Patterns of Ongoing Thought in the Real World and Their Link to Mental Health and Well-Being

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Abstract

The thoughts we experience in daily life have important implications for our health and well-being. However, it is often difficult to measure thoughts patterns outside of laboratory conditions due to concerns about the voracity of measurements taken outside of controlled laboratory conditions. To address this gap in the literature, our study set out to measure patterns of thought as they occur in daily life and assess the robustness of these measures and their associations with traits measurements of health and well-being. A sample of undergraduate participants completed multi-dimensional experience sampling (mDES) surveys eight times per day for five days in daily life. Principal component analysis (PCA) reduced these data to identify the dimensions that explained the patterns of thoughts reported in our study. We used (LMM) modelling to map how these 'thought patterns' relate to the activities taking place, highlighting good consistency within the sample, as well as substantial overlap with prior work. Multiple regression was used to examine the association between patterns of ongoing thought and aspects of mental health and well-being, highlighting a pattern of negative intrusive distraction that had a positive association with anxiety, and a negative association with social well-being. Notably, states of intrusive distraction tended to be most prevalent in solo activities and was relatively suppressed when interacting with other people (either in person or virtually). Our study, therefore, highlights the use of mDES as a tool to understand how thoughts in daily life impact on our mental health and well-being and highlight an important role in social connectedness in the etiology of intrusive thinking.

Introduction

A fundamental goal of cognitive psychology is to understand how the thoughts we experience in daily life relate to our productivity, and health and well-being. Contemporary work indicates a link between patterns of ongoing thought, as determined by experience sampling, and various aspects of health and well-being (e.g., Asztalos et al., 2009 and Kucyi et al., 2023). However, research on human thought has focused heavily on observations made in controlled laboratory contexts such as brain imaging (e.g., Vatansever et al., 2020) or behavioral tasks (e.g., Kane et al., 2007) because of the assumption that the robustness of these measures is improved when they are ascertained in controlled laboratory conditions. However, recent work in the laboratory and in daily life has emphasized that patterns of thought are intimately related to the context in which they emerge, which may be one reason why links between traits and patterns often do not generalize from the laboratory to daily life (Kane et al., 2017).

Recent work by Konu et al. (2021) and Mulholland et al. (2023) used multi-dimensional experience sampling (mDES [Smallwood et al., 2016]) to examine how the nature of ongoing activities impact on the pattern of thoughts people experience. Specifically, Konu et al. (2021) used a battery of laboratory-based activities including cognitive and attentional tasks, videos, and audiobooks to assess how thought patterns determined by mDES change as a function of the tasks people engage in. Mulholland et al. (2023) used a similar mDES approach to understand how the activities people are engaged in daily change their thought patterns. In both of these studies we identified clear evidence that thought patterns are anchored in the context in which they occur. Moreover, we found clear similarities in the types of thought patterns that participants reported; in both studies patterns of thought with (i) unpleasant, intrusive, and distracting features were identified that dominated low demanding situations in both the lab and

daily life, (ii) social episodic thoughts were found that were important in social situations in daily life and in tasks relying on social cognition in the lab, and (iii) patterns of detailed focus that were important during homework and while working in daily life and were present during demanding laboratory task such as those depending on working memory. In other studies using mDES, associations with brain activity have been established. Konu et al. (2020) found that patterns of episodic social cognition were related to greater activity within the medial prefrontal cortex, a region of the default mode network, while McKeown et al. (2023) found that patterns of detailed task focus are linked to greater activity in the fronto-parietal network. Finally, Wallace and et al. (2024) established that during movies, patterns of negative intrusive distraction was related to moments when fronto parietal activity was reduced. Together these finding suggest that context plays an integral role in driving ongoing thought patterns as identified by mDES and emphasize the need for more directed and concrete studies examining exactly how patterns of experience in the situations in which they naturally occur relate to mental health and well-being.

Prior evidence has already used experience sampling in daily life and in the laboratory to highlight important links between patterns of ongoing thought and factors that impact health and well-being such as depression (e.g., Chaieb et al., 2022 and Smallwood et al., 2011), anxiety (Foster et al., 2015) and obsessional thinking (Gaynor et al., 2023). Consistent with this emerging evidence, Konu et al. (2021) discovered that higher levels of depression are associated with higher scores on a “negative” and “intrusive” thought component, providing evidence to suggest that cognitive traits influence ongoing thought as determined by mDES. The primary goal of the current study, therefore, was to extend our understanding of how patterns of thought, determined using mDES in daily life, are related to measures of health and well-being.

