Patterns of Ongoing Thought in the Real World

By

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Abstract

Health and well-being are impacted by our thoughts and the things we do. In the laboratory, studies suggest specific task contexts impact thought processes. More broadly, this suggests the people we are with, the places we are in, and the activities we perform may influence our thought patterns. In this study, participants completed experience sampling surveys for five days in daily life. Principal component analysis decomposed this data to identify common "patterns of thought," and linear mixed modelling related these patterns to the participants' activities. This study replicated the influence of socializing on patterns of thought and established this as part of a broader set of relationships linking activities to how thoughts are organized in daily life. This study suggests that sampling thinking in the real world may help map thoughts to activities, and these "thought-activity" mappings may be useful to researchers and health care professionals interested in health and well-being.

Co-Authorship

This study was conducted at Queen's University in the ThinC Lab by Bridget Mulholland, under the supervision of Dr. Jonathan Smallwood. Bridget Mulholland and Dr. Jonathan Smallwood contributed to study design, with consultations from Dr. Elizabeth Jefferies, Dr. Michael Milham, Dr. Arno Klein, Dr. Adam Turnbull, Dr. Robert Leech, Dr. Giulia L. Poerio, Dr. Brontë Mckeown, Louis Chitiz, Raven Wallace, and Ian Goodall-Halliwell. Data collection was organized by Bridget Mulholland. Formal analysis was completed by Bridget Mulholland, with assistance from Louis Chitiz and Raven Wallace. Figure development was completed by Bridget Mulholland, with assistance from Dr. Brontë Mckeown, Ian Goodall-Halliwell, Louis Chitiz, and Raven Wallace. The final manuscript was written by Bridget Mulholland, with valuable writing and editing contributions from Dr. Jonathan Smallwood, Dr. Brontë Mckeown, Raven Wallace, Louis Chitiz, Dr. Giulia L. Poerio, Dr. Adam Turnbull, Dr. Elizabeth Jefferies, Dr. Arno Klein, Dr. Jeffrey D. Wammes, Aryanna Rastan, Dr. Robert Leech, and Dr. Michael Milham. Funding was acquired by Dr. Jonathan Smallwood and Dr. Jeffery D. Wammes from the Government of Canada's New Frontiers in Research Fund [grant ID NFRF-2021-00183]. The research presented in this thesis has been accepted by Consciousness and Cognition for publication at time of thesis submission.

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List of Abbreviations

C	Component
CI	Confidence interval
COVID-19	Coronavirus disease 2019
DAN	Dorsal attention network
DMN	Default mode network
ES	Experience sampling
F	f-value
fMRI	Functional magnetic resonance imaging
DLPFC	Dorsolateral prefrontal cortex
LMM	Linear mixed model
mDES	Multidimensional experience sampling
MDN	Multiple demand network
O	Oblique rotation
p	p-value
PCA	Principal component analysis
r	Pearson correlation
REML	Restricted maximum likelihood
S	Subset
Std.	Standard
V	Varimax rotation
VAN	Ventral attention network
vmPFC	Ventromedial prefrontal cortex

*	Correlation is significant at the 0.05 level (2-tailed)
**	Correlation is significant at the 0.01 level (2-tailed)

Chapter 1: Introduction and Literature Review

The different types of tasks individuals chose to perform in daily life depend on the contexts individuals find themselves in. The types of activities selected and subsequently, the way these activities are performed and the thoughts associated with these activities, are important when considering health and well-being. A fundamental goal of cognitive neuroscience, therefore, is to understand how brain processes give rise to these different forms of cognition and behaviour. Originally, emphasis was placed on investigating brain regions (e.g., the motor cortex, the somatosensory cortex, etc.). Over time, this emphasis has shifted to include brain networks (e.g., the multiple demand network (MDN), the default mode network (DMN), etc.). More recently, it has become important to understand whole brain states. However, how brain states map onto cognitive function is complicated. One problem is that brain states involve multiple brain networks, making it unclear how these relate to more localized views of function. A second problem is that brain states can be similar across situations that are, at the very least, superficially different (e.g., common regions are activated when people engage in demanding tasks) (Duncan, 2010). As a result, an accurate understanding of brain states depends on mapping how similar cognition is across different activites and other contexts. My research begins exploring this question with a behavioural study that maps thinking in daily life to better understand the landscape of psychological states that, in the future, brain states can be related to.

1.1 Brain States

Brain states are neural snapshots that contain multiple neural features and are, in principle, associated with features of cognition and behaviour that are taking place (Greene et al., 2023). Conceptually, brain states are whole brain phenomena (i.e., they are a combination of multiple neutral networks) and so are assumed to relate to how the co-operation between brain systems leads to cognition and behaviour (Greene et al., 2023). However, we currently lack an understanding of how brain states map onto cognition and behaviour. My research begins to explore this question by mapping thoughts onto activities in daily life, with the ultimate goal of understanding the landscape of cognitive states in daily life, which could be used in future investigations of brain states.

Several important questions arise when considering how to map between brain states and ongoing cognitive function, one of which is, why do similar brain states emerge during superficially different situations? One example of a brain state that emerges in seemingly different contexts comes from work on the MDN. The MDN is a combination of three different networks; when tasks are difficult, the frontoparietal, dorsal attention (DAN), and ventral attention (VAN) networks come together to create the MDN (Duncan, 2006; Duncan, 2010; Japee et al., 2015; Vossel et al., 2014; Wang et al., 2021). Notably, there are a number of different tasks that are difficult and resultantly activate the MDN in similar ways. However, since the MDN is activated in many different situations, the specific set of cognitive and behavioural outputs this system enables is unknown. Another area of research that highlights the complex nature between brain states, cognition, and behaviour comes from research into the DMN (Raichle et al., 2001), which is a distributed system (Smallwood et al., 2021a) implicated in a wide range of tasks, such as some types of social thinking (Frith & Frith, 1999) and past and future mental time travel (as mentioned by Endel Tulving in Struss & Knight, 2002). Research into the DMN and the MDN highlight how common brain states can emerge in different situations. This highlights the value of understanding how people think in different situations, as this will help researchers understand why similar brain states can emerge in a range of different contexts.

One possible reason why similar brain states emerge in different contexts is because the brain states may share certain cognitive similarities. For example, the MDN may be important in situations that depend on focused attention or cognitive effort (Duncan, 2010), while the DMN may emerge when cognition and behaviour is guided by information from memory (Smallwood et al., 2021a). In order to move beyond a descriptive account of the links between different states, cognition, and behaviour, it will be important to better understand the cognitive similarities of different contexts. To do so, it will be necessary to sample multiple contexts and understand how cognition changes across them. Thus, an overarching goal of my research is to begin to understand mapping between cognition and brain function in different contexts, and I begin to unpack this question by sampling thinking during activities in the real world to understand the cognitive similarities across contexts in daily life. In the future, this data will be important in helping researchers understand how brain states map onto cognition.

