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Patterns of Ongoing Thought in the Real World

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Introduction

A core goal of cognitive science is to understand the processes that support cognition. Contemporary work suggests that the content and form of everyday thoughts varies widely across people, places, and activities (Smallwood et al., 2021). Variation in how we think and feel (Fitzgerald et al., 2008) and the sorts of activities we engage in (Ingram et al., 2020) both have important contributions to individual health and well-being. While relationships between different brain states and thought content has been investigated (Cardeña & Marcusson-Clavertz, 2016; Kane et al., 2017; Klinger, 1978; Klinger, 1979; Klinger & Cox, 1987; Klinger & Kroll-Mensing, 1995; Marcusson-Clavertz et al., 2016), empirical research has rarely considered both the content and form of everyday thoughts to determine how patterns of thinking emerge across these different contexts, particularly within natural environments. Understanding the relationship between context and thought will help build better connections between theoretical models of how we think and how these play out in the activities we perform in daily life (Smallwood et al., 2021). The broad research aim of this study, therefore, was to empirically map ongoing patterns of thought and behaviour across real-world contexts to provide a preliminary description of how thoughts map onto activities in daily life.

Important aspects of cognition can be measured under controlled conditions in the laboratory, allowing insight into processes underlying human thought. However, it is unclear the extent to which laboratory findings generalize beyond their tightly controlled context. As noted in Kingstone et al. (2003), research based in natural environments is needed to establish ecological validity within real-world contexts. Consistent with this perspective, previous research suggests that lab-based descriptions of ongoing thought may not generalize to the real world (Ho et al., 2020; Ladouce et al., 2017). Accordingly, it is useful to gain contextualized measurements of thinking in activities that occur in the real world (such as socialising with friends, exercising, and watching television) to provide a provisional description of the components that impact the landscape of thinking as it unfolds in daily life (Ladouce et al., 2017). In the future, this approach will allow comparisons between patterns of thinking in real-world situations and in controlled laboratory situations (for prior examples, see Ho et al., 2019 and Kane et al., 2017).

Experience sampling (ES) is a methodology that has been used in the past to provide a description of thinking in daily life. ES allows researchers to capture what people are thinking during everyday activities and lab-based tasks (Conner et al., 2009; Smallwood et al., 2021). This technique has previously been used to provide descriptions of psychopathology (Myin-Germeys et al., 2018) and how emotions unfold in the real world (Zelenski & Larsen, 2000). Studies have also examined how states like mind wandering emerge in daily life (Franklin et al., 2013; Kane et al., 2007; Kane et al., 2017; Poerio, Totterdell, & Miles, 2013; Poerio et al., 2016). Finally, some studies have looked at how experiences emerge in specific activities in the real world, like running (Miś & Kowalczyk, 2019).

Our current study sought to build upon and extend these approaches via the use of a specific type of ES, called multidimensional experience sampling (MDES), which can map patterns of ongoing thought onto primary activities in the lab and in real-world settings (Ho et al., 2020; Smallwood et al., 2016). MDES asks participants to describe their thinking across several dimensions (Smallwood et al., 2016). For example, across a “task” dimension, participants might be asked to score themselves on a 1-to-5 Likert scale (1 = Not at all, 5 = Completely) in relation to the associated statement, “My thoughts were focused on the task I was performing” (Smallwood et al., 2016). MDES questions are traditionally decomposed via principal component analysis (PCA) into a low-dimensional space, and these patterns can be visualized as word clouds. MDES is a technique that can be used to determine associations in response which can be linked to brain activity (e.g., Konu et al., 2020, Smallwood et al., 2021, and Turnbull et al., 2019), and in the lab can be linked to traits related to autism (Turnbull et al., 2020) and attention deficit hyperactivity disorder (Vatansever et al., 2019). One advantage of applying decomposition algorithms like PCA to MDES data is that it becomes possible to compare these components across different situations (e.g., between daily life and the lab, as seen in Ho et al., 2020).

Although prior work has established associations between thinking patterns measured using MDES and both brain activity and personality traits, little is known about the state-level differences in task and context that drive thought patterns in daily life. Our central goal in this study is to establish state-level associations between activity, social contexts, and patterns of thought, in order to describe how thinking in ecological contexts depends on the activity someone is doing, and who they are with. Critically, prior work by Mckeown et al. (2021) used MDES to map ongoing thought patterns in the real world onto primary activities during the first coronavirus disease 2019 (COVID-19) lockdown in the United Kingdom, providing some of the first evidence for the link between activities and thought patterns. Specifically, they found that specific behavioural changes associated with lockdown, including reduced opportunities for working and socializing, were systematically related to changes in ongoing thought patterns. The first step, therefore, of this study was to replicate the influence of socializing on patterns of ongoing thought. Consistent with Mckeown et al. (2021), we hypothesized that thought patterns with social and episodic features, which relate to thinking about other people, would dominate activities that involved other people.

In addition, we also aimed to extend our understanding of the links between daily life activities and concurrent thought patterns. Although there are no existing studies from which we can directly derive predictions, previous research capturing ongoing thought across ecological and controlled conditions can provide some initial insights. For instance, a recent study using MDES in daily life showed that ongoing thought patterns varied with the degree of perceived challenge imposed by the task at hand (Turnbull et al., 2021). Participants tended to show increasing levels of deliberate, external, goal-directed thought as the degree of challenge of a concurrent task increased. A different study used experience-sampling method to understand how different levels of atypical mental states affect mentation in daily life (Cardeña & Marcusson-Clavertz, 2016). Results indicated that task-characteristics, such as attention-demanding activities, related to thought characteristics. In laboratory contexts, Konu et al. (2021) used MDES to investigate how ongoing thought patterns varied across a range of 15 different laboratory tasks. This study found coherence between ongoing thought patterns and the tasks in which they emerged. For instance, "episodic social cognition" thought patterns predominated as a mode of thinking during tasks requiring thinking about the self and others but not when watching affective TV clips and engaging in working memory tasks. In contrast, "detailed task focus" thought patterns predominated during tasks requiring executive control (e.g., working memory and task switching) but were absent when participants engaged in passive listening (e.g., audiobooks). This study provides empirical evidence that PCA applied to MDES provides a low dimensional space based on self-reports which in turn provides a scheme to organize laboratory tasks in terms of the similarities and differences in their self-reported experiential states. Although one might expect similar relationships between thought patterns and current activity in daily life settings, this has yet to be tested outside the laboratory and is a question that we address in the current study.

We had two additional exploratory questions more specific to real-world contexts. First, we were interested in understanding whether physical location is associated with ongoing thought patterns. Studies have suggested that a person being indoors or outdoors impacts their psychological state (Duvall, 2011; Weng & Chiang, 2014). Since natural variation in where participants were when an MDES probe occurred allowed us to sample thinking in a variety of different locations in our study, we also ascertained whether the participants were indoors or outdoors when the probe occurred. Using this data, we explored whether this impacted their experience. Second, we were interested in understanding whether the time of day has an effect on both activities and concurrent thoughts. Since certain types of activities are more likely to occur at certain times of the day (e.g., eating at lunch time), we examined whether the time of day in which the MDES probe occurred was reflected to the patterns of thought the participants described.