Current Study

As described above, the goal of this study was to identify thought patterns in daily life using mDES and explore associations with trait indices of health and well-being. As described earlier, mDES is an experience sampling method that can be administered in both laboratory settings (including brain imaging studies) and to participants in their natural environments using mobile devices (e.g., Konu et al., 2021 and Mulholland et al., 2023). mDES requires participants to describe their experience on a set of dimensions (e.g. the level of detail and the emotional tone) on multiple occasions and has been used to assess experiential links between (i) brain function (e.g., Ho et al., 2020, Konu et al., 2020, Turnbull et al., 2019, and Wallace et al., 2024), (ii) the impact of the corona virus disease (Covid-19) pandemic (McKeown et al., 2021), associations with traits (Vatansever et al., 2018; Turnbull et al., 2020), and (iii) changes with age (Turnbull et al., 2021). mDES has also demonstrated an ability to discriminate between different types of activity in both laboratory settings and in daily life (Konu et al., 2021; Mulholland et al., 2023).

Before examining links to mental health and well-being, the first goal of this study was to investigate the reproducibility of relationships between patterns of ongoing thought and self-reported activities as this would help assess the robustness of the mDES approach when applied outside of controlled laboratory conditions in daily life. To this end we sought to determine the reproducibility of the thought patterns found by Mulholland et al. (2023) as well as the situations in which they are most likely to emerge (i.e. their mappings to activities in daily life). Next, we examined how the thought patterns identified in the current study relate to aspects of mental health and well-being as measured by a battery of questionnaires administered in daily life.

Methods

Participant Population

A total of 261 participants (women = 227, men = 29, non-binary or similar gender identity = 4, prefer not to say = 1; *M* = 21.44; *SD* = 6.164159; range = 17-52; note, two ages were recorded incorrectly and therefore not included and two additional ages were absent) were included in this study, resulting in a total of 6892 responses. This study was granted ethics clearance by the Queen's University General Research Ethics Board. Participants were recruited between February 2022 and April 2022 through the Queen's University Participant Pool. Eligible participants were Queen's University students enrolled in designated first- and second-year psychology courses. Participants gave informed, written consent through electronic documentation prior to taking part in any research activities and were awarded two course credits and fully debriefed upon the completion of their participation.

Procedure

Participants completed demographic (i.e., age, gender, gender identity, sex assigned at birth, language(s) spoken most often at home, country of primary place of residence, program, and year of study) and health and wellness (i.e., the Quick Inventory of Depressive Symptomatology self-report [QIDS-SR_{16}; Rush et al., 2003], the Anxiety Sensitivity Index [ASI; Reiss et al., 1986], the Autism Spectrum Quotient [AQ; Baron-Cohen et al., 2001], the Adult ADHD Self-Report Scale [ASRS; Kessler et al., 2005], the Montgomery Asberg Depression Rating Scale self-report [MADRS-S; Montgomery & Asberg, 2018], the Overall Anxiety Severity and Impairment Scale [OASIS; Norman et al., 2006], the MOS 36-item short form survey [SF-36; Ware & Sherbourne, 1992], the Sheehan Disability Scale [SDS; Sheehan, 1983], and the World Health Organization Quality-of-Life Brief Version [WHOQOL-BREF;

WHOQOL Group, 1998]) questionnaires. For the purpose of this study, further analysis was limited to the AQ, ASRS, MADRS, OASIS, and WHOQOL-BREF questionnaires, as they were deemed the most relevant indicators of mental health and well-being. Once participants completed these questionnaires, they were notified via Samply Research (Shevchenko, 2020), a mobile application, to complete mDES questionnaires eight times daily for five consecutive days between 7:00 am and 11:00 pm. Each questionnaire was randomly delivered within this 16-hour time window, with a minimum of 30 minutes in between each noticiation. .

Multi-dimensional Experience Sampling

Participants received notifications on their phones through the Samply Research mobile application. All responses were made in reference to their thoughts, feelings, environment, location, and activities immediately before receiving the notification. 16 questions about various dimensions of thought content (Table 1) were always asked first. Participants then rated their stress on a 1-to-10 Likert scale. For the purpose of this study, responses to this stress question were not analyzed. Participants then answered questions about their physical and virtual social environment (Table 2). Participants also indicated the type of physical location they were in (Table 3) and their primary activity (Table 4). The 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) and Mulholland et al. (2023).

Table 1

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
Images	My thoughts were in the form of images:	Not at all	Completely
Words	My images were in the form of words:	Not at all	Completely
Sounds	My thoughts were in the form of sounds:	Not at all	Completely
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-10 Likert scale.

