clusters 1 (ASW = 0.517), 2 (ASW = 0.654), and 4 (ASW = 0.538), were adequately defined and showed a moderate level of homogeneity between sequences. Cluster typologies 1 through 4 were similar in thought content prevalence to those identified in other tasks. When applied to other tasks, the 6 clusters explained between 4.5% to 10.7% of discrepancy in the other tasks (see Table 4). Interestingly, clusters of sequences identified in the Arrow Flanker explained a noteworthy amount of discrepancy in the Number Stroop (pseudo- $R^2 = 0.107$).

Six clusters were optimal in the Letter Flanker that explained 22.9% of discrepancy. Only Cluster 2 (ASW = 0.611)

showed reasonable homogeneity between sequences. Clusters 1 (ASW = 0.347) and 3 (ASW = 0.346) were less defined but showed more homogeneity than Clusters 4 (ASW = 0.234), 5 (ASW = -0.070), and 6 (ASW = -0.030). Cluster typologies 1 through 4 were similar to those identified in other tasks. The 6 clusters explained between 3.7% to 5.8% of discrepancy in other tasks.

Eight clusters were optimal in the Number Stroop that explained 32.3% of discrepancy. Only Clusters 3 (ASW = 0.642), 4 (ASW = 0.651), and 8 (ASW = 0.599) were reasonably defined. Clusters 1 (ASW = 0.362) and 2 (ASW = 0.203) were less defined but were more specified than the remaining clusters (ASW range = -0.066 to -0.025). Again, cluster typologies 1 through 4 were similar to those in other tasks. The 8 clusters explained between 4.4% to 11.1% of discrepancy in other tasks. Notably, the Number Stroop clusters explained (pseudo- $R^2 = 0.111$) a moderate amount of discrepancy among sequences from the Arrow Flanker.

Three clusters were optimal in the 2-Back that explained 19.8% of discrepancy. Clusters were generally ill-defined, with Clusters 1 (ASW = 0.295) and 2 (ASW = 0.335) being the most homogenous, whereas Cluster 3 had poor levels of

Figure 6: Observed differences between transition probabilities of cognitive tasks in columns compared to those in rows are shown for pairs of transitions that were significantly extreme with respect to the null distribution of permuted differences.

homogeneity (ASW = 0.084). Finally, the 3 clusters were poor predictors of sequences in other tasks, as they explained only 1.3% to 2.7% of discrepancy.

Clustering of all sequences combined. Importantly, hierarchical clustering across all 2406 thought probe sequences combined across tasks suggested that 4 global clusters were optimal. Figure 9 depicts each global cluster typology of sequences and the corresponding proportion of thought probes for clusters. Global clusters together explained 17.1% of the discrepancy among all 2406 sequences. While the structure of clusters was poorly defined (ASW range = 0.057 to 0.179), they each appeared visually distinct and were differentiated based on their proportions of thought probes (Kolmogorov–Smirnov p s < .001). The

typology of sequences comprising Cluster 1 reflected sequences with a high proportion of on-task reports. Cluster 2 reflected sequences with a high proportion of task-related interference. Cluster 3 reflected sequences with a high proportion of thoughts about their current physical, cognitive or emotional state of being. Finally, Cluster 4 reflected sequences with a high proportion of worries, daydreams, and other kinds of task-unrelated thoughts. Cluster 4 also appeared more heterogeneous than other clusters. A χ^2 test of independence indicated that the assignment of sequences to clusters were dependent on cognitive task, $\chi^2(12) = 565.94$, $p < .001$. Table 5 provides the number of sequences from each cognitive task that were assigned to clusters. Cluster 3 occurred most frequently in the SART, whereas Cluster 4

Figure 7: Three cluster selection criteria including the Point Biserial Correlation (red), Huberts Gamma (light blue), and the weighted Average Silhouette Width (dark blue) are depicted for each cognitive task for cluster solutions 1 through 20. Selection of optimal clusters was determined based on the local maxima of criteria with the smallest number of clusters.

occurred most frequently in the Letter Flanker and least frequently in the SART.