1.2 Mapping Brain States onto Contexts

Similar patterns of neural activity can be linked to a variety of different contexts. The MDN and the DMN are classic examples of this puzzling phenomena, as both are important networks for a variety of different contexts. Previous research has indicated that increased neural activity in the DMN is important for self-relevant thinking (Kelley et al., 2002), some types of social thinking (Frith & Frith, 1999), past and future mental time travel (as mentioned by Endel Tulving in Struss & Knight, 2002), and some types of mental imagery (Hassabis & Maguire, 2007). While these situations are different, they do all share a reliance on information from memory (Smallwood et al., 2021a). Similar to the DMN, research on the MDN emerges in many different situations. Research has indicated that increased neural activity in the MDN is associated with new task assembly (Dumontheil, Thompson, & Duncan, 2011), novel problem-solving, and attention demanding tasks (Duncan, 2010). Cognitive features such as focus, rapid reorganization, and intentional separation of task steps may be linking features (Duncan, 2010). Although these situations are all superficially different, they require the application of cognitive effort, and therefore may be linked to processes like executive control (Duncan, 2010).

The importance of the MDN and the DMN across a variety of different tasks provides evidence that brain states may be similar across many different contexts. Accordingly, if brain states are important across different situations, it would be helpful to map cognition across these different situations to better understand the landscape of thoughts to which these states need to be mapped. To be able to map between cognition and activities, it will be important to map cognition across many situations, which could be very expensive if using techniques like functional magnetic resonance imaging (fMRI). My research will begin to address this issue by developing a methodology that can relate patterns of ongoing thought to the contexts that people find themselves in, in daily life.

1.3 Mapping Cognition onto Contexts

My research begins with a focus on methodologically mapping out the high level relationship between cognition and activities. Specifically, I will map patterns of ongoing thought onto activities individuals are performing in the real world. Accordingly, by understanding thought-activity mappings in daily life, I hope to create a framework that provides normative data describing peoples’ thoughts across contexts. Understanding how cognition changes during different activities (and other contexts) within my framework will eventually allow for the future integration of brain activity, ultimately helping researchers to better understand brain states.

To begin to address thought-activity mappings, I chose to use multidimensional experience sampling (mDES), which is sensitive to different contexts (allowing me to map between cognition and activities) and also brain activity (allowing me to eventually expand to mapping between cognition and brain states). One reason that mDES is a useful starting point for my research is because previous studies have illustrated that mDES is sensitive to differences in cognition between activities in the lab and daily life. For example, a recent study by Konu et al. (2021) used mDES to investigate the influence of a variety of different laboratory task contexts on patterns of ongoing thought. Konu et al. (2021) discovered that different laboratory task contexts contribute to different patterns on ongoing thought. Building on these results, Mckeown et al. (2021) used mDES to highlight the relationship between cognition and specific contexts in daily life (e.g., primary activities). Mckeown et al. (2021) discovered that behavioural changes, notably ones that reduced opportunities for certain activities, also related to patterns of ongoing thought. These studies by Konu et al. (2021) and Mckeown et al. (2021) indicate an ability to effectively use mDES as a tool to map between cognition and different contexts in daily life, and resultantly, suggest that mDES can be utilized to determine how cognition changes during different activities.

A second reason why mDES is relevant to my research is that it has recently been shown to be sensitive to brain activity. A study by Turnbull et al. (2019) used mDES to investigate the prioritization of off-task thought when external task demands were low. Participants alternated between tasks with high cognitive demand (1-back task, which relies heavily on working memory) and tasks with low cognitive demand (0-back task) in laboratory and fMRI settings. mDES was used to sample task experience. Results showed that in the fMRI, the 0-back task increased off-task personally relevant thinking (when compared to the 1-back task). Further, principal component analysis (PCA) was used to decompose the mDES data, identifying an off task thought component for each task type. fMRI analysis also indicated increased off-task thinking during the 0-back task and increased on-task thinking during the 1-back task was linked to increased neural activity in the left dorsolateral prefrontal cortex (DLPFC). Specifically, neural activity in the left DLPFC correlated with on-task thinking when task demand was high and off-task thinking when task demand was low, indicating that the left DLPFC is activated in similar ways when the type of ongoing thought matches the demands of the external environment, highlighting the importance of context consideration as a factor for variation in ongoing thought. Moreover, the results of Turnbull et al. (2019) highlight the need for improved (i.e., more accurate) task selection (i.e., tasks that capture what people are thinking about in daily life) to better represent certain contexts researchers wish to further investigate in the real world, the laboratory, and in the scanner.

A study by Konu et al. (2020) also established that mDES data is sensitive to variation in brain activity. Building on Turnbull et al. (2019), participants completed a single task with low attentional demands (Go/No-go), in an effort to better understand patterns of ongoing thought produced under these environmental conditions and to better detect brain activity associated with certain thought patterns. As per Turnbull et al. (2019), mDES was used to sample task experience. Three different thought patterns, “off-task episodic social cognition,” “deliberate task focus,” and “intrusive verbal self-relevant” were discovered. When investigating possible associated brain regions, results indicated that the ventromedial prefrontal cortex (vmPFC) was significantly more active during thought patterns with off-task episodic social cognition features. Notably, the vmPFC overlaps with the DMN, which has previously been linked to memory and people, indicating an ability to map activities and tasks to brain regions and states via cognition.

Research such as Turnbull et al. (2019) and Konu et al. (2020), therefore, establish that mDES is sensitive to brain activity and thus a viable indirect proxy for brain activity, making it a good tool to use to map between cognition in daily life.

When considered together, research such as Konu et al. (2021), Mckeown et al. (2021), Turnbull et al. (2019), and Konu et al. (2020) highlight that mDES can (a) map cognition across contexts, and (b) is sensitive to variation in brain activity. My research, which began during a lockdown situation when data collection in an fMRI scanner was not possible, uses mDES to understand state-level differences in task and context that drive thought patterns in daily life. In the future, I hope to extend this framework created by mDES to provide more direct insights into relationships between brain states and cognition.

1.4 Thoughts in Daily Life

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., 2021b). 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 when determining 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., 2021b). 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., 2020 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., 2021b). 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).

My research sought to build upon and extend these approaches via the use mDES, a specific type of ES 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 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., 2021b, 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. The central goal in this study was 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, Mckeown et al. (2021) 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), I 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, I 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 I 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 ES method to understand how different levels of atypical mental states affected 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” predominated as a mode of thinking during tasks requiring thinking about the self and others but not when watching affective TV clips or engaging in working memory tasks. In contrast, “detailed task focus” 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 is addressed in my research.

I had two additional exploratory questions more specific to real-world contexts. First, I was 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 me to sample thinking in a variety of different locations for this study, I also ascertained whether the participants were indoors or outdoors when the probe occurred. Using this data, I explored whether this impacted their experience. Second, I was 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), I 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 this 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, I expected that social activities would be related to higher rates of social thinking patterns (Mckeown et al., 2021). Second, I 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, I aimed to discover whether mDES was linked to variation in location and/or time of day.