In summary, the broad goal of our study was to examine how thinking patterns in the real world relate to the activity in which they naturally emerged. First, based on prior work, we expected that social activities would be related to higher rates of social thinking patterns (Mckeown et al., 2021). Second, we aimed to determine whether there is a relationship between activities and ongoing thought patterns in the real world that parallels the one seen in laboratory tasks (Konu et al., 2021). Third, we aimed to discover whether MDES was linked to variation in location and/or time of day.

Methods

Participant Population

A total of 101 participants (women = 83, men = 13, non-binary = 2, did not specify = 3; age: M = 21.11; SD = 5.33; and range = 18-52) completed MDES surveys with additional stress, environment, location, and activity questions. This study was granted ethics clearance by the Queen's University Health Sciences & Affiliated Teaching Hospitals Research Ethics Board. Participants were recruited between February 2022 and April 2022 though the Queen's University Psychology Participant Pool. This recruitment timeline was determined by the Psychology Participant Pool participation end date. Eligible participants were Queen's University students enrolled in designated first- and second-year psychology courses. Participants gave informed, written consent via electronic documentation prior to taking part in any research activities. Participants were awarded two course credits and fully debriefed upon the completion of this study.

Procedure

Participants were emailed a MindLogger invitation for an applet called "THOUGHTLOG," which they were instructed to accept. MindLogger is a smartphone application that allows researchers to collect, analyze, and visualize data through custom activities such as surveys, quizzes, digital diaries, and cognitive tasks, using mobile devices (Klein et al., 2021). The THOUGHTLOG applet contains an MDES survey with additional stress, social environment, physical location, and activity questions that participants completed for this study. MDES dimensions were selected based on previous studies, such as Kahneman et al. (2004) and Mckeown et al. (2021). Participants were required to download the MindLogger application onto their smartphone to access the THOUGHTLOG applet, and consequently, the

MDES survey and additional questions. Participants were notified to complete the THOUGHTLOG applet eight times daily for five consecutive days between the hours of 7:00 am and 11:00 pm. Each prompt was randomly delivered within a specific two-hour time interval. Each applet was expected to take approximately two minutes to complete. Maximum daily participation time was approximately 16 minutes, and maximum total participation time was approximately 80 minutes over five days. Due to the relatively short duration of this study, response fatigue was not expected.

Multidimensional Experience Sampling and Additional Questions

Participants received MindLogger notifications on their phones and all responses were made with reference to their thoughts, feelings, environment, location, and activities immediately before receiving the notification. 14 MDES questions about thought content across a variety of dimensions (Table 1) were always asked first and in the same order. Participants then answered a single question about their stress level followed by questions about their physical and virtual social environment (Table 2). Participants also indicated the type of physical location they were in and their primary activity (Table 3). The primary activity list was developed from the day reconstruction method (Kahneman et al., 2004) and modified based on the activity options in Mckeown et al. (2021).

Table 1

Summary of MDES Questions

Dimension	Question	Scale Low	Scale High
Task	My thoughts were focused on an external task or activity:	Not at all	Completely
Future	My thoughts involved future events:	Not at all	Completely
Past	My thoughts involved past events:	Not at all	Completely
Self	My thoughts involved myself:	Not at all	Completely
Person	My thoughts involved other people:	Not at all	Completely
Emotion	The emotion of my thoughts was:	Negative	Positive
Modality	My thoughts were in the form of:	Images	Words
Detailed	My thoughts were detailed and specific:	Not at all	Completely
Deliberate	My thoughts were:	Spontaneous	Deliberate
Problem	I was thinking about solutions to problems (or goals):	Not at all	Completely
Intrusive	My thoughts were intrusive:	Not at all	Completely
Knowledge	My thoughts contained information I already knew (e.g., knowledge or memories):	Not at all	Completely
Absorption	I was absorbed in the contents of my thoughts:	Not at all	Completely
Distracting	My thoughts were distracting me from what I was doing:	Not at all	Completely

Note. Participants rated statements on a 1-to-5 Likert scale. For all relevant figures, the "modality" dimension was further split into two independent scales ("images" and "words") to more accurately describe each identified thought pattern. The original "modality" dimension score was assigned to "words," and the inverse score was assigned to "images."

Table 2

Summary of Social Environment Questions

Environment	Question	Environment Type
Physical	Were you alone, or physically with other people?	Alone Around people but not interacting with them Around people and interacting with them
Virtual	Were you alone, or virtually with other people?	Alone Around people but not interacting with them (e.g., reading messages but not replying, being on a video call but not participating, etc.) Around people and interacting with them (e.g., direct communication with another person by text, instant messaging, calling, or video calling, etc.)

Table 3

Summary of Location and Activity Questions

List Type	Question	Location List
Location	Where were you?	Inside a home
		Inside a shop
		Inside a workplace
		Inside (other)
		Outside in a city or town
		Outside in nature
		Outside (other)
Activity	What were you doing?	Eating
		Homework
		Household chores
		Listening to music
		Napping or resting
		Nothing or waiting
		Personal exercise
		Personal hygiene care
		Physical leisure or sports
		Reading
		Shopping
		Talking in person
		Talking on the phone
		Texting by phone
		Traveling or commuting
		Using a computer or an electronic device
		Walking the dog
		Watching TV
		Working (paid or volunteer)
		Other activity

Note. If participants selected “Inside (other),” or “Outside (other),” they were asked to specify their location. If participants selected “Other activity,” they were asked to specify their primary activity.

Analysis

Data and Code Availability Statement

All custom code used to prepare data for analysis and figure development is openly available online at https://github.com/ThinCLabQueens and https://github.com/Bronte-Mckeown/ThoughtSpace/releases/tag/lab-to-life-uncert-version. Anonymized data has been uploaded to a publicly accessible database, Mendeley Data, and is available online at https://doi.org/10.17632/zpmm72bg6s.1. All other study data and materials are included in the article and/or the supplementary material.

Principal Component Analysis (PCA)

Common "patterns of thought" were identified by applying PCA with varimax rotation to all thought data generated from responses to the 14 MDES questions (Table 1) using IBM SPSS (version 28). This is the standard method, as seen in studies such as Konu et al. (2021), Mckeown et al. (2021), Smallwood et al. (2016), Sormaz et al. (2018), and Turnbull et al. (2019). PCA was applied at the observation level and included 1458 observations. The large observation size provides sufficient power to yield robust solutions (Tabachnick & Fidel, 2015). The loadings from the four components with an eigenvalue > 1 were retained for further analysis (Table 4).

Table 4

Thought Data Loadings Generated by PCA with Varimax Rotation

Dimension	Component 1	Component 2	Component 3	Component 4
Task	0.49	-0.26	0.08	0.08
Future	0.06	0.08	0.76	0.12
Past	-0.01	0.52	0.09	0.54
Self	0.04	0.16	0.79	-0.05
Person	-0.001	0.02	-0.03	0.85
Emotion	-0.10	-0.75	0.08	0.22
Modality	0.57	0.20	-0.11	-0.15
Detailed	0.72	0.01	0.19	0.19
Deliberate	0.77	-0.04	0.06	-0.02
Problem	0.51	0.15	0.51	-0.09
Intrusive	-0.08	0.72	0.22	0.17
Knowledge	0.22	0.04	0.38	0.37
Absorption	0.36	0.43	0.22	0.13
Distracting	-0.13	0.59	0.34	0.25

Note. Component 1 = "detailed task focus," component 2 = "negative intrusive distracting," component 3 = "future problem-solving," and component 4 = "episodic social cognition."