Global cluster typologies differed in terms of the five dependent measures characterizing the overall dynamics of sequences. Comparisons between cluster typologies are described below for each measure, and parameter estimates from mixed effects models are given in Table 6. The number of unique thought content categories reported significantly differed between global clusters, $F(3, 2318.5) = 3.23, p = .022$. More unique categories were reported in Cluster 2 ($b = 0.209, p = .031, 95\% \text{ CI } [0.019, 0.399]$), Cluster 3 ($b =$

$0.313, p = .004, 95\% \text{ CI } [0.097, 0.528]$), and Cluster 4 ($b = 0.170, p = .036, 95\% \text{ CI } [0.010, 0.330]$), compared to Cluster 1 (intercept $b = 4.202, 95\% \text{ CI } [4.060, 4.344]$). Cluster 1, which reflected those sequences with a high proportion of on-task probe reports, was therefore more homogeneous in thought content than other clusters. Clusters explained little observed variance ($R^2 = .004$) in unique thought content.

The proportion of transitions significantly differed between global clusters, $F(3, 2231.9) = 60.15, p < .001$. The proportion of transitions was significantly lower in Cluster 3 ($b = -0.056, p < .001, 95\% \text{ CI } [-0.084, -0.027]$) but higher in Cluster 2 ($b = 0.051, p < .001, 95\% \text{ CI } [0.025, 0.076]$) and Cluster 4 ($b = 0.099, p < .001, 95\% \text{ CI } [0.078, 0.120]$), compared to Cluster 1 (intercept $b = 0.462, 95\% \text{ CI } [0.442, 0.483]$). There were thus fewer transitions among sequences belonging to Cluster 1 and Cluster 3 than the remaining clusters. Clusters explained 5% of the observed variance ($R^2 = .051$) in the proportion of transitions.

Entropy significantly differed between global clusters, $F(3, 2284.9) = 35.53, p < .001$. Entropy was significantly higher in Cluster 2 ($b = 0.058, p < .001, 95\% \text{ CI } [0.034, 0.081]$) and Cluster 4 ($b = 0.094, p < .001, 95\% \text{ CI } [0.074, 0.114]$) compared to Cluster 1 (intercept $b = 0.478, 95\% \text{ CI } [0.459, 0.496]$). Cluster 3 did not significantly differ from Cluster 1 ($b = 0.010, p = .455, 95\% \text{ CI } [-0.017, 0.037]$). Thought probe content was therefore more unpredictable in Clusters 2 and 4 compared to other clusters. Figure 10 shows individual participant data for these comparisons, along with the model estimated means for each task. Clusters explained 4% of observed variance ($R^2 = .035$) in entropy.

Complexity significantly differed between global clusters, $F(3, 2229.5) = 49.68, p < .001$. Complexity was significantly higher in Cluster 2 ($b = 0.052, p < .001, 95\% \text{ CI } [0.029, 0.075]$) and Cluster 4 ($b = 0.094, p < .001, 95\% \text{ CI } [0.074, 0.113]$) compared to Cluster 1 (intercept $b = 0.466, 95\% \text{ CI } [0.448, 0.485]$). Cluster 3 did not significantly differ from Cluster 1 ($b = -0.025, p = .065, 95\% \text{ CI } [-0.051, 0.001]$). Sequences had more complexity in Clusters 2 and 4 compared to other clusters (see Figure 10). Clusters explained 4% of observed variance ($R^2 = .042$) in complexity.

Finally, turbulence significantly differed between global clusters, $F(3, 2231.5) = 87.91, p < .001$. Turbulence was significantly higher in Cluster 2 ($b = 0.042, p < .001, 95\% \text{ CI } [0.019, 0.064]$) and Cluster 4 ($b = 0.104, p < .001, 95\% \text{ CI } [0.085, 0.122]$) compared to Cluster 1 (intercept $b = 0.476, 95\% \text{ CI } [0.458, 0.494]$). In contrast, Cluster 3 had significantly lower turbulence ($b = -0.066, p < .001, 95\% \text{ CI } [-0.091, -0.040]$). Compared to Cluster 1, sequences had more turbulence in Clusters 2 and 4, and less turbulence in

Table 4: Proportion of sequence dissimilarity explained by sequence cluster solutions