Chapter 2: Materials and Methods

2.1 Participant Population

A total of 101 participants (women = 83, men = 13, non-binary = 2, did not specify = 3; age: mean = 21.11; standard deviation = 5.33; range = 18 to 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.

2.2 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 (participant response rate: mean = 14.44/40 (36.1%), standard deviation = 11.04). Each prompt was randomly delivered within a specific two-hour time interval (arriving no later than 30 minutes before the end of the associated two-hour time interval). The availability of each applet was limited to the duration of the associated 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.

2.3 Multidimensional Experience Sampling (mDES) 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 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.

2.4 Analysis

2.4.1 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.

2.4.2 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.”

2.4.3 Component Reliability Analysis

Component reliability analysis was conducted in IBM SPSS (version 28). All mDES data was randomly shuffled and divided into two halves (subsets), with each subset 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 me to estimate whether the component structure seen in the whole sample is generalizable to subsets of the data.

2.4.4 Linear Mixed Modelling (LMM): Physical and Virtual Social Environments

To analyze contextual distributions of thought in relation to social settings in physical and virtual environments, I 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 (categorical) 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. Restricted maximum likelihood (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).

2.4.5 Linear Mixed Modelling (LMM): Primary Activity

To analyze contextual distributions of thought in relation to activities, I conducted a series of LMMs, one with each thought component as the dependent variable and activity as the (categorical) 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. 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.

2.4.6 Linear Mixed Modelling (LMM): Physical Location

To analyze contextual distributions of thought in relation to physical location, I conducted a series of LMMs, one with each thought component as the dependant variable and physical location as the (categorical) 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).

2.4.7 Time of Day Categorization

Analysis of activity time was assessed using IBM 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

Note. Gaps between time bins represent periods of time where no prompts were responded to.

2.4.8 Linear Mixed Modelling (LMM): Time of Day

To analyze contextual distributions of thought in relation to time of day, I conducted a series of LMMs, one with each thought component as the dependant variable and time of day as the (categorical) 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 the 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).

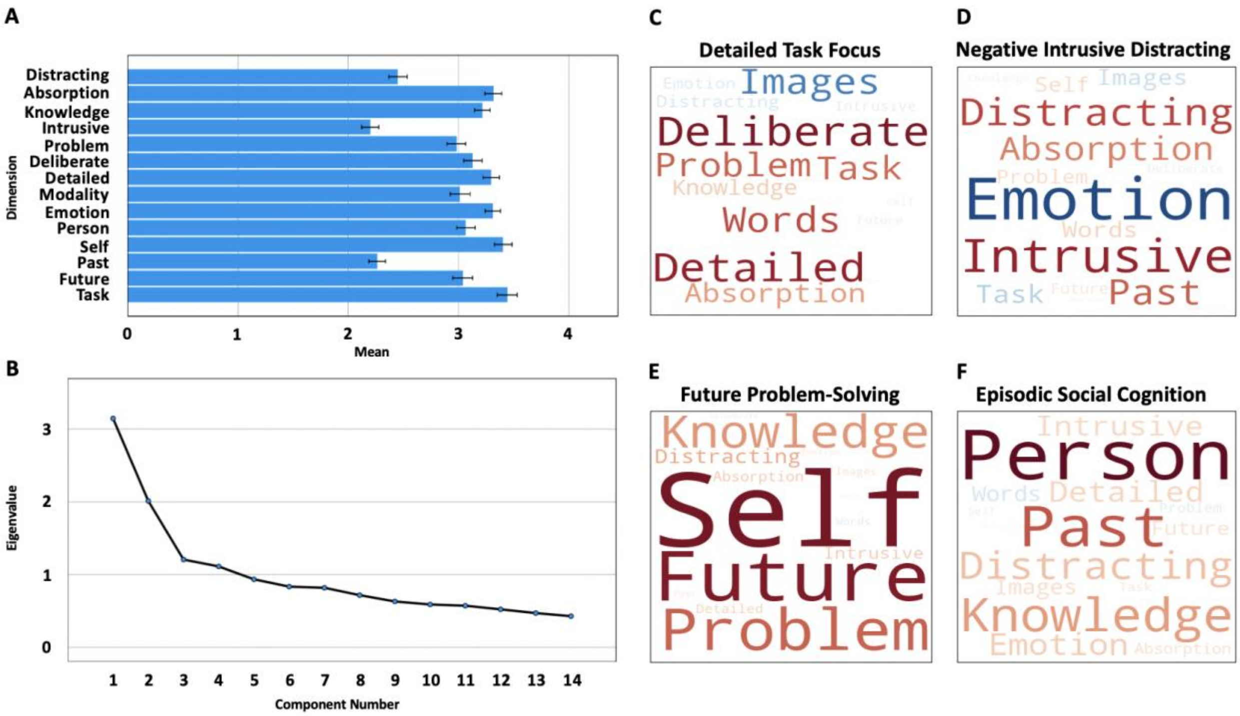
Chapter 3: Results

3.1 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 dimensions such as “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



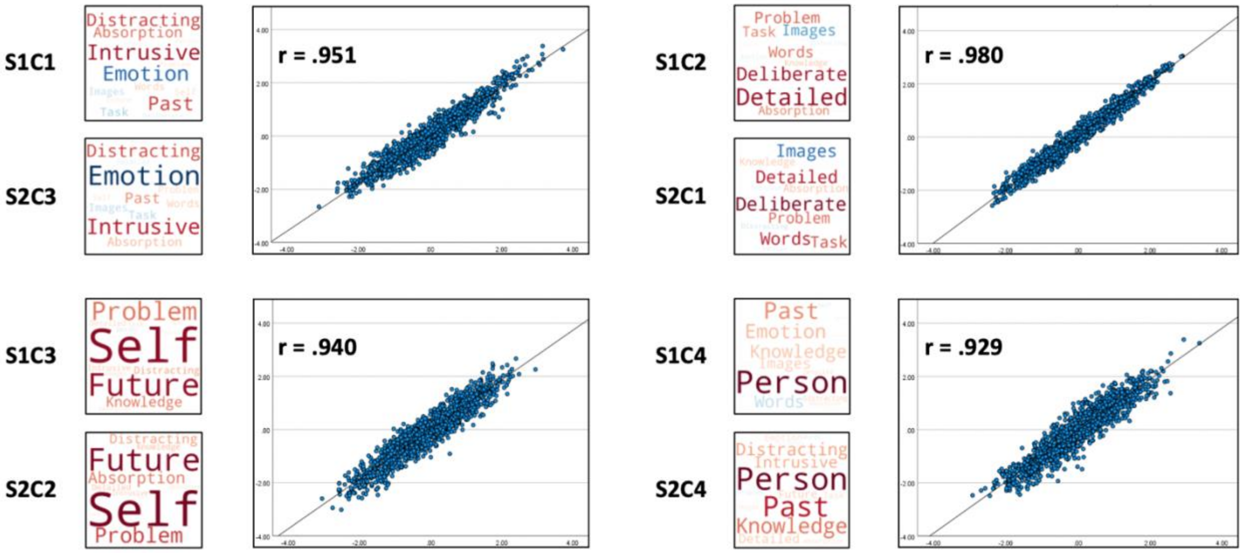
Note. (A) Horizontal bar graph of mean dimension scores. Error bars represent 99% confidence intervals (CIs). (B) Scree plot generated from PCA of mDES data. (C-F) Thought word clouds. Words represent PCA (varimax) scores for mDES dimensions. Larger fonts are items with more importance (i.e., higher 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.