Component Reliability

Component reliability analysis was conducted in IBM SPSS (version 28). All MDES data was randomly shuffled, and divided into two halves, with each half containing a sample of 729 probes. To assess component reliability, PCA with varimax rotation was applied to each random subset separately. Further, per-observation component scores were estimated using the Thurstone regression method for all thought data based on the components generated from each subset. Afterwards, Pearson correlations were run on the component scores between each of the components generated from each subset. This analysis allowed us to estimate whether the component structure seen in the whole sample is generalizable to sub samples of our data.

Linear Mixed Modelling (LMM): Physical and Virtual Environments

To analyze contextual distributions of thought in relation to social settings in physical and virtual environments, we conducted a series of linear mixed models (LMMs), one with each thought component as the dependant variable and either physical or virtual environment as the independent variable, examining whether patterns of thought varied in a meaningful way across social settings. Observations that were not clearly labelled during data collection were filtered out. REML was used as the estimation method and a variance components model was used as the covariance type. To account for the nested nature of the data, participants were included as a random intercept. In total, 1443 observations for physical environment or 1421 observations for virtual environment were included in these models. This is the standard method, as seen in Konu et al. (2021), Mckeown et al. (2021), Sormaz et al. (2018), and Turnbull et al. (2019).

Linear Mixed Modelling (LMM): Primary Activity

To analyze contextual distributions of thought in relation to activities, we conducted a series of LMMs, one with each thought component as the dependent variable and activity as the independent variable, examining whether patterns of thought varied in a meaningful way across activity categories. Observations for activities "Physical leisure or sports," and "Walking the dog" were filtered out due to small sample size. REML was used as the estimation method and a variance components model was used as the covariance type. To account for the nested nature of the data, participants were included as a random intercept. In total, 1451 observations were included in these models. This is the standard method, as seen in Konu et al. (2021), Mckeown et al. (2021), Sormaz et al. (2018), and Turnbull et al. (2019). The parameter estimates for each activity in each model were saved for the eventual generation of activity word clouds to demonstrate how each thought pattern is distributed across different activities (Figure 4). This analysis is identical to that found in Konu et al. (2021), with the only exception being the use of activities found in the real world, rather than lab-based tasks.

Linear Mixed Modelling (LMM): Physical Location

To analyze contextual distributions of thought in relation to physical location, we conducted a series of LMMs, one with each thought component as the dependant variable and physical location as the independent variable, examining whether patterns of thought varied in a meaningful way across location. Observations that were not clearly labelled during data collection were filtered out. REML was used as the estimation method and a variance components model was used as the covariance type. To account for the nested nature of the data, participants were included as a random intercept. In total, 1423 observations were included in these models. This is the standard method, as seen in Konu et al. (2021), Mckeown et al. (2021), Sormaz et al. (2018), and Turnbull et al. (2019).

Time of Day Categorization

Analysis of activity time was assessed using SPSS (version 28). The “time” variable was recoded into bins that divided the 24-hour period into six time bins using a visual binning function. Each time bin contained an equal percentile of total cases based on five cut-points. Categorization of bins can be found in Table 5. A frequency analysis was applied to each time bin to evaluate the frequency of reported activities engaged in by participants.

Table 5

Summary of Time Bins

Categorization	Time Bin
Early morning	00:00:00 - 10:26:40
Late morning	10:33:20 - 12:26:40
Early afternoon	12:33:20 - 15:06:40
Late afternoon	15:13:20 - 17:40:00
Evening	17:46:40 - 20:26:40
Night	20:33:20 - 23:53:20

Linear Mixed Modelling (LMM): Time of Day Data

To analyze contextual distributions of thought in relation to time of day, we conducted a series of LMMs, one with each thought component as the dependant variable and time of day as the independent variable, examining whether patterns of thought varied in a meaningful way across time. REML was used as the estimation method and a variance components model was used as the covariance type. To account for the nested nature of our data, participants were included as a random intercept. In total, 1458 observations were included in these models. This is the standard method, as seen in Konu et al. (2021), Mckeown et al. (2021), Sormaz et al. (2018), and Turnbull et al. (2019).

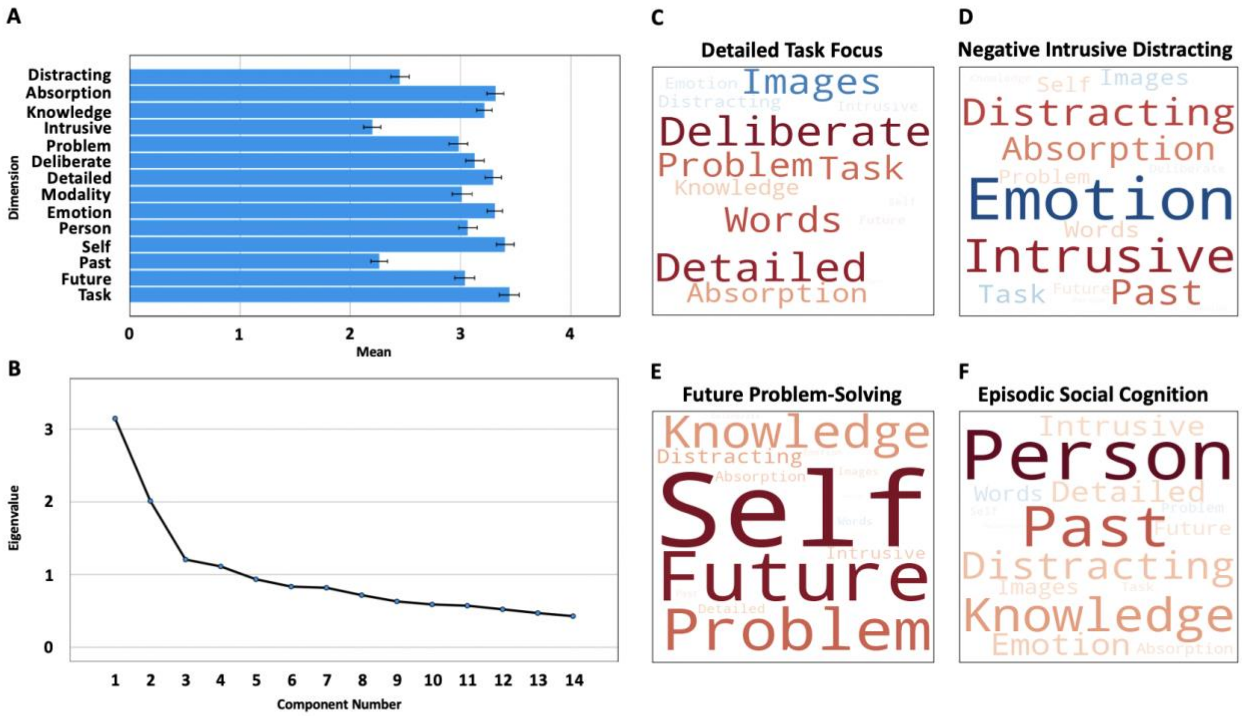
Results

Patterns of Ongoing Thought

First, mean scores for each dimension of thinking measured were calculated and are shown in Figure 1A. Next, the thought data was decomposed using PCA to reveal patterns of thought from the underlying dimensions. Based on eigenvalue > 1, four components were selected for further analysis (see Figure 1B for scree plot). PCA loadings (Table 4) from the four components were used to generate thought word clouds (Figure 1C-F). Thought word clouds were named based on MDES dimensions that dominated their composition. Component 1 (22.48 % of variance, Table S1) was labelled “detailed task focus” because loadings were high for dimensions such as “detailed,” and “task” (Figure 1C). Component 2 (14.38% of variance, Table S1) was labelled “negative intrusive distracting” because loadings were high for dimensions such as “(negative) emotion,” “intrusive,” and “distracting” (Figure 1D). Component 3 (8.62 % of variance, Table S1) was labelled “future problem-solving” because loadings were high for dimensions such as “future” and “problem” (Figure 1E). Component 4 (7.94 % of variance, Table S1) was labelled “episodic social cognition” because loadings were high for “past,” “knowledge,” and “person” (Figure 1F). Please note that these terms are used for convenience when discussing the components; they do not constitute the only label which could be applied to these patterns.