Table 2

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
	Where you alone, or physically with a pet?	Not with a pet
		Around a pet but not interacting with them
		Around a pet 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

Physical Environment Question

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)

Note. If participants selected "Inside (other)," or "Outside (other)," they were asked to specify their location.

Table 4

Primary Activity Question

List Type	Question	Activity List
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
		Video-calling
		Messaging by phone/device
		Traveling or commuting
		Using a computer or an electronic device
		Walking the dog
		Watching TV
		Working
		Other activity

Note. If participants selected "Other activity," they were asked to specify what they were doing. If participants selected "Using a computer or an electronic device," they were asked to further specify their activity from a list of alternative activities that included "Social media: Passive scrolling," "Social media: Active engagement," "Gaming," "Admin (e.g., banking, calendar, etc.)," and "Other." If participants selected "Other," they were asked to specify what they were doing).

Analysis

Data and Code Availability Statement

All custom code used to prepare data for analysis and figure development is available online at https://github.com/ThinCLabQueens and https://github.com/BridgMul10. Anonymized data has been uploaded to a publicly accessible database, Mendeley Data, and is available online at https://doi.org/10.17632/gfhwg3p8r6.1.

Principal Component Analysis: mDES Questions

Common patterns of thought (Figure 1) were identified by applying PCA (varimax) to the data generated from responses to the 16 mDES questions (Table 1) using IBM SPSS Statistics (version 29). PCA was applied at the observation level and included 6776 observations. The loadings from the five components with an eigenvalue > 1 were retained for further analysis (Table 5).

Table 5

PCA Loadings Generated from mDES Questions

Dimension	Detailed Task Focus	Negative Intrusive Distraction	Episodic Social Cognition	Future Problem-Solving	Sensory Engagement
Task	.605	-.207	.017	-.033	.142
Future	.228	.068	.106	.797	.064
Past	-.021	.408	.636	.054	.169
Self	.003	.166	.227	.730	-.009
Person	-.079	-.004	.645	.253	.208
Emotion	.018	-.730	.115	.042	.351
Images	.017	.048	.032	.216	.742
Words	.435	.020	.452	-.092	-.264
Sounds	.051	.080	.127	-.177	.680
Detailed	.748	.038	.224	.102	.034
Deliberate	.702	-.109	-.059	.009	-0.137
Problem	.609	.146	.010	.412	-0.052
Intrusive	-.013	.710	.211	.137	0.207
Knowledge	.240	.059	.651	.141	-.002
Absorption	.560	.267	.084	.155	.230
Distracting	-.015	.689	.174	.220	.228

Reliability Analysis: mDES Question Data

Component reliability analysis was conducted in IBM SPSS Statistics (version 29). mDES thought dimension data was randomly shuffled and divided into two halves (n = 3445 probes per sample). PCA (varimax) was applied to each subset separately to assess component reliability. Pearson correlations were run on the component loadings generated from each subset.

Linear Mixed Modeling: Primary Activity Data

To analyze contextual distributions of thought in relation to activities, we conducted a series of linear mixed models (LMMs), one with each thought component as the dependent variable and activity as the independent variable, to examine whether patterns of thought varied meaningfully across activity categories. Restricted maximum likelihood (REML) was used as the estimation method and a variance components model was used as the covariance type. Participants were included as a random intercept. 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 2). This analysis is identical to that found in Mulholland et al. (2023). The parameter estimates were also saved to be used in reliability analysis (Figure 3).

Reliability Analysis: Primary Activity Data

Primary activity data reliability analysis was conducted in IBM SPSS Statistics (version 29). Component scores were split into two subset (n = 3445 probes per subset). We conducted a series of LMM, one with each thought component and subset as the dependent variable and activity as the independent variable. Restricted maximum likelihood (REML) was used as the estimation method and a variance component model was used as the covariance type. Participants were included as a random intercept. Pearson correlations were run on the parameter

estimates generated from each subset. This analysis allowed us to estimate whether the results of our whole sample LMM are generalizable to sub-samples of the data.

Reliability Analysis: Comparing Associations with Activities Across Studies

Reliability analysis was conducted in IBM SPSS Statistics (version 29). The LMM parameter estimates from Mulholland et al. (2023) contained a sample of n = 1451 probes and the LMM parameter estimates from our current study contained a sample of n = 6889 probes. Pearson correlations were run on the parameter estimates for overlapping activity from each of the datasets. This analysis allowed us to estimate whether the results of our whole sample LMM in the current data generalizable to the prior dataset.