3.2 Component Reliability Results

To further understand the robustness of the components from my analysis, I conducted a split-half reliability for my sample. In this analysis, I divided my data into two random samples and then examined how the components generated in each half of the data related to each other. I 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. I also conducted a supplementary analysis in which I 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-.998), but for consistency with other studies using similar methods, I used components derived using varimax rotation.

Figure 2

4-Component Solution Reliability Analysis



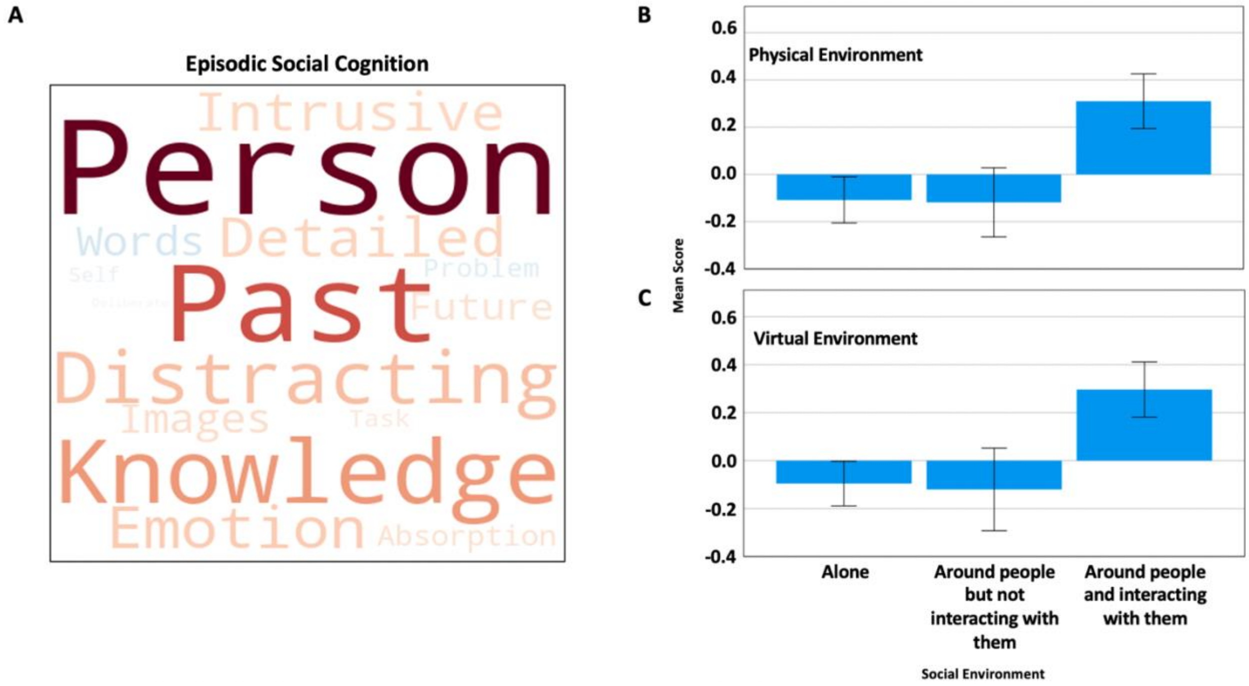
Note. Scatter plot of average homologue similarity. "S" indicates subset, and "C" indicates component. Component scores for subset 1 are found on the y-axes and component scores for subset 2 are found on the x-axes.

3.3 The Influence of Socializing on Ongoing Thought

The first goal of this study was to replicate the influence of socializing on patterns of ongoing thought, as seen in Mckeown et al. (2021). To do so, I 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.

3.4 Thought-Activity Mappings

A second goal of the 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 I 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), and "episodic social cognition" (*F*(17, 1399.07) = 4.53, *p* <.001)). To visualize these relationships, I 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 Linear Mixed Modelling (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

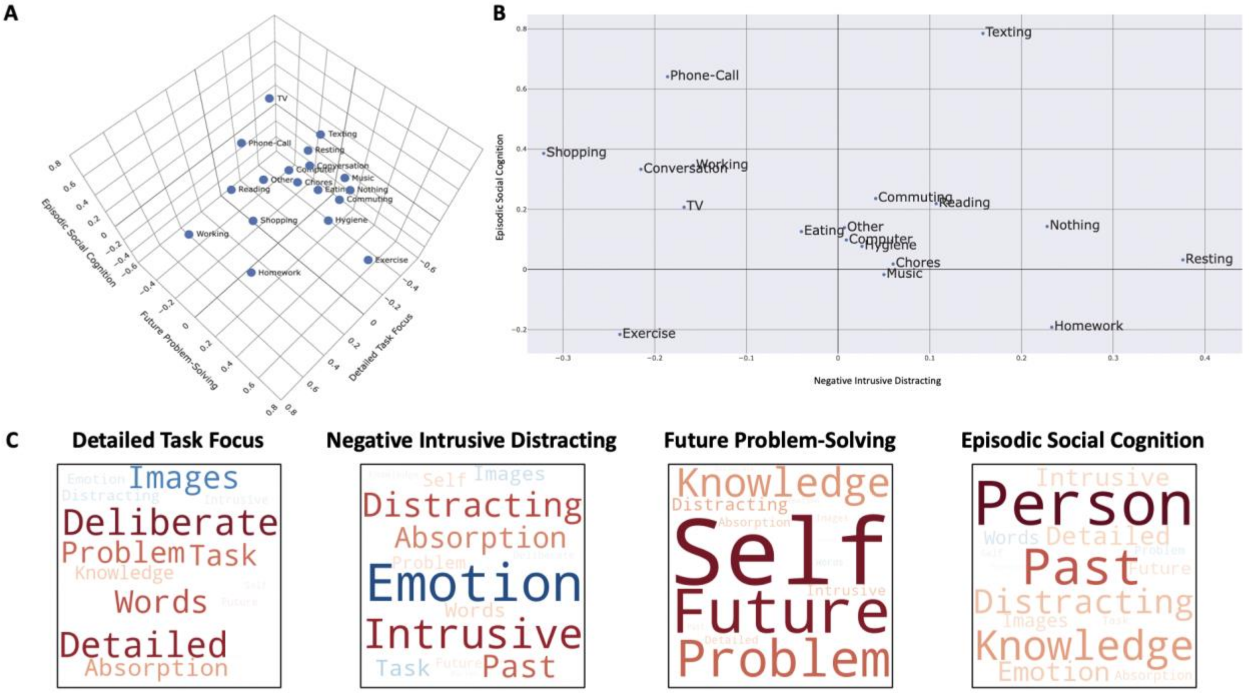
Primary Activity	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Eating	0.13	0.09	-0.05	0.31
Homework	-0.19	0.07	-0.32	-0.06
Chores	0.02	0.15	-0.29	0.32
Music	-0.02	0.13	-0.27	0.24
Resting	0.03	0.09	-0.16	0.21
Nothing	0.14	0.11	-0.06	0.35
Exercise	-0.21	0.20	-0.61	0.18
Hygiene	0.08	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 my analysis is that it allows for an understanding of 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, I 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