Figure 1

Patterns of Ongoing Thought Identified Through PCA on Thought Data



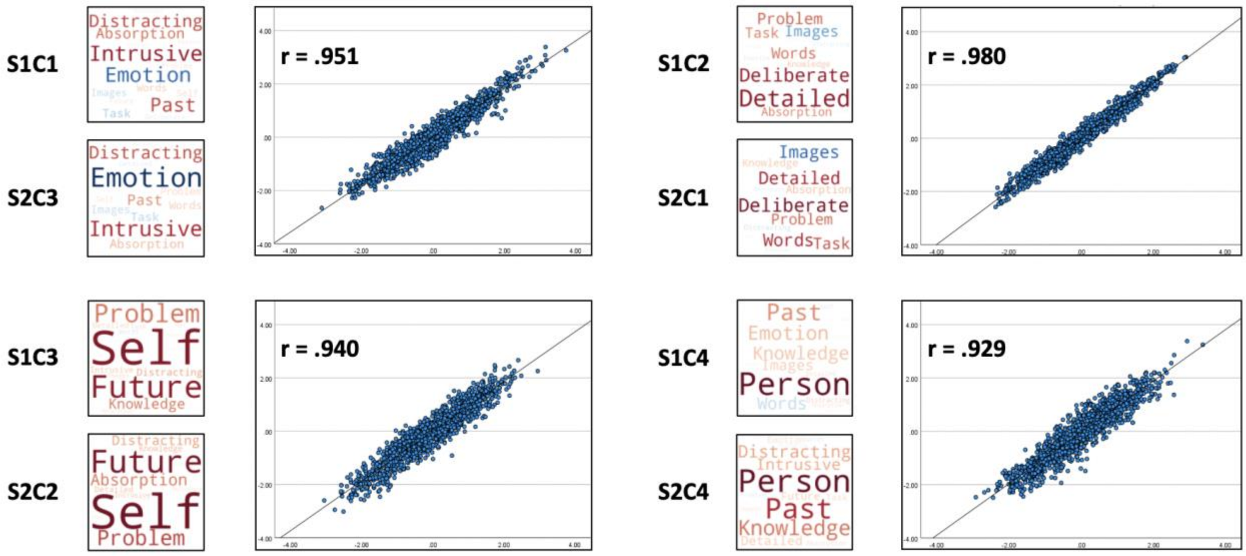
Note. (A) Horizontal bar graph of mean dimension scores. Error bars represent 99 % confidence intervals (CIs). (B) Scree plot generated from PCA of MDES data. (C-F) Thought word clouds. Words represent PCA (varimax) scores for MDES dimensions. Larger fonts are items with more importance (i.e., higher loadings) and colour denotes direction (i.e., warm colours relate to positive loadings). (C) "Detailed task focus" word cloud. (D) "Negative intrusive distracting" word cloud. (E) "Future problem-solving" word cloud. (F) "Episodic social cognition" word cloud.

Component Reliability

To further understand the robustness of the components from our analysis, we conducted a split-half reliability for our sample. In this analysis we divided our data into two random samples and then examined how the components generated in each half of the data related to each other. We used the robustness of the solutions across PCAs with 3-, 4-, and 5-component solutions as a complementary method to determine the best solution for the entire sample (see Figure S1, 2, and S2). The mean correlation for the set of homologous pairs from each solution was calculated with a higher score reflecting the most reproducible components. The 4-component solution produced the most reliable components, with an average homologue similarity score of .950 ($r = .929-.980$) (Figure 2), agreeing with the criterion of eigenvalue > 1. We also conducted a supplementary analysis in which we compared the 4-component PCA solutions generated using varimax rotation (Table 4) with solutions using oblique rotation (Table S2 and Figure S3). These revealed very similar structure of components and had high similarity ($r = .978-.999$), but for consistency with other studies using similar methods we used components derived using varimax rotation in the main body of the paper.

Figure 2

4-Component Solution Reliability Analysis



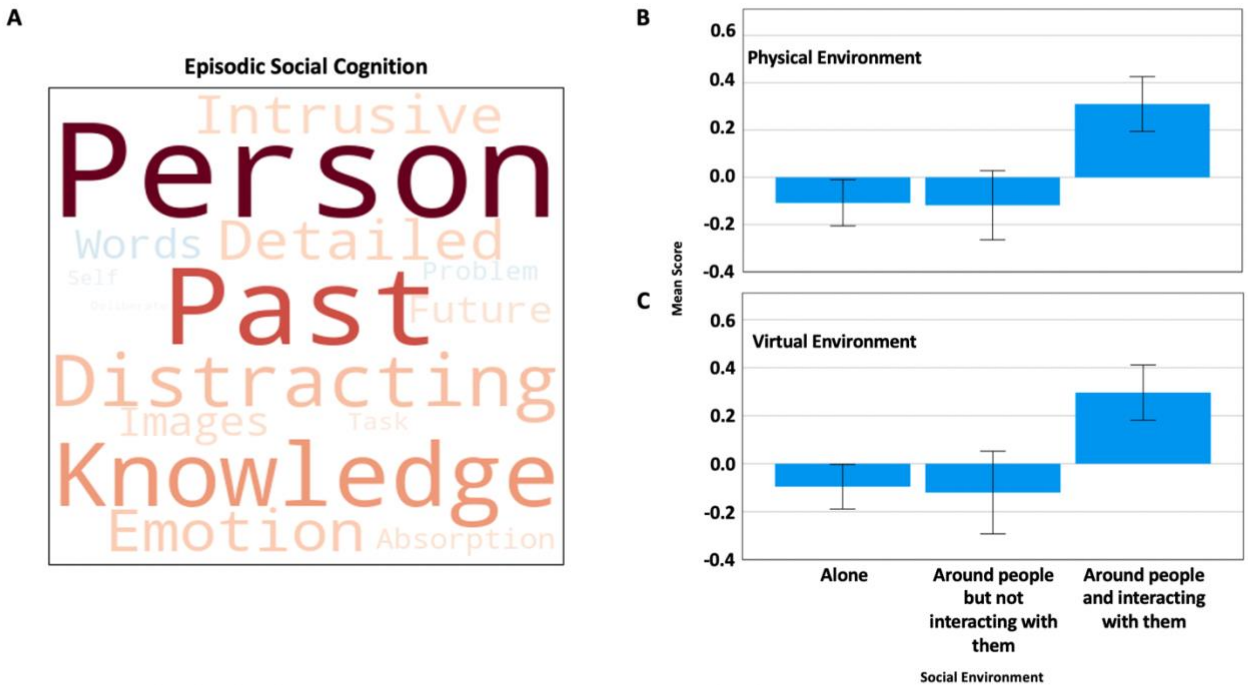
Note. Scatter plot of average homologue similarity. "S" indicates subset, and "C" indicates component. Component scores for subset 1 are found on the y-axes and component scores for subset 2 are found on the x-axes.