Linear Mixed Modeling: Social Environment Data

To analyze contextual distributions of thought in relation to socialization, we conducted a series of LMMs, one with each thought component as the dependent variable and social environment as the independent variable (i.e., physical environment with people, physical environment with a pet, or virtual environment with people were all options as independent variables), to examine whether patterns of thought varied meaningfully across social environments. Restricted maximum likelihood (REML) was used as the estimation method and a variance components model was used as the covariance type. Participants were included as a random intercept. This analysis is identical to that found in Mulholland et al. (2023).

Multiple Regression: Underlying Traits

To analyze whether mDES questions can differentiate individuals based on underlying traits, we performed a series of multiple regression with PCA component scores as the dependent variable and trait questionnaires as explanatory variables. Trait questionnaires included in this analysis includes the AQ, ASRS, MADRS, OASIS, and WHOQOL-BREF, all of which were z-

scored. The WHOQOL-BREF questionnaire was subdivided into four categories based on scoring domains: physical health, psychological health, social relationships, and environment. mDES questionnaire data was reduced to a single score for each participant.

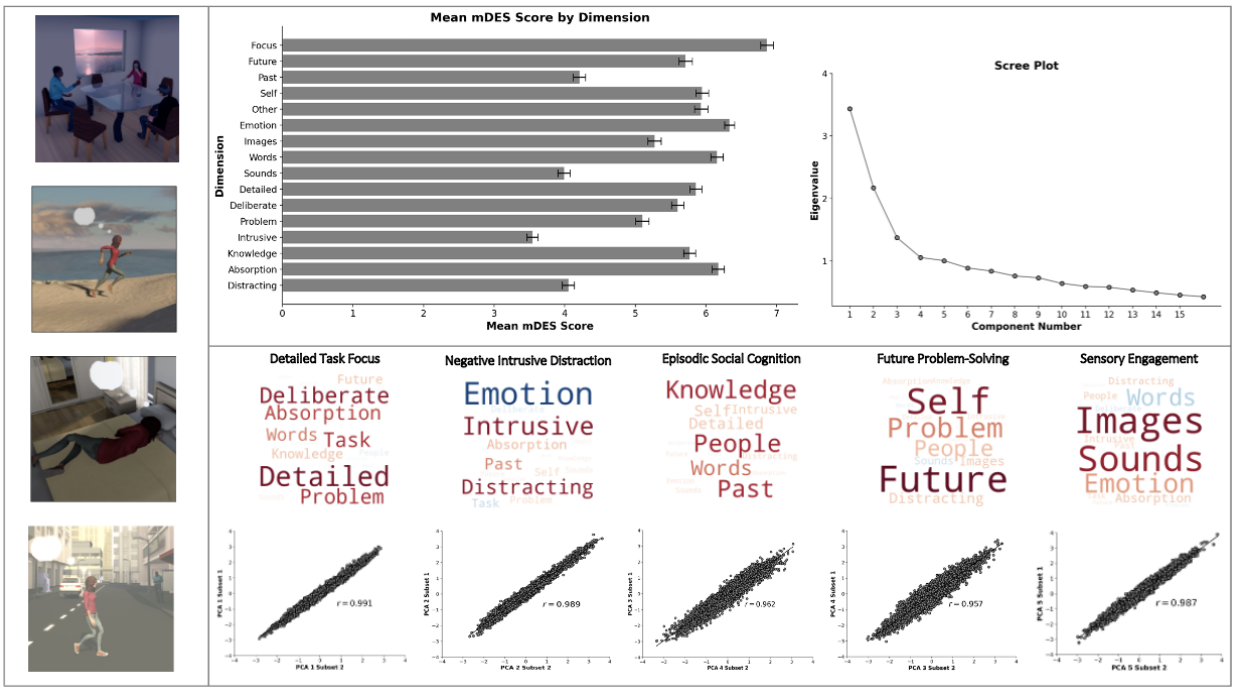
Results

Patterns of Ongoing Thought

First, mean scores for each thought dimension measured were calculated and are shown in Figure 1. Next, as is standard in our laboratories work (Smallwood et al., 2016; Turnbull et al., 2019; McKeown et al., 2023; Konu et al., 2020; Mulholland et al., 2021), the mDES data was decomposed using PCA (varimax) to reveal the dimensions that best described the patterns of ongoing thought reported by the participants. Based on eigenvalue > 1, five components were selected for further analysis (see Figure 1 for scree plot). PCA loadings (Table 5) from the five components were used to generate thought word clouds (Figure 1). Thought word clouds were named based on mDES thought dimensions that dominated their composition. Component 1 (21.5% of variance) was labelled “Detailed Task Focus” because loadings were high for dimensions such as “detailed,” “deliberate,” “problem,” and “task” (Figure 1). Component 2 (13.6% of variance) was labelled “Negative Intrusive Distraction” because loadings were high for dimensions such as “(negative) emotion,” “intrusive,” and “distracting” (Figure 1). Component 3 (8.6% of variance) was labelled “Episodic Social Cognition” because loadings were high for dimensions such as “knowledge,” “person,” and “past” (Figure 1). Component 4 (6.6% of variance) was labelled “Future Problem-Solving” because loadings were high for dimensions such as “future,” “self,” and “problem” (Figure 1). Component 5 (6.3% of variance) was labelled “Sensory Engagement” because loadings were high for dimensions such as “images,” and “sounds” (Figure 1). Please note that these terms are used for convenience when discussing the components; they do not constitute the only labels which could be applied to these patterns.

Figure 1

mDES Questionnaire Data