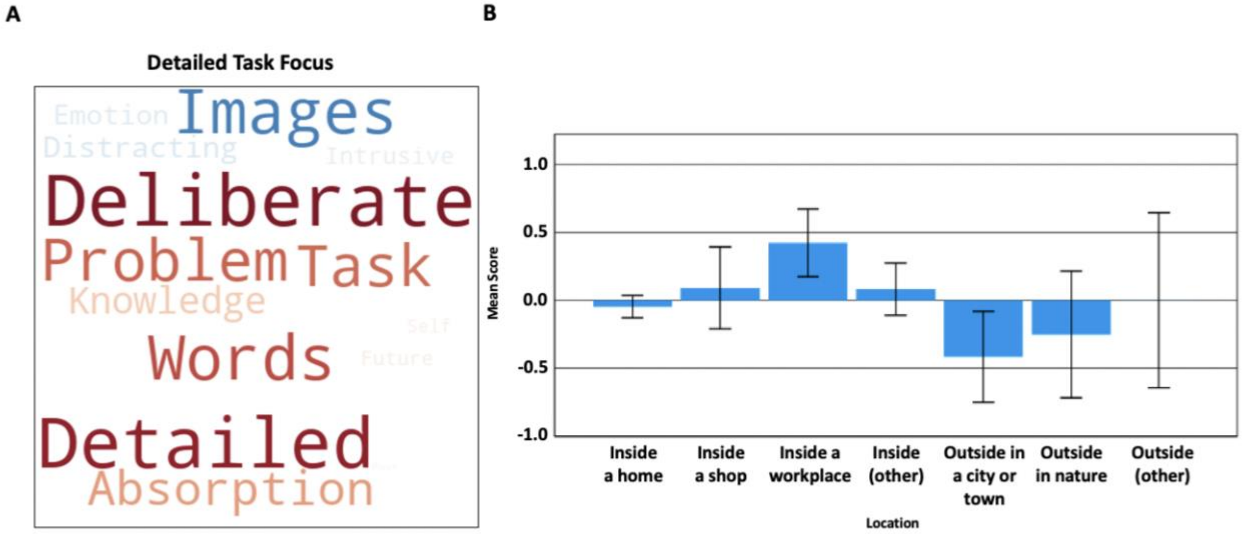
Note. These data are presented in (A) three- and (B) two-dimensional spaces to provide the opportunity to visualize the relationships between activities and multiple dimensions identified in the study in a convenient way. (C) Thought word clouds. Words represent PCA (varimax) scores for mDES dimensions. Larger fonts are items with more importance (i.e., higher loadings) and colour denotes direction (i.e., warm colours relate to positive loadings).

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

Having examined the links between activities and thought in daily life, I next turned to the two exploratory aims. First, I explored how physical location (inside versus 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, I 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) = .24, *p* = .943) or “future problem-solving” thought (*F*(5, 1397.85) = 1.88, *p* = .095) (Figure 7).

Figure 6

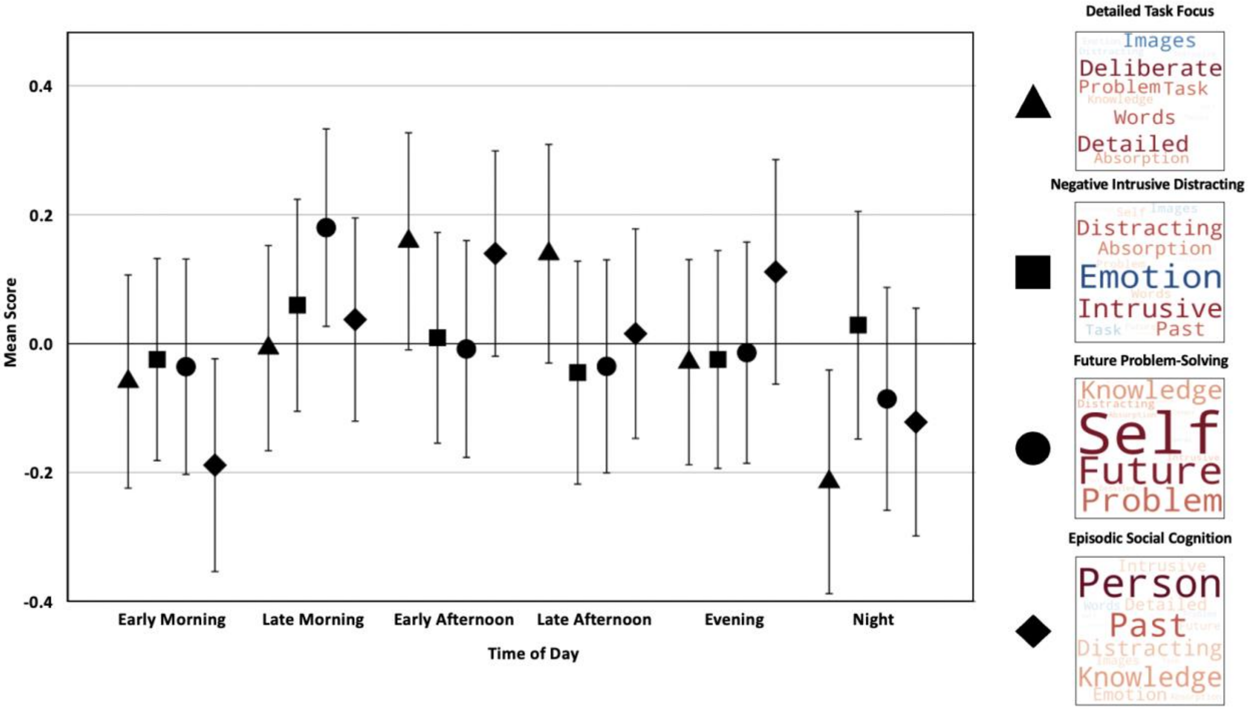
The Influence of Location on Ongoing Thought Patterns



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, or 7) outside (other). Error bars represent 99% CIs.