The Influence of Socializing on Ongoing Thought

The first goal of our study was to replicate the influence of socializing on patterns of ongoing thought, as seen in Mckeown et al. (2021). To do so, we compared the prevalence of the pattern of "episodic social cognition" across different types of social settings in physical or virtual environments (Figure 3). The "episodic social cognition" thought component varied significantly across physical social environments ($F(2, 1432.87) = 21.18$, $p < .001$). It also varied significantly across virtual social environments ($F(2, 1410.17) = 20.17$, $p < .001$). This pattern was most prevalent when participants were around people and interacting with them either in person or virtually (see CIs in Figure 3).

Figure 3

The Influence of Socializing on Ongoing Thought



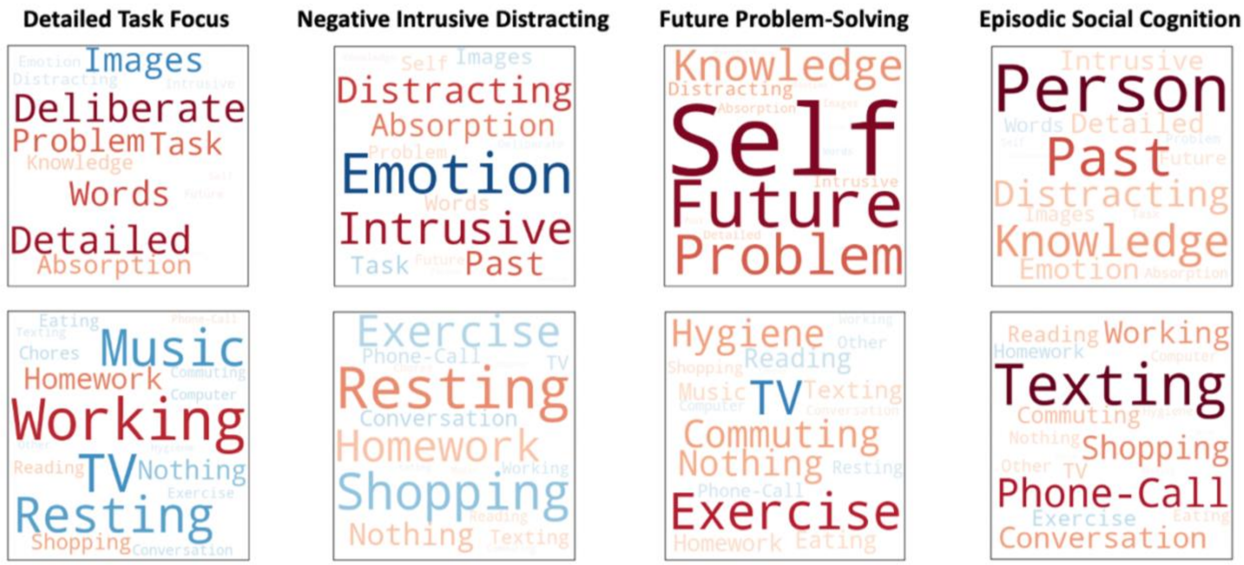
Note. (A) "Episodic social cognition" word cloud. Words represent PCA (varimax) scores for MDES dimensions. Larger fonts are items with more importance (i.e., higher loadings) and colour denotes direction (i.e., warm colours relate to positive loadings). (B) Bar chart comparing mean MDES scores when participants reported they were 1) alone, 2) physically around people but not interacting with them, and 3) physically around people and interacting with them. Error bars represent 99 % CIs. (C) Bar chart comparing mean MDES scores when participants reported they were 1) alone, 2) virtually around people but not interacting with them, and 3) virtually around people and interacting with them. Error bars represent 99 % CIs.

Thought-Activity Mappings

A second goal of our study was to extend research from the laboratory to examine whether associations between activities in the real world and ongoing activities generalized beyond social interaction. In each case we found a significant association between reported patterns of thought and ongoing activities ("Detailed task focus" ($F(17, 1412.80) = 11.73$, $p < .001$), "negative intrusive distracting" ($F(17, 1388.10) = 3.82$, $p < .001$), "future problem-solving" ($F(17, 1395.49) = 4.87$, $p < .001$), "episodic social cognition" ($F(17, 1399.07) = 4.53$, $p < .001$)). To visualize these relationships, we generated a set of word clouds based on activity loadings for each component, and these are displayed in Figure 4. It can be seen that the "detailed task focus" pattern had high loadings when at work or doing homework, the "negative intrusive distracting" pattern had high loadings when resting, doing homework, or doing nothing, the "future problem solving" pattern had high loadings when exercising, and the "episodic social cognition" pattern had high loadings when texting, in conversation, on the phone, shopping, or working.

Figure 4

Thought and Activity Word Cloud Mappings



Note. Words represent PCA (varimax) scores for MDES dimensions and LMM loadings for primary activities. Larger fonts are items with more importance (i.e., higher loadings) and colour denotes direction (i.e., warm colours relate to positive loadings). See Table 4 and Table 6 for specific component loadings.

Table 6

Estimated Marginal Means from LMM Analysis

Component 1				
Primary Activity	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Eating	-0.20	0.09	-0.36	-0.03
Homework	0.40	0.06	0.28	0.52
Chores	-0.20	0.15	-0.50	0.09
Music	-0.46	0.13	-0.70	-0.21
Resting	-0.44	0.09	-0.61	-0.26
Nothing	-0.32	0.10	-0.52	-0.12
Exercise	-0.18	0.20	-0.57	0.21
Hygiene	-0.10	0.18	-0.44	0.25
Reading	0.20	0.20	-0.19	0.59
Shopping	0.32	0.24	-0.16	0.80
Conversation	-0.19	0.10	-0.39	0.01
Phone-Call	0.11	0.16	-0.21	0.42
Texting	-0.14	0.22	-0.56	0.29
Commuting	-0.18	0.20	-0.57	0.22
Computer	-0.20	0.10	-0.38	-0.01
TV	-0.48	0.10	-0.69	-0.28
Working	0.60	0.11	0.38	0.82
Other	-0.02	0.12	-0.25	0.22
Component 2				
Primary Activity	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Eating	-0.04	0.09	-0.22	0.14
Homework	0.23	0.07	0.09	0.37
Chores	0.06	0.15	-0.23	0.35

Music	0.05	0.13	-0.20	0.30
Resting	0.38	0.10	0.19	0.56
Nothing	0.23	0.11	0.02	0.43
Exercise	-0.24	0.19	-0.62	0.14
Hygiene	0.03	0.17	-0.31	0.36
Reading	0.11	0.20	-0.28	0.50
Shopping	-0.32	0.24	-0.78	0.15
Conversation	-0.21	0.11	-0.42	-0.002
Phone-Call	-0.18	0.16	-0.48	0.13
Texting	0.16	0.21	-0.25	0.57
Commuting	0.05	0.20	-0.34	0.43
Computer	0.01	0.10	-0.19	0.21
TV	-0.17	0.11	-0.38	0.04
Working	-0.15	0.12	-0.38	0.08
Other	0.01	0.12	-0.23	0.25