Note. Upper horizontal panel: Horizontal bar graph of mean mDES score by dimension. Error bars represent 99% confidence intervals (CIs). Scree plot generated from PCA of mDES questionnaire data. Lower horizontal panel: Thought dimension word clouds. Words represent PCA (varimax) scores for mDES questionnaire thought dimensions. Larger fonts are items with more importance (i.e., higher loadings) and colour denotes direction (i.e., warm colours relate to positive loadings). “Detailed Task Focus” word cloud., “Negative Intrusive Distraction” word cloud, “Future Problem-Solving” word cloud, and “Episodic Social Cognition” word cloud. Pearson Correlation scatter plots of PCA loading split-half reliability (Y-axis: Subset 1; X-axis: Subset 2). Left vertical panel: Illustrations of different activities in daily life.

Component Reliability

To further understand the robustness of the components from our analysis, we conducted split-half reliability analyses for our sample. In this analysis, the data was divided into two random samples (n = 3445 probes per sample) and then was examined to determine 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. The mean correlation for the set of the homologous pairs from each solution was calculated with a higher score reflecting the most reproducible components. The 3-, 4- and 5-component solutions all produced highly reliable results, with average homologue similarities scores of r = .996 (range r = .994-.995, Figure 1), r = .93525 (range r = .869-.978, Figure 1), and r = 0.9772 (r =.957-.991, Figure 1).

Thought-Activity Mappings

One goal of our study was to examine the robustness of mDES as a tool for mapping cognition in daily life by measuring the similarity in how the thought patterns map onto activities in daily life. To this end we ran LMM in which the activities are the explanatory variables and the mDES patterns are the dependent variables. In each case we found a significant association between reported patterns of thought and activities ("Detailed Task Focus" (F(21, 6639.501) = 74.077, p <.001); "Negative Intrusive Distraction" (F(21, 6591.466) = 10.206, p <.001); "Episodic Social Cognition" (F(21, 6632.078) = 19.083, p <.001); "Future Problem-Solving" (F(21, 6648.665) = 18.255, p <.001); "Sensory Engagement" (F(21, 6559.038) = 16.820, p <.001)). To visualize these relationships, we generated a set of word clouds based on activity estimated marginal means for each component (Figure 2). It can be seen that the "Detailed Task Focus" pattern has high loadings when doing homework and working (paid or volunteer) and low loadings when napping or resting, watching TV, and nothing or waiting. The "Negative Intrusive Distraction" pattern had high loadings when doing nothing or waiting, napping or resting, and doing homework, and low loadings during physical leisure or sports, and shopping. The "Episodic Social Cognition" pattern had high loadings when talking on the phone, messaging by phone/device, video-calling, walking the dog, talking in person, traveling or

commuting, and physical leisure or sports, and low loadings when watching TV, napping or resting, using a computer or electronic device, and doing homework. The “Future Problem-Solving” pattern had high loadings for hygiene, texting, commuting, phone-call, exercise, and shopping, and low loadings when watching tv, reading, and doing homework. Lastly, the “Sensory Engagement” pattern had high loadings when watching TV, listening to music, playing sports, and using a computer, and low loadings when doing homework, talking on the phone, and working.