Figure 7

The Influence of Time of Day on Ongoing Thought Patterns



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

Chapter 4: Discussion

This study set out to map patterns of ongoing thought and behaviour across real-world contexts as people went about their daily lives. I 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, I sought to replicate the influence of socializing on patterns of ongoing thought found in Mckeown et al. (2021). Consistent with that study, I 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.

I 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., 2021b) 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, this 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, I discovered associations between 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). These 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).

This study established that the patterns identified by PCA are reproducible within this 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.

The exploratory analyses examined the relationship between thought patterns and (1) physical location, and (2) time of day. I first examined how physical location (inside versus outside) was related to thought patterns, finding that the “detailed task focus” thought pattern was highest when participants were inside a workplace and lowest when they were outside in a city or town. 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, I 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, location, and time variables, as they are likely mediated by a number of other variables in addition to activity.

In conclusion, these results suggest that patterns of thinking in the real world indirectly reflect the broader ecological contexts in which experiences emerge. This 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 contribution to this phenomenon less directly. I 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 the data establishes the utility of mDES for mapping cognition in daily life, there are also several open questions 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 my 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 I 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, I 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 the 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 used here show that I 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, as seen in Figure 5, my approach allowed me to position activities into a low dimensional space as described by self-report. In the future, this may be able to organize activities of daily life in terms of their similarities (or differences) within self-reported experience. This would therefore provide a map of similarities (or differences) between activities that could be used to generate hypotheses about underlying mechanisms and trait variations (e.g., personality and/or psychiatric disorders like depression). To achieve this goal, it will be necessary to replicate the associations seen in the current data set.

I close by noting that these 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., 2021b), something that should be reflected in ongoing thought patterns. Extroverted 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.

Chapter 5: Future Implications

My research used mDES to successfully map between cognition and contexts (such as activities in daily life). The success of mDES mapping between cognition and activities in the real world, coupled with prior studies linking mDES thought patterns to brain states, suggests this framework may be useful in the future when mapping between cognition and brain states. Specifically, the mapping between mDES thought patterns and activities in daily life may help researchers understand brain states recorded in the scanner or in the behavioural laboratory. For example, as seen in Konu et al. (2020), cognition anchored to “deliberate” and “detailed” thoughts relates to cognitively demanding activities, such as working memory tasks, or gambling, in the laboratory. This means that the laboratory task found by Konu et al. (2020) may generalize to situations in daily life where a similar pattern was present (e.g., working). In addition, Turnbull et al. (2019) discovered that brain activity patterns in the DLPFC associated with external task focus were also related to “detailed” thoughts. Notably, the DLPFC, which is active during complex and demanding tasks (Kaller et al., 2011), is associated with regions of the MDN (Jung et al., 2022), which is also implicated in difficult tasks (Duncan, 2006; Duncan, 2010; Japee et al., 2015; Vossel et al., 2014; Wang et al., 2021). By extrapolating from my research, therefore, it is possible that the DLPFC plays a role in the maintenance of deliberate thoughts in daily life. Since mDES can be used to sample experience in the daily life, in the lab, and in the scanner (which is associated with brain activity), it may provide a general method for mapping between experiences in real life, which are ecologically valid, and brain states assessed using the tools of neuroscience.

Further, mDES may provide answers to both conceptual and specific questions regarding how to map cognition onto brain states. As noted, prior studies suggest that brain states may relate to superficially different situations. Resultantly, seemingly unrelated activities may activate the same or similar brain states. For example, thoughts about other people (Schurz et al., 2021) and thoughts about the future (Schacter et al., 2017), which have objective differences in terms of context (i.e., social thoughts versus future-planning thoughts), are both associated with the DMN. Patterns of thought identified by mDES, for example, could provide insight into what cognitive similarities there are between social cognition and prospection. Similar conclusions can be made for the MDN. For example, the MDN is associated with activities like homework and working. My research has indicated that homework and working are both heavily anchored by detailed and deliberate thinking. This pattern of thought identified by mDES may provide insight into other types of activities (e.g., studying, driving, learning a new task, etc.) that the MDN might be active during.

The goal of my research was 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. My research indicates that cognition has many experiential features that can be mapped onto activities of daily life. Assuming mDES can be extended to mapping cognition and brain activity (based on the success of my research), I have created a methodology that will give researchers the ability to strengthen their understanding of the neurological landscape of specific contexts and states. The use of mDES to map between activity, cognition, and brain activity may be used in the future to continue to unpack these phenomena by providing insight into how many different contexts specific brain states relate to, and differences within how specific brain states relate to the contexts under which they unfold.

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Appendix A: Research Ethics Board Approval

Queen's University Health Sciences & Affiliated Teaching Hospitals Research Ethics Board (HSREB)
HSREB Initial Ethics Clearance
January 19, 2022
Bridget Mulholland
Centre for Neuroscience Studies
Queen's University
TRAQ #: 6035084
Department Code: PSYC-257-21
Supervisor: Dr. Jonathan Smallwood
Co-Investigators: Mr. Ian Goodall-Halliwell
Review Type: Delegated
Date Ethics Clearance Issued: January 19, 2022
Ethics Clearance Expiry Date: January 19, 2023

Dear Mulholland:
The Queen's University Health Sciences & Affiliated Teaching Hospitals Research Ethics Board (HSREB) has reviewed the application and granted ethics clearance for this study as of the date noted above.

Document Name	Comments	Version Date
Debriefing Form/Letter	Written debriefing form	2022/01/17
Questionnaire	Questionnaire	2022/01/17
Other document	Demographic information form	2022/01/17
Letter of Information/Consent Form (combined document)	Letter of information and consent form	2022/01/17
Data Summary Sheet	Data collection: Participant identification and demographic information form	2022/01/17
Data Summary Sheet	Data collection extraction form	2022/01/17

Documents Acknowledged:
- Ethics Training Certificates

Amendments: No deviation from, or changes to the protocol, informed consent form and conduct of study should be initiated without prior written clearance or an appropriate amendment event from the HSREB, except when necessary to eliminate immediate hazard(s) to study participants or when the change(s) involves only administrative or logistical aspects of the study.

Renewals: An annual renewal event form or a study closure event form must be submitted annually as per the TCPS 2 Article 6.14. As a courtesy, the Office of Research Ethics Compliance may send reminders 30 days in advance of the ethics clearance expiry date. All lapses in ethics clearance will be documented on the annual renewal clearance letter. A Suspension letters may be issued for lapses in ethics clearances, with subsequent termination and closure of the ethics file for lapses greater than 10 business days. Terminations should be reported to regulatory authorities (e.g., Health Canada, FDA) as applicable.

Completion/Termination: The HSREB must be notified of the completion or termination of this study through the submission of a study closure event form in TRAQ.

Reporting of Serious Adverse Event (SAE)/Privacy Breach: Any SAEs that meet the HSREB reporting criteria (i.e. definition of an unanticipated problem) and all privacy breaches must be reported as outlined in 410 HSREB Reporting Adverse Events.