Clusters	SART	Arrow Flanker	Letter Flanker	Number Stroop	2-Back
SART (<i>N</i>)	526	470	454	469	455
4 Clusters	0.175	0.043	0.054	0.046	0.036
Arrow Flanker (<i>N</i>)	470	479	414	474	456
6 Clusters	0.046	0.295	0.045	0.107	0.049
Letter Flanker (<i>N</i>)	454	414	462	410	399
6 Clusters	0.058	0.052	0.229	0.047	0.037
Number Stroop (<i>N</i>)	469	474	410	478	454
8 Clusters	0.056	0.111	0.044	0.323	0.049
2-Back (<i>N</i>)	455	456	399	454	461
3 Clusters	0.019	0.025	0.013	0.027	0.198

Note: The proportion of discrepancy explained (pseudo- R^2) from analyses of sequence dissimilarity is provided for optimal clusters of sequences from each of five cognitive tasks, as well as the discrepancy explained when cluster membership from one task is applied to other tasks. The sample size (*N*) for the set of individuals with complete pairwise data is also provided.

Cluster 3 (see Figure 10). Clusters explained 7% of observed variance ($R^2 = .072$) in turbulence.

Discussion

The stream of thought rarely follows the same meandering path twice for an individual, but nevertheless flows with some predictability in the cognitive task context. Sequence analytic methods applied to experience sampling thought probes revealed a modicum of order and consistency in streams of thought for individuals based on examination of systematic patterns of transitions between probe responses and information theoretic measures of entropy, complexity, and turbulence. Individuals were highly likely to report the same cognitive state or kind of task-unrelated thought on probes which followed their current probe report, as transition pairs between the same kinds of thought content were more likely to occur than if sequences had been ordered at random. That the same thought probe content was highly likely to re-occur over time also meant that other transition pairs were less likely to systematically occur.

Sequences of thought probes varied more within individuals across different sessions of cognitive tasks than they did between individuals. Participants completed five different cognitive tasks with embedded thought probes across three different cognitive-behavioral assessment sessions. The intra-class correlation coefficient (ICC) calculated from mixed effects models of sequence entropy, complexity, and turbulence demonstrated that a minority of variance ($< 50\%$) was explained by variability between individuals, whereas a majority could be attributable to unexplained within-person variability across tasks. This was consistent with low ICC calculated from pairwise dissimilarities of entire thought probe sequences. Together, these values indicate poor to fair levels of measurement reliability when considering common standards for interpreting ICC in relation to test re-test reliability (Koo & Li, 2016). These findings also suggest that streams of thought as assessed by sequences of thought probe

responses demonstrate considerable variability across different task contexts, even minutes later when completing a similar cognitive task.

There were also systematic differences between cognitive tasks in thought probe sequences that contributed to within-person variability between sessions. Differences between cognitive tasks explained about 8% of the overall discrepancy in pairwise sequence dissimilarities. Indeed, tasks also differed overall in the frequency distribution of thought probes, the number of unique categories reported, patterns of transition probabilities, and sequence entropy, complexity, and turbulence. The temporal dynamics of thought therefore differed on average between cognitive tasks. These findings are in line with the notion that contextual task constraints are associated with not only the frequency and content of thought probe responses but how entire sequences of responses unfold over the course of task performance.

Differences between tasks may result from specific features of the cognitive task context, such as the kind of cognitive processes engaged during performance, features of stimuli and stimulus presentation, the number of experience sampling probes presented, and the duration of the task in question. Tasks in the current study varied along each of these dimensions. While prior research has suggested that the overall frequency of task-unrelated thought is reduced when probes are presented more frequently (Schubert, Frischkorn, & Rummel, 2019; Seli, Carriere, Levene, & Smilek, 2013), it is unknown whether probe rate influences the variety of reported thought content or the dynamics of thought probe sequences. At least in the present study, the 45 probes of the SART exhibited the greatest variety of reported thought content and corresponding sequence entropy. Conversely, the Letter Flanker had the fewest probes but had content that was the most temporally volatile, demonstrating the greatest proportion of transitions, and greatest sequence complexity and turbulence among tasks. Future studies should continue

Table 5: Numbers of sequences for global cluster typologies by task

Task	1	2	3	4
SART	168	125	177	56
Arrow Flanker	175	84	47	173
Letter Flanker	73	43	15	331
Number Stroop	161	127	56	134
2-Back	133	92	29	207

Note: The number of sequences assigned to global cluster typologies 1 through 4 are provided for each of five cognitive tasks.