Next, we investigated the robustness of these associations. Our first analysis examined the consistency of these mappings within the current data by performing a split half reliability analysis with current data. We created two subsets of our data (n = 3445 probes per subset). In each case, we found a significant association between reported patterns of thought and activities in each subset (“Detailed Task Focus” subset 1 ($F(21, 3284.102) = 36.957$, $p < .001$) and subset 2 ($F(21, 3333.340) = 36.101$, $p < .001$); “Negative Intrusive Distraction” subset 1 ($F(21, 3274.046) = 4.632$, $p < .001$) and subset 2 ($F(21, 3285.565) = 6.533$, $p < .001$); “Episodic Social Cognition” subset 1 ($F(21, 3323.136) = 8.919$, $p < .001$) and subset 2 ($F(21, 3271.062) = 10.315$, $p < .001$); “Future Problem-Solving” ($F(21, 3285.555) = 10.020$, $p < .001$) and subset 2 ($F(21, 3294.731) = 9.062$, $p < .001$); “Sensory Engagement” subset 1 ($F(21, 3242.374) = 9.693$, $p < .001$) and subset 2 ($F(21, 3239.056) = 8.125$, $p < .001$)). Next, the subset of each component was correlated to the resulting associations with activities in each half (see Methods). Split-half reliability on the LMM activity estimated marginal means determined correlations with a range of $r = 0.602$-$.910$ with the highest reproducibility for the “Detail Task Focus” component and the lowest for “Sensory Engagement” component. Next, we examined how estimated marginal means from the homologous components from Mulholland et al. (2023) correlated to the current data. To this end

we used Pearson Correlation to compare the activity mappings from our prior study (Mulholland et al., 2023) to the mappings found in our omnibus sample. Mulholland et al. (2023) did not include a “Sensory Engagement” component, so only four components were compared. We discovered correlations with a range of r = .676-.859, with the strongest mappings for “Detailed Task Focus” and the lowest for “Future Problem-Solving”. Note in our initial study (Mulholland et al., 2020) there was no “Sensory Engagement” component.

One feature of our analysis is that it allows us to understand specific activities in terms of their location along several dimensions of ongoing thought. To visualize the data this way the estimated marginal means for each activity derived from the LMMs were plotted against multiple mDES components. We generated a three-dimensional space constructed from the most reliable components (i.e., “Detailed Task Focus,” “Negative Intrusive Distraction,” and “Episodic Social Cognition”) and also included a two-dimensional space to capture the relationship between the “Future Problem-Solving” and “Sensory Engagement” components (i.e., the least reliable components in terms of their activity mappings). These are presented in Figure 3. These figures show how certain activities occupy extreme values on multiple components. For example, “homework” is high on both the “Detailed Task Focus” and “Negative Intrusive Distraction” components while low on the “Episodic Social Cognition,” “Future Problem-Solving,” and “Sensory Engagement” components.