Reporting of Complaints: Any complaints made by participants or persons acting on behalf of participants must be reported to the HSREB within 7 days of becoming aware of the complaint using the protocol deviation event form. If your study is registered you are responsible for ensuring that the registration information is accurate and complete.

Regards,

Albert F. Clark.

Albert F. Clark, PhD
Chair, Queen's University Health Sciences and Affiliated Teaching Hospitals Research Ethics Board

The HSREB operates in compliance with, and is constituted in accordance with, the requirements of the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TCPS 2); the international Conference on Harmonisation Good Clinical Practice Consolidated Guideline (ICH GCP); Part C, Division 5 of the Food and Drug Regulations; Part 4 of the Natural Health Product Regulations;

Part 3 of the Medical Devices Regulations, and the provisions of the Ontario Personal Health Information Protection Act (PHIPA 2004) and its applicable regulations. The HSREB is qualified through the CTO REB Qualification Program and is registered with the U.S. Department of Health and Human Services (DHHS) Office for Human Research Protection (OHRP). Federalwide Assurance Number: FWA#: 00004184, IRB#: 00001173. HSREB members involved in the research project do not participate in the review, discussion or decision.

Appendix B: Supplementary Tables

Table S1

Variance Explained by Component

Component	Eigenvalue	% of Variance	Cumulative % of Variance
1	3.15	22.48	22.48
2	2.01	14.38	36.86
3	1.21	8.62	45.48
4	1.11	7.94	53.42
5	.94	6.68	60.10
6	.84	5.96	66.06
7	.82	5.85	71.91
8	.72	5.12	77.03
9	.63	4.51	81.54
10	.59	4.21	85.75
11	.57	4.09	89.84
12	.52	3.73	93.57
13	.47	3.37	96.94
14	.43	3.06	100.00

Table S2

Pearson Correlation between PCA with Varimax Rotation and PCA with Oblique Rotation

Component	Values	Component			
		Varimax 1	Varimax 2	Varimax 3	Varimax 4
Oblique 1	r	.109**	.142**	.978**	.110**
	p	<.001	<.001	.000	<.001
Oblique 2	r	.996**	-.003	.085**	.006
	p	.000	.904	.001	.812
Oblique 3	r	-.032	-.998**	-0.055*	.030
	p	.226	.000	.036	.259
Oblique 4	r	-.001	.131**	.126**	.983**
	p	.955	<.001	<.001	.000

Note. r = Pearson correlation. p = p-value. ** = Correlation is significant at the 0.01 level (2-tailed). * = Correlation is significant at the 0.05 level (2-tailed). Component positions differ for the varimax and oblique rotations. The first varimax component corresponds to the second oblique component, the second varimax component corresponds to the third oblique component, the third varimax component corresponds to the first oblique component, and the fourth varimax component corresponds to the fourth oblique component.

Table S3

Thought Data Component Loadings Generated by PCA with Oblique Rotation

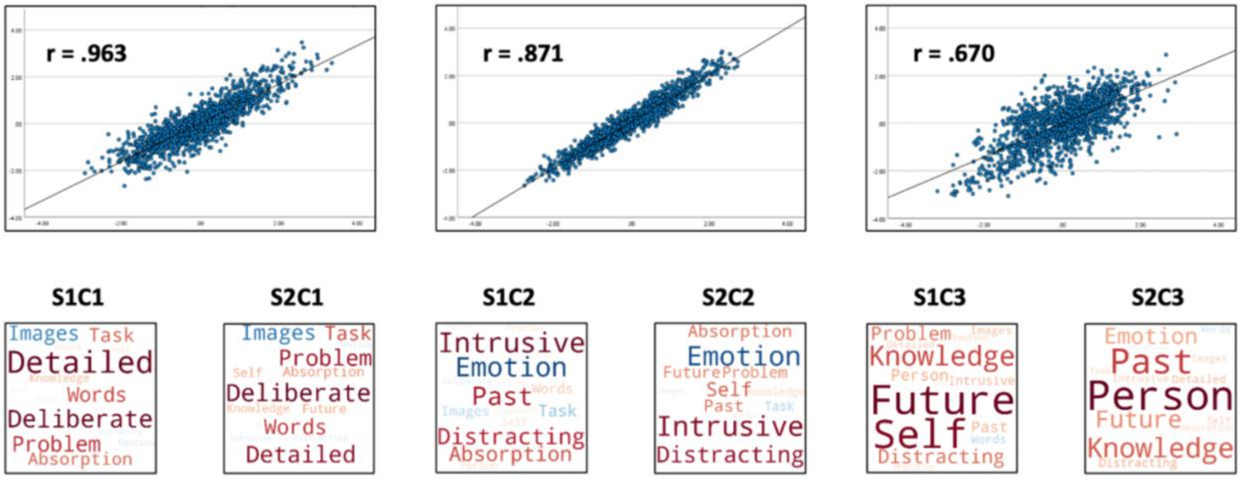
Dimension	Component			
	1	2	3	4
Task	.04	.50	.27	.07
Future	.78	-.03	.03	.04
Past	-.01	-.02	-.44	.57
Self	.83	-.05	-.06	-.15
Person	-.14	.02	.07	.87
Emotion	.11	-.09	.80	.18
Modality	-.16	.58	-.24	-.13
Detailed	.11	.71	.02	.18
Deliberate	-.001	.77	.04	-.03
Problem	.50	.45	-.10	-.15
Intrusive	.18	-.12	-.67	.18
Knowledge	.34	.19	.05	.33
Absorption	.16	.34	-.40	.12
Distracting	.30	-.18	-.52	.24