Table 6: Parameter estimates from mixed effects models for dependent measures of global cluster typologies

Measure	Num. Reported	Prop. Transitions	Entropy	Complexity	Turbulence
Fixed Effects					
Cluster 1 (Intercept)	4.202 (0.073)***	0.462 (0.010)***	0.478 (0.009)***	0.466 (0.010)***	0.476 (0.009)***
Cluster 2	0.209 (0.097)*	0.051 (0.013)***	0.058 (0.012)***	0.052 (0.012)***	0.042 (0.011)***
Cluster 3	0.313 (0.110)**	-0.056 (0.015)***	0.010 (0.014)	-0.025 (0.013)	-0.066 (0.013)***
Cluster 4	0.170 (0.081)*	0.099 (0.011)***	0.094 (0.010)***	0.094 (0.010)***	0.104 (0.009)***
Random Effects					
Intercept variance	0.893 (0.945)	0.025 (0.157)	0.017 (0.132)	0.021 (0.145)	0.020 (0.140)
Residual variance	1.967 (1.403)	0.033 (0.181)	0.030 (0.172)	0.027 (0.165)	0.026 (0.160)
Subjects	537	537	537	537	537
Observations	2406	2406	2406	2406	2406

Note: Restricted maximum likelihood estimates are given from mixed effects models of the number of unique thought content categories reported, the proportion of total transitions, and thought probe sequence entropy, complexity, and turbulence for fixed effects of global cluster typology. Cluster 1 serves as the reference condition. The number of subjects (*N*) and observations contributing to the analyses are provided. Standard errors are reported in parentheses for fixed effects and standard deviations for random effects. * $p < .05$, ** $p < .01$, *** $p < .001$.

to examine the influence of probe rate and other task factors on the dynamics and content of thought beyond simply assessing the overall frequency of task-unrelated thought.

In contrast to patterns of within-person variability, there were also a great many similarities between participants overall. Despite having significantly different proportions of specific thought probe content, the distribution of thought content among tasks were also highly similar: on-task reports and task-related interference being the most prevalent, and thoughts about one's own current state followed by daydreams as the next most frequent categories of thoughts. Similarly, the overall transition matrices of transition probabilities between thought probes were highly correlated between tasks, demonstrating that individuals tend to mind wander in a similar manner across cognitive task contexts. Finally, a number of sequence typologies could be identified through hierarchical clustering of thought probe sequences that explained between 17% to 32% of discrepancy between sequences.

There was a large degree of visual and conceptual similarity between clusters identified from different cognitive tasks. Four clusters were prevalent throughout tasks: a cluster of individuals who reported a high degree of task-related focus; individuals who reported a high degree of task-related interference; individuals who primarily mind wandered about their current state; and those who primarily daydreamed. But

consistent with broader patterns of within-person variability, individuals tended to be grouped according to different typologies across cognitive tasks. Clusters of individuals in one cognitive task were therefore poor predictors of groupings of sequence dissimilarities for each other task, explaining roughly 1% to 11% of discrepancy in other tasks. Clustering of sequences from all tasks combined also identified common typologies of mind wandering. Indeed, 17% of discrepancy among all thought probe sequences was explained by these broader profiles of mind wandering. Notably, Cluster 1, representing those individuals who reported high levels of task-related focus, were more homogeneous in thought content than other clusters, and tended to display less temporal variability. Cluster 4, however, demonstrated the greatest levels of temporal variability, as sequences had more entropy, complexity, and turbulence than other typologies.

In total, the present analyses of the dynamics of thought probe sequences illustrates the conceptual tension between spontaneity and consistency in patterns of thought over time. One's stream of thoughts, represented by sequences of experience sampling thought probes, appear to show a modicum of consistency in the cognitive task context. But even minutes later these dynamic patterns are likely to differ between task sessions. Yet, on the whole, consistent typologies of mind wandering were identified from individuals according to how their mind wandering unfolded over time. It is thus clear that individuals mind wander about

Figure 8: Sequences of experience sampling thought probe responses (rated according to 8 categories) are depicted for optimal clusters for each cognitive task. Clusters were labeled and organized in order according to their visual similarity between tasks.

a range of topics even under the constraints of task performance, and patterns of thought vary considerably from one moment to the next. Given the large degree of variability within and between thought probe sequences across different cognitive tasks, it seems likely that appropriately characterizing these constraints will be challenging for theoretical definitions that define mind wandering according to their degree of influence (cf. Seli et al., 2018b).