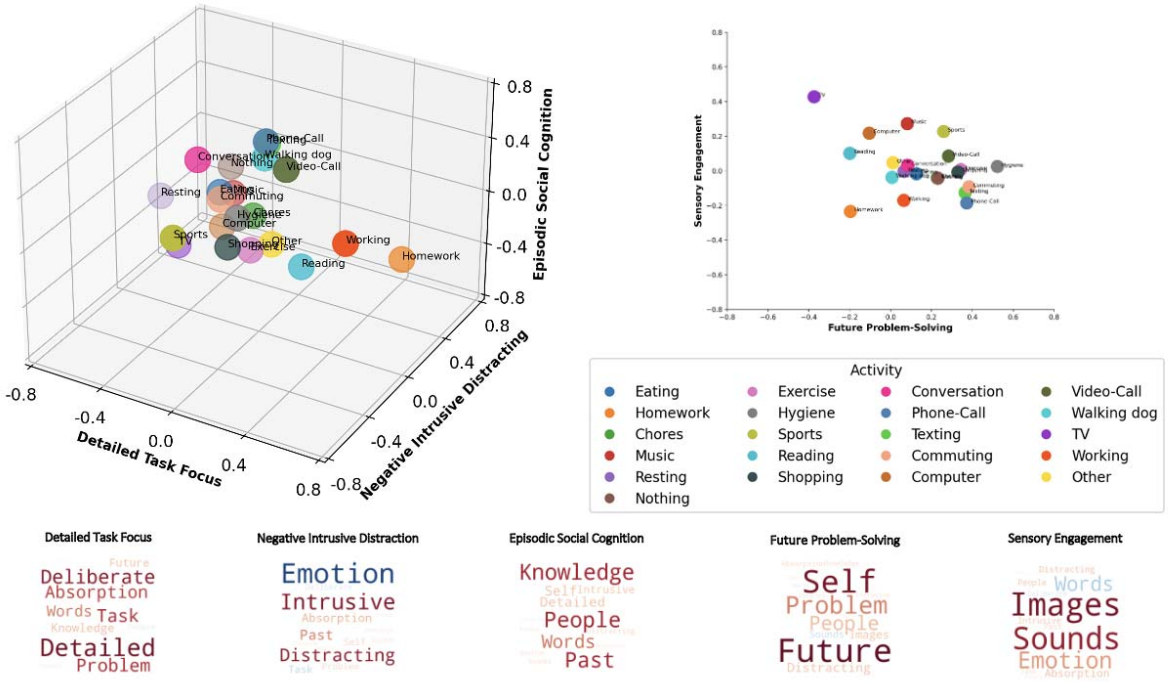
Figure 2

Thought and Activity Word Cloud Mappings and Reliability Analysis

Note. First row: "Thought Patterns." Words represent PCA (varimax) loadings for mDES data 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 5-10 for specific component loadings. Second row: "Activity Loadings." Third row: LMM split half reliability (Y-axis: Subset 1; X-axis: Subset 2). Fourth row: Mulholland et al. (2024) and Mulholland et al. (2023) correlation (Y-axis: Mulholland et al. (2023); X-axis: Mulholland et al. (2024).

Figure 3

mDES and Activity Data in 2- and 3-Dimensional Spaces



Note. Data are presented in two- and three-dimensional spaces to provide the opportunity to visualize the relationships between multiple dimensions and activities identified in our study in a convenient way. Left image: In the three-dimensional space, the “Detailed Task Focus” LMM loadings can be found on the x-axis, the “Negative Intrusive Distraction” LMM loadings can be found along the y-axis, and the “Episodic Social Cognition” LMM loadings can be found on the z-axis. Right image: In the two-dimensional space, the “Sensory Engagement” LMM loadings can be found on the y-axis, and “Future Problem-Solving” LMM loadings can be found on the x-axis. Lower panel: 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).

Table 6

LMM Estimated Marginal Means for the "Detailed Task Focus" Component

Primary Activity	Mean	Std. Error	Lower Bound 95% Confidence Interval	Upper Bound 95% Confidence Interval
Eating	-.198	0.044	-.284	-.112
Homework	.664	.033	.599	.729
Chores	-.017	.058	-.130	.096
Music	-.205	.062	-.326	-.083
Resting	-.686	.043	-.770	-.602
Nothing	-.344	.057	-.455	-.233
Exercise	.042	.080	-.114	.199
Hygiene	-.029	.060	-.146	.088
Sports	-.149	.127	-.398	.099
Reading	.281	.080	.124	.438
Shopping	-.042	.094	-.226	.143
Conversation	-.293	.043	-.377	-.209
Phone-call	.043	.102	-.157	.243
Video-call	.168	.089	-.007	.344
Texting	.025	.084	-.140	.189
Commuting	-.139	.077	-.291	.012
Computer	-.250	.042	-.333	-.167
Walking dog	-.005	.165	-.329	.318
TV	-.388	.042	-.470	-.306
Working	.544	.052	.441	.646
Other	.122	.043	.038	.206

Table 7

LMM Estimated Marginal Means for the "Negative Intrusive Distraction" Component

Primary Activity	Mean	Std. Error	Lower Bound 95% Confidence Interval	Upper Bound 95% Confidence Interval
Eating	-.036	.048	-.130	.059
Homework	.232	.038	.157	.308
Chores	0.026	.062	-.147	.095
Music	.102	.066	-.028	.232
Resting	.199	.048	-.106	.292
Nothing	.316	.061	.197	.436
Exercise	-.156	.084	-.320	.009
Hygiene	-.160	.064	-.285	-.035
Sports	-.552	.131	-.810	-.295
Reading	-.079	.084	-.244	.086
Shopping	-.229	.098	-.422	-.037
Conversation	-.084	.047	-.177	.009
Phone-call	-.006	.106	-.214	.202
Video-call	-.031	.093	-.214	.152
Texting	.041	.088	-.131	.214
Commuting	-.133	.081	-.293	.026
Computer	.070	.047	-.022	.162
Walking dog	.063	.171	-.272	.397
TV	-.121	.047	-.213	-.030
Working	-.125	.057	-.236	-.014
Other	-.090	.043	-.183	.004

Table 8

LMM Estimated Marginal Means for the "Episodic Social Cognition" Component

Primary Activity	Mean	Std. Error	Lower Bound 95% Confidence Interval	Upper Bound 95% Confidence Interval
Eating	0.170	0.047	0.078	0.262
Homework	-0.178	0.036	-0.247	-0.108
Chores	0.057	0.062	-0.063	0.178
Music	0.070	0.066	-0.060	0.200
Resting	-0.194	0.046	-0.284	-0.104
Nothing	0.082	0.061	-0.036	0.201
Exercise	-0.089	0.085	-0.256	0.078
Hygiene	0.124	0.064	-0.001	0.249
Sports	0.195	0.135	-0.070	0.459
Reading	-0.171	0.085	-0.338	-0.003
Shopping	-0.050	0.100	-0.246	0.147
Conversation	0.405	0.046	0.315	0.494
Phone-call	0.610	0.109	0.397	0.823
Video-call	0.469	0.095	0.283	0.656
Texting	0.561	0.089	0.385	0.736
Commuting	0.202	0.083	0.040	0.364
Computer	-0.178	0.045	-0.267	-0.089
Walking dog	0.429	0.176	0.085	0.773
TV	-0.243	0.045	-0.331	-0.155
Working	0.136	0.056	0.026	0.245
Other	-0.058	0.046	-0.148	0.032