Component 3

Primary Activity	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Eating	0.15	0.09	-0.03	0.33
Homework	0.16	0.07	0.03	0.29
Chores	-0.02	0.15	-0.32	0.28
Music	0.16	0.13	-0.09	0.41
Resting	-0.15	0.09	-0.33	0.04
Nothing	0.30	0.11	0.09	0.50
Exercise	0.62	0.20	0.23	1.01
Hygiene	0.33	0.18	-0.02	0.67
Reading	-0.18	0.20	-0.58	0.21
Shopping	0.13	0.24	-0.35	0.60
Conversation	0.07	0.11	-0.14	0.28
Phone-Call	-0.15	0.16	-0.47	0.16
Texting	0.17	0.21	-0.25	0.59

Commuting	0.32	0.20	-0.07	0.72
Computer	-0.09	0.10	-0.29	0.10
TV	-0.54	0.11	-0.75	-0.33
Working	-0.07	0.12	-0.30	0.16
Other	-0.14	0.12	-0.38	0.11

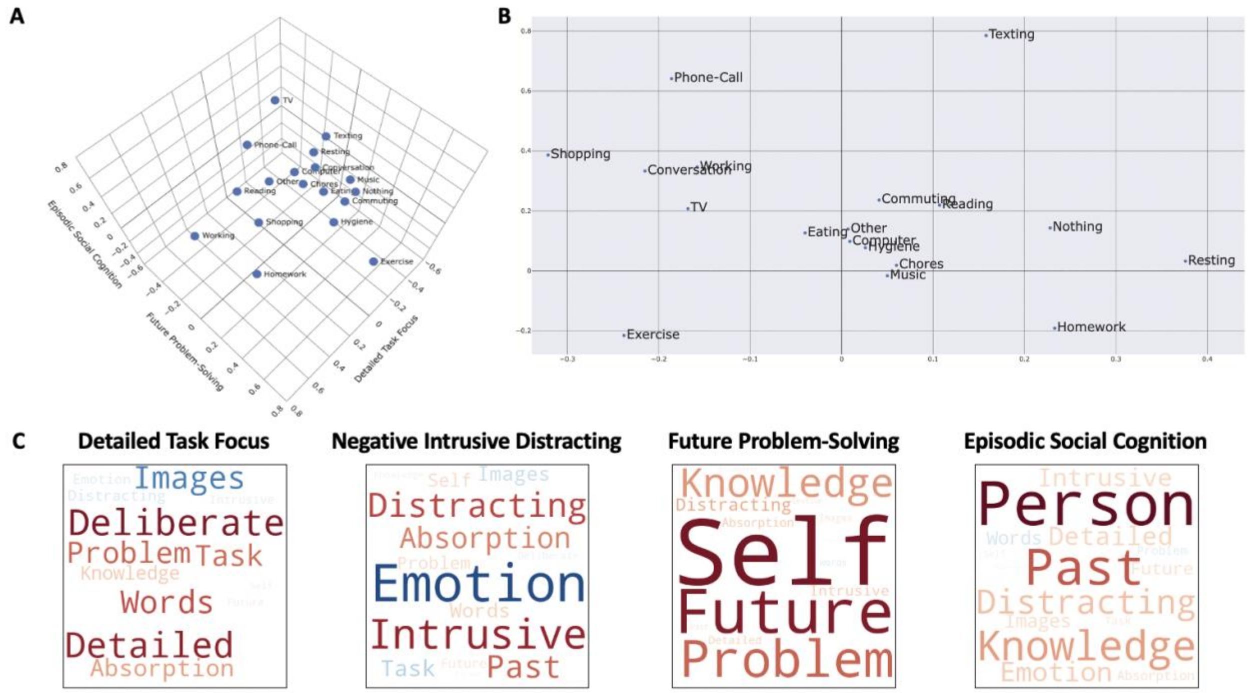
Component 4				
Primary Activity	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Eating	0.13	0.09	-0.05	0.31
Homework	-0.19	0.07	-0.32	-0.06
Chores	0.02	0.15	-0.29	0.32
Music	-0.02	0.13	-0.27	0.24
Resting	0.03	0.09	-0.16	0.21
Nothing	0.14	0.11	-0.06	0.35
Exercise	-0.21	0.20	-0.61	0.18
Hygiene	0.08	0.18	-0.27	0.43
Reading	0.22	0.20	-0.18	0.62
Shopping	0.39	0.25	-0.10	0.87
Conversation	0.34	0.11	0.13	0.55
Phone-Call	0.64	0.16	0.33	0.96
Texting	0.79	0.22	0.36	1.21
Commuting	0.24	0.20	-0.16	0.64
Computer	0.10	0.10	-0.10	0.29
TV	0.21	0.11	-0.01	0.42
Working	0.35	0.12	0.12	0.58
Other	0.14	0.13	-0.10	0.39

Note. Component 1 = “detailed task focus,” component 2 = “negative intrusive distracting,” component 3 = “future problem-solving,” and component 4 = “episodic social cognition.”

One feature of our analysis is that it allows us to understand specific activities as located along several dimensions of ongoing thought. To further visualize these relationships, the unstandardized parameters for each activity derived from the LMMs were plotted against multiple components. For simplicity, in Figure 5 we generated a three-dimensional space constructed from the “episodic social cognition,” “future problem-solving,” and “detailed task focus” components (Figure 5A) and also included a two-dimensional space to capture the relationship between the “episodic social cognition” and the “negative intrusive distracting” thought patterns (Figure 5B). These figures show how certain activities occupy extreme values on multiple components. For example, “working” is high on both “detailed task focus” and “episodic social cognition,” indicating that ongoing thought in this activity is well described by a combination of two components identified by PCA.

Figure 5

Mappings between Thought Patterns and Activities in Daily Life



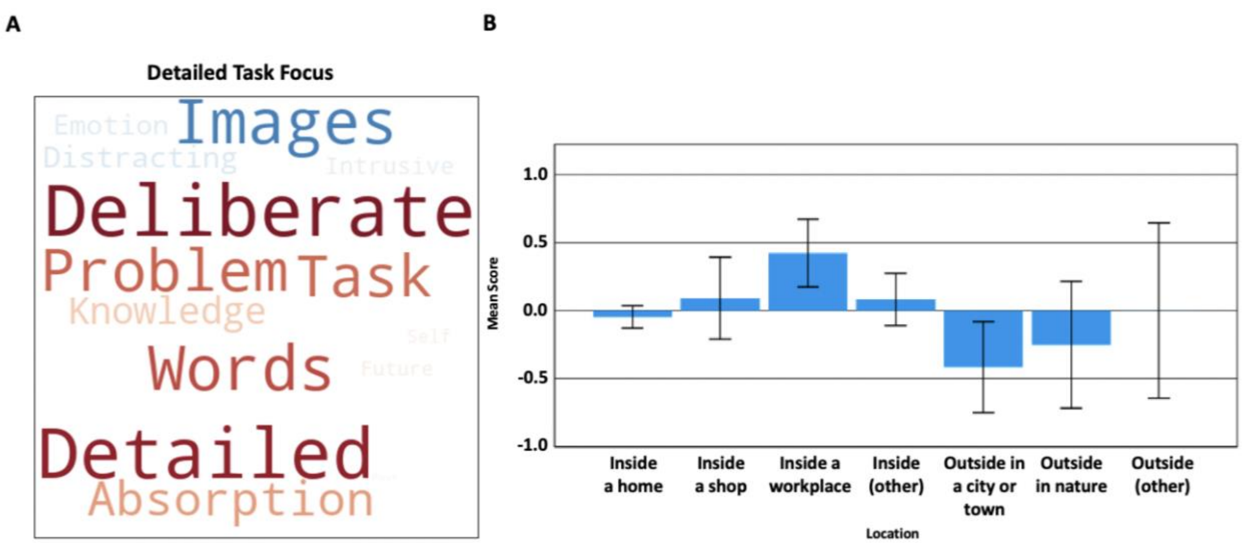
Note. These data are presented in (A) three- and (B) two-dimensional spaces to provide the opportunity to visualize the relationships between activities and multiple dimensions identified in our study in a convenient way. (B) "Episodic social cognition" component loadings can be found on the y-axis, and "negative intrusive distracting" component loadings can be found on the x-axis. (C) Thought word clouds. Words represent PCA (varimax) scores for MDES dimensions. Larger fonts are items with more importance (i.e., higher loadings) and colour denotes direction (i.e., warm colours relate to positive loadings).