Nevertheless, contextual task constraints are associated with how mind wandering unfolds over time.

Studies considering only the frequency of off-task thought ignore the large range of reported thought content and the considerable dynamics evinced during task performance. One open question is whether thought probe variability is behaviorally meaningful? Studies should therefore continue to explore how mind wandering dynamics predict task

Figure 9: Sequences of experience sampling thought probe responses (rated according to 8 categories) are depicted based on 2406 sequences in total from all five cognitive tasks. The distribution of thought probe responses for clusters is also shown. Sequences differ in length because more or less thought probes were presented in different cognitive tasks.

performance and relate to individual differences in cognitive abilities over and above mind wandering frequency (cf. Welhaf et al., 2019). Given the importance of the dynamics of thought for prominent theoretical perspectives of mind wandering (i.e., Christoff et al., 2016, 2018), it is my hope to have demonstrated the value of sequence analysis and related methods for quantifying and analyzing dynamics of experience sampling thought probe sequences. It is clear to me that researchers ought to consider not only whether

individuals' experience spontaneous, deliberate, or task-unrelated thoughts, but also the content and qualities of those thoughts, and the kinds of cognitive states that precede and follow.

One limitation of dissimilarity-based sequence analyses and clustering are the many possible choices of measures for quantifying sequence dissimilarity. For dissimilarity based on edit distances, such as optimal matching (OM), there is

Figure 10: Model estimated means and 95% confidence intervals are provided from mixed effects models for sequence entropy, complexity, and turbulence for global clusters of individuals' thought probe sequences for Cluster 1 ($n = 710$), Cluster 2 ($n = 471$), Cluster 3 ($n = 324$), and Cluster 4 ($n = 901$). Observed subject data are plotted from individuals' sequences as dots in grey.

also the challenge of specifying appropriate indel and substitution costs, which determines how sequences are matched, and can influence sequence dissimilarity by emphasizing certain properties of the data over others (Elzinga & Studer, 2015). Future studies utilizing OM to

quantify sequence dissimilarities in thought probes ought to consider edit costs that might be interpreted and defined based on explicit theories from the cognitive science of mind wandering. That is, in determining whether two sequences are dissimilar, should the ordering of thoughts in sequence take precedence over the kind of thoughts reported? OM dissimilarities in general are less sensitive to the fixed order of sequence states in time (Elzinga & Studer, 2015; Lesnard, 2010), and, by determining substitution costs using transition probabilities, sequences are considered more similar if substitutions involve states that were more likely to transition to and from one another. Indeed, a stream of thought probe responses from $1 \rightarrow 2 \rightarrow 1 \rightarrow 2$, indicating transitions between on-task focus and task-related interference, seems conceptually more similar in the present case to $2 \rightarrow 1 \rightarrow 2 \rightarrow 1$ than it does for a sequence from $1 \rightarrow 6 \rightarrow 1 \rightarrow 6$. Likewise, this is the conclusion based on OM, but alternative specification of indel and substitution costs can change how dissimilarities might be calculated.

Other methods that can account for the time-varying nature of thoughts should continue to be used in studies of mind wandering during cognitive task performance and in daily life. For example, past studies have applied latent growth curve models to examine systematic trends in dimensions of thought over time (Smith et al., 2018), or have reconstructed thought trajectories over time (Nakatani, Ganschow, & van Leeuwen, 2019), or employed hidden Markov modeling methods to characterize mind wandering dynamics and the processes underlying thought probe sequences (Bastian & Sackur, 2013; ZanESCO, Denkova, Witkin, & Jha, 2019). Even more straightforward are approaches quantifying counts of transitions of different thought content (Welhaf et al., 2019), or those that add new dimensions of responses to thought probes such as by asking individuals to reflect on their own thought dynamics (Mills, Raffaelli, Irving, Stan, & Christoff, 2018). Alongside sequence analysis, these methods have much to offer the cognitive science of mind wandering and our understanding of the dynamics of thought. Likewise, there are many viable applications of sequence analysis for investigation of time ordered cognitive and behavioral processes from other domains of psychological research.

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Data Availability Statement

The data that support the findings of this study are openly available in the OSF repository and can be found at:

<https://osf.io/mjk3t/>

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