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

Appendix C: Supplementary Figures

Figure S1

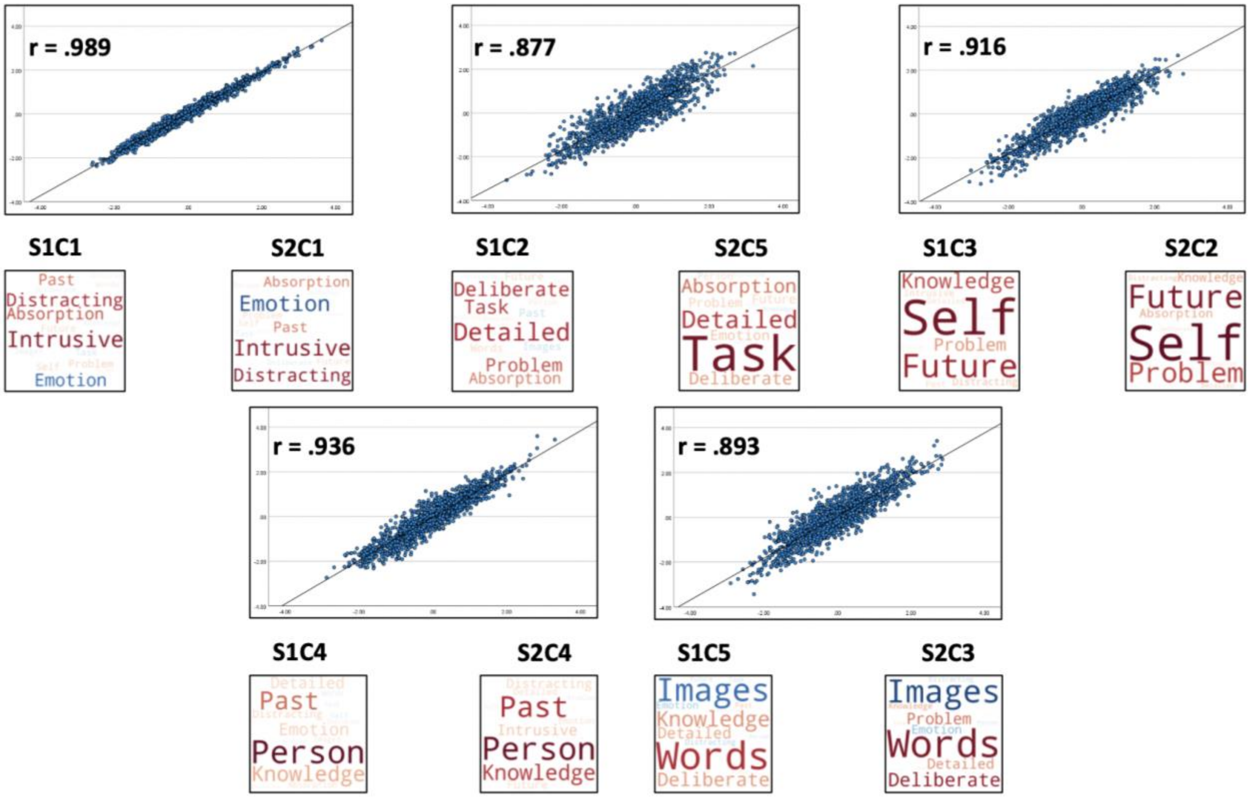
3-Component Solution Reliability Analysis



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

Figure S2

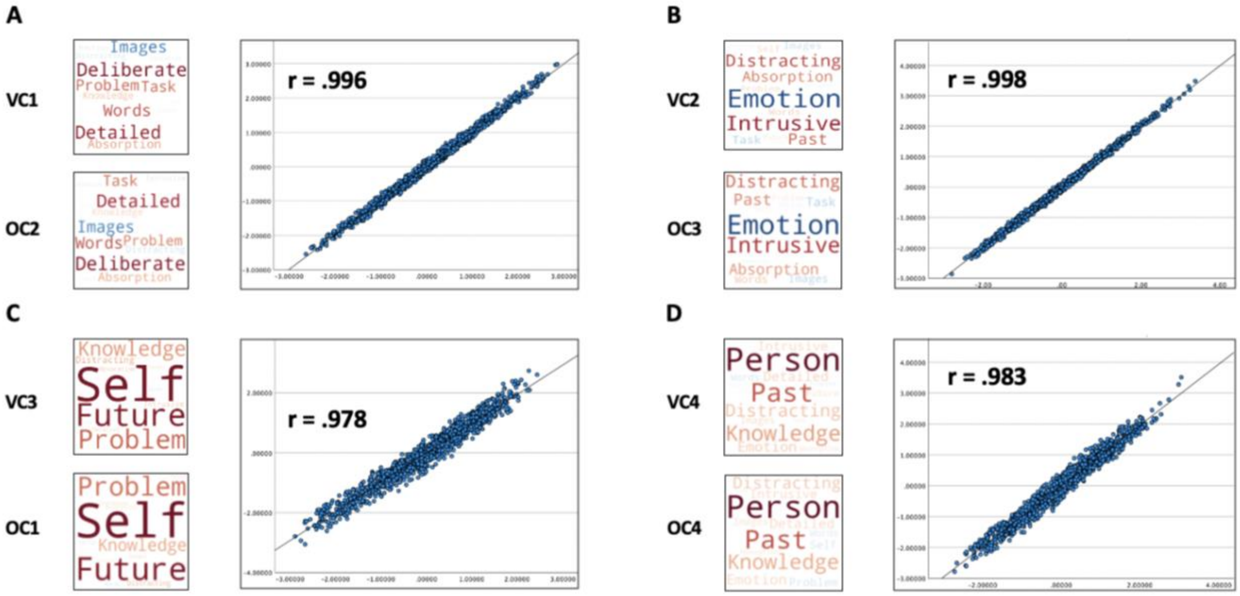
5-Component Solution Reliability Analysis



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

Figure S3

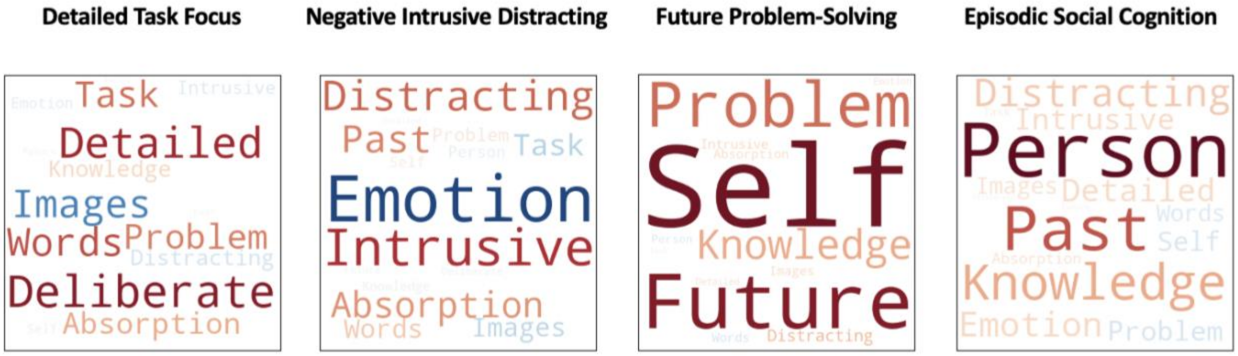
Pearson Correlation Between PCA with Varimax Rotation and PCA with Oblique Rotation



Note. Scatter plots of Pearson correlations between thought data PCA with varimax rotation and thought data PCA with oblique rotation. “V” indicates varimax rotation, “O” indicates oblique rotation, and “C” indicates component. Component loadings for varimax rotation are found on the y-axes, and component loadings for oblique rotation are found on the x-axes. For display purposes, the oblique rotation loadings for component 3 (Figure S3B and Figure S4) were reversed.

Figure S4

Thought Word Clouds for PCA with Oblique Rotation



Detailed Task Focus

Negative Intrusive Distracting

Future Problem-Solving

Episodic Social Cognition

Note. Words represent PCA with oblique rotation loadings. 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 S3 for specific component loadings. For display purposes, the component loadings used to generate the negative intrusive distracting word cloud were reversed.