The Influence of Physical Location and Time of Day on Ongoing Thought

Having examined the links between activities and thought in daily life, we next turned to our two exploratory aims. First, we explored how physical location (inside vs outside) related to thought patterns. Physical location was a significant predictor of "detailed task focus" thought (F(6, 1397.65) = 6.63, p <.001), which was highest when inside a workplace (Figure 6). Physical location was not associated with any other thought component ("negative intrusive distracting" (F(6, 1376.31) = 0.94, p = .465), "future problem-solving" (F(6, 1382.83) = 0.89, p = .502), and "episodic social cognition" (F(6, 1388.04) = 1.08, p = .374). Next, we explored whether time of day was associated with patterns of ongoing thought. Time of day was a significant predictor for patterns of "detailed task focus" thought (F(5, 1425.23) = 4.32, p <.001) and "episodic social cognition" thought (F(5, 1401.07) = 4.26, p <.001), but not for patterns of "negative intrusive distracting" thought (F(5, 1402.80) = 0.24, p = .943) or "future problem-solving" thought (F(5, 1397.85) = 1.88, p = .095 (Figure 7).

Figure 6

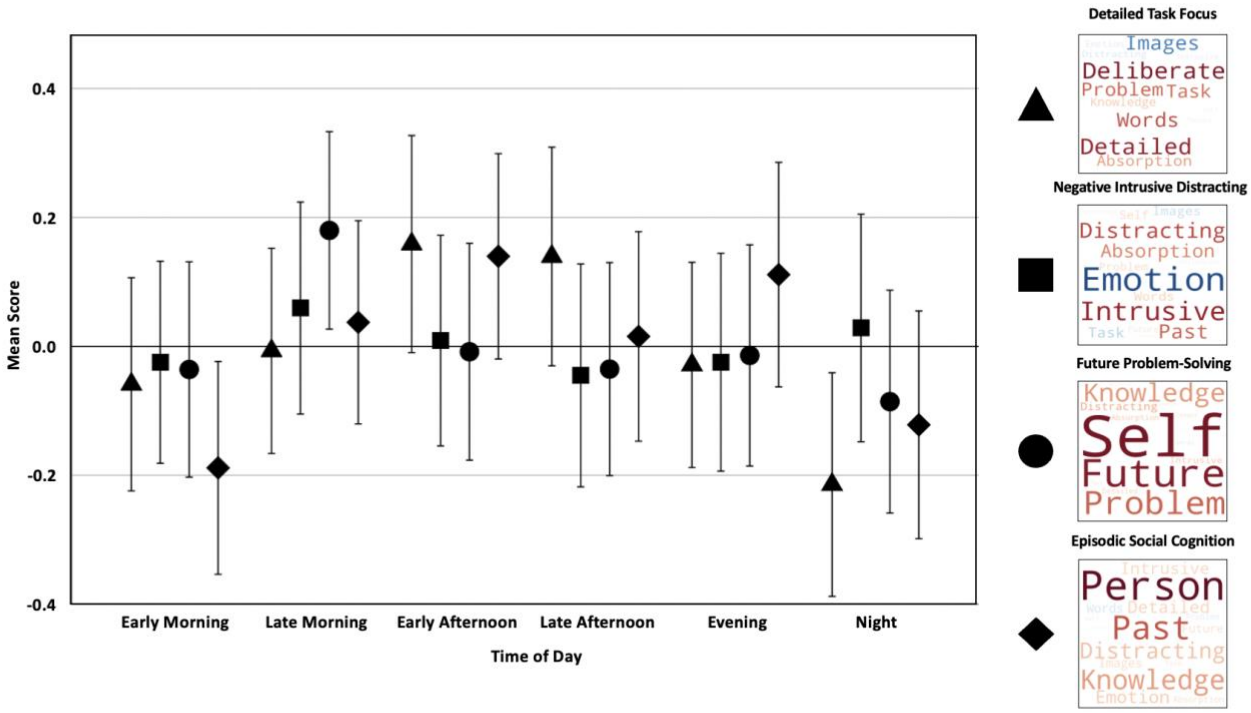
The Influence of Location on Ongoing Thought Patterns



Note. (A) "Detailed task focus" word cloud. Words represent PCA (varimax) scores for MDES dimensions. Larger fonts are items with more importance (i.e., higher loadings) and colour denotes direction (i.e., warm colours relate to positive loadings). (B) Bar chart comparing mean MDES scores when participants reported they were 1) inside a home, 2) inside a shop, 3) inside a workplace, 4) inside (other), 5) outside in a city or town, 6) outside in nature, and 7) outside (other). Error bars represent 99 % CIs.

Figure 7

The Influence of Time of Day on Ongoing Thought Patterns



Note. The graph compares mean MDES scores across different time intervals. “Early morning” = 00:00-10:26:40, “late morning” = 10:33:20-12:26:40, “early afternoon” = 12:33:20-15:06:40, “late afternoon” = 15:13:20-17:40:00, “evening” = 17:46:40-20:26:40, “night” = 20:33:20-23:53:20. Error bars represent 99 % CIs.

Discussion

Our study set out to map patterns of ongoing thought and behaviour across real-world contexts as people went about their daily lives. We hoped that measures of experience generated via MDES would be able to differentiate the context in which the probes occurred, and in particular, the activities that people were engaged in. First, we sought to replicate the influence of socializing on patterns of ongoing thought found in Mckeown et al. (2021). Consistent with that study, we found that participants reported patterns of thought with episodic and social features when they were interacting with people in either a physical or a virtual manner.

We also examined whether MDES can more broadly capture thinking patterns that reflect the sorts of activities participants performed in the real world. Prior studies had established that in the laboratory, MDES can capture patterns of thought that discriminate between the types of tasks that people performed (Diaz et al., 2013; Huba et al., 1982; Konu et al., 2020; McMillan et al., 2013; Smallwood et al., 2021) and vary with measures of brain activity (Konu et al., 2020; Sormaz et al., 2018; Turnbull et al., 2019), pupil dilation (Konishi et al., 2017), and with evoked responses in electroencephalogram (Simola et al., 2023). Therefore, our study hoped to map patterns of thought identified via the application of PCA to MDES data onto activities in daily life. Consistent with this goal we discovered associations between our four ongoing thought patterns captured by MDES and the everyday activities people were engaged in.

First, "detailed task focus" thought patterns were most prevalent when people were working and doing homework. Mckeown et al. (2021) found a similar thought pattern in COVID-19 lockdown populations and Turnbull et al. (2021) also found this pattern to be more prevalent in daily life when tasks were perceived as challenging. In the laboratory, this thought pattern is known to emerge consistently when participants perform tasks requiring executive control such as working memory or task switching (Cardeña & Marcusson-Clavertz, 2016; Konu et al., 2021; Sormaz et al., 2018; Turnbull et al., 2020) and can be associated with better accuracy (Simola et al., 2023).

Second, "negative intrusive distracting" thought patterns were present when resting, doing nothing, and homework. Interestingly, many features of this thought pattern are consistent with the state of rumination (Poerio et al., 2013), and laboratory studies suggests that rumination may be most detrimental when it occurs in situations of high or low demands (Hubbard et al., 2015). Our results reflect the idea that ruminative or intrusive thinking may be more prevalent at the extremes of cognitive demand since this thought pattern was most strongly associated with states of rest (low demand) and homework (high demand).

Third, "future problem-solving" thought patterns were more prevalent during activities like exercise, commuting, and doing nothing in particular. In the lab, this style of thinking emerges when cognitive task demands are lower (Marcusson-Clavertz et al., 2016; Ruby et al., 2013; Turnbull et al., 2020), and can be associated with individuals generating personal goals with greater detail (Medea et al., 2018). Notably, the association with prospection during exercise is consistent with a recent study examining patterns of thought during running in natural settings (Miś & Kowalczyk, 2019).

Fourth, consistent with an association with social cognition (Konu et al., 2021; Mckeown et al., 2021), patterns of "episodic social cognition" thought predominated during activities involving other people, such as conversations, texting, and shopping. Intriguingly, task studies have shown that this thought pattern emerges when people make decisions about themselves or close others (Konu et al., 2021) and brain imaging studies link this thought pattern to medial prefrontal cortex activity (Konu et al., 2020).

Our study established that the patterns identified by PCA are reproducible within our data, however, the order that the components emerged in each half of the data was different (see Figure 2). One possible reason for why this happened is that differences in the activities in each half of the data altered the types of experiences represented in each half of the sample, therefore altering the components that emerged. This is an important question for future research to investigate.

Our exploratory analyses examined the relationship between thought patterns and (1) physical location, and (2) time of day. We first examined how physical location (inside vs outside) was related to thought patterns, finding that “detailed task focus” were highest when participants were inside a workplace and lowest when they were inside (a home, a shop, or other), and outside (in a city or town, in nature, or other). Physical location did not significantly predict the experience of other thought patterns in daily life (i.e., “negative intrusive distracting,” “future problem-solving,” or “episodic social cognition”).

Second, we explored how time of day was reflected in participant responses to MDES probes. “Detailed task focus” patterns were highest in the middle of the day and lowest at night. In contrast, “episodic social cognition” thought patterns were highest in the early afternoon and lowest in the early morning. Note that these exploratory analyses should not be taken to indicate direct consequences of location or time of day on ongoing experience. Instead, they likely reflect the fact that activities are generally more likely to occur in specific locations or at particular times of the day. For example, results relating time of day to “detailed task focus” thought patterns might be dramatically different in a sample of night shift workers who engage with cognitively demanding activities when most other people are asleep. It will be important for future studies to disentangle the specific variables which drive associations between thought patterns and location and time variables, as they are likely mediated by a number of other variables in addition to activity.

In conclusion, our results suggest that patterns of thinking in the real world indirectly reflect the broader ecological contexts in which experiences emerge. Our study suggests that ongoing activities are likely to be important in the types of thoughts a person has, and that other factors such as location or time of day may contribute to this phenomenon less directly. We have established that MDES can differentiate patterns of ongoing thought based on the situations in daily life that people are in, highlighting the value of MDES as a tool for understanding cognition from an ecological perspective. Moreover, because MDES can be used across both controlled and naturalistic settings, as well as in conjunction with brain imaging to reveal the neural correlates of different thought patterns (Konu et al., 2020; Turnbull et al., 2019; Turnbull et al., 2020), it is an especially useful tool for bridging the gap between the experimental control afforded by laboratory studies and the richness and variation that comes with more ecological studies. Ultimately, the ability to harness and combine the advantages of both methods, something enabled with MDES, will facilitate a much needed comprehensive account of real-world cognition (Kingstone et al., 2003; Poerio & Smallwood, 2016).

Although our data establishes the utility of MDES for mapping cognition in daily life, there are also several methodological limitations that should be considered and more fully explored with future research. First, because data collection began during a COVID-19 lockdown, this likely reduced the types of activities participants could self-select, potentially biasing the patterns of thoughts identified towards thoughts that more typically occur when activities are restricted. Thus, while our study clearly shows the utility of MDES in daily life, there may be types of activities, and therefore patterns of experience, that would be captured outside of a lockdown situation. Physical location and time of day may also impact patterns of experience in a similar way, making it important for research to examine ongoing cognition across a range of individuals at different points in their lives.

Second, notification response rate and timing varied across participants, which could relate to participant motivation or possibly activity enjoyment or value. For example, participants may have been less likely to immediately respond, or to respond at all, to a notification during particularly enjoyable activities. Similarly, participants may have been less likely to respond if engaged in an important task requiring concentration. Although we do not have data on the extent to which a participant's current activity affects response rates, it seems reasonable to assume that these factors may systematically alter the prevalence or prevent the discovery of certain thought patterns.

Third, we should note that participants were students enrolled in designated first- and second-year psychology courses, with a mean age of 21.11. Participant age and occupation are likely to be important factors in regard to the types of activities self-selected, and thus, the thought components produced in our study may be less generalizable to a broader, more representative sample (Turnbull et al., 2021).

Fourth, it is important to highlight that potential thought components derived through MDES are always in some way dependent on the selection of questions asked. Although the items we used here show that we can dissociate the links between activity and thoughts, it is likely that other and additional items (that are more relevant to daily life activities) may have better explanatory power for understanding differences in ongoing thought. For example, during the analysis process, it was noted that the "detailed task focus" component was negatively anchored by music and TV. Although images may be a useful characteristic of watching TV, it is less useful as a way to characterize thoughts while listening to music. Future studies using MDES, therefore, could benefit from breaking the modality probe into three questions, giving participants the opportunity to describe their experience in terms of images, words, and/or sounds. Indeed, since MDES dimensions were initially derived to capture aspects of cognition in laboratory settings, it would be prudent to ensure that MDES items used in future studies are expanded to capture greater variation in features of thought and their relevance to cognition as it operates in daily life.

Finally, we close by noting that our results are likely to depend in a complex way on how people select the activities they engage with in daily life. Presumably, unlike laboratory studies, daily life presents individuals with a much wider degree of choice about the tasks they perform (Kahneman et al., 2004; Smallwood et al., 2021), something that should be reflected in ongoing thought patterns. Extraverted people may spend more time socializing and engaged in social cognition, athletic individuals may engage in exercise more often, and those who are more studious may spend more time working and engaged in detailed task focused thought. The role of individual differences such as temperament, expertise, and other dispositional traits likely interact in interesting ways with both the activities that people enjoy or are good at when outside of the laboratory and their associated ongoing consciously experienced thoughts. Perhaps, it is *this* ability to *choose* which activities we engage with in our daily lives that explains why thought patterns captured in the laboratory do not always generalise to the real world (Ho et al., 2020; Kane et al., 2017), where they arguably matter the most.

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