Table 9

LMM Estimated Marginal Means for the "Future Problem-Solving" Component

Primary Activity	Mean	Std. Error	Lower Bound 95% Confidence Interval	Upper Bound 95% Confidence Interval
Eating	.127	0.047	0.035	0.218
Homework	-0.196	0.035	-0.265	-0.128
Chores	0.229	0.062	0.108	0.349
Music	0.082	0.066	-0.048	0.213
Resting	0.066	0.046	-0.023	0.156
Nothing	0.232	0.061	0.113	0.351
Exercise	0.344	0.086	0.176	0.512
Hygiene	0.523	0.064	0.398	0.648
Sports	0.260	0.136	-0.007	0.528
Reading	-0.199	0.086	-0.367	-0.030
Shopping	0.330	0.101	0.132	0.529
Conversation	0.084	0.045	-0.005	0.174
Phone-call	0.373	0.110	0.158	0.588
Video-call	0.284	0.096	0.096	0.473
Texting	0.365	0.090	0.188	0.541
Commuting	0.384	0.083	0.221	0.546
Computer	-0.104	0.045	-0.192	-0.015
Walking dog	0.007	0.177	-0.340	0.355
TV	-0.374	0.045	-0.461	-0.286
Working	0.065	0.056	-0.044	0.175
Other	0.012	0.046	-0.078	0.101

Table 10

LMM Estimated Marginal Means for the "Sensory Engagement" Component

Primary Activity	Mean	Std. Error	Lower Bound 95% Confidence Interval	Upper Bound 95% Confidence Interval
Eating	-0.017	0.049	-0.113	0.080
Homework	-0.235	0.041	-0.315	-0.155
Chores	-0.041	0.061	-0.160	0.079
Music	0.272	0.065	0.145	0.400
Resting	-0.003	0.049	-0.098	0.092
Nothing	-0.043	0.060	-0.161	0.075
Exercise	0.007	0.081	-0.152	0.165
Hygiene	0.025	0.063	-0.098	0.148
Sports	0.227	0.125	-0.018	0.471
Reading	0.101	0.081	-0.059	0.260
Shopping	-0.007	0.094	-0.191	0.177
Conversation	0.032	0.048	-0.063	0.126
Phone-call	-0.186	0.101	-0.385	0.013
Video-call	0.085	0.090	-0.091	0.261
Texting	-0.127	0.085	-0.293	0.039
Commuting	-0.093	0.079	-0.248	0.061
Computer	0.217	0.048	0.123	0.311
Walking dog	-0.038	0.162	-0.355	0.279
TV	0.427	0.048	0.333	0.520
Working	-0.171	0.057	-0.282	-0.060
Other	0.047	0.049	-0.048	0.143

Thought Dimensions and Social Environments

Another goal of our study was to examine the robustness of mDES as a tool for mapping cognition in daily life by measuring the similarity in how the thought patterns map onto social environments in daily life. To this end we ran LMM in which different social environments (Table 2) were the explanatory variable and the mDES patterns were the dependent variables. We found a significant association between reported patterns of thought and physical social environments for each component. "Detailed Task Focus" ($F(3, 6721.873) = 16.057$, $p < .001$) was lowest when with people and interacting with them ($M = -.077$, 95% CI = -.078 to -.125) and highest when around people but not interacting with them ($M = .144$, 95% CI =.078 to -.211). "Negative Intrusive Distraction" ($F(3, 6656.388) = 37.537$, $p < .001$) was lowest when with people and interacting ($M = -.147$, 95% CI = -.215 to -.078) and highest when alone ($M = .113$, 95% CI = .048 to .178). "Episodic Social Cognition" ($F(3, 6699.281) = 56.290$, $p < .001$) was highest when around people and interacting ($M = .221$, 95% CI = .158 to .284) and lowest when around people but not interacting ($M = -.146$, 95% CI = -.078 to -.215). "Future Problem-Solving" ($F(3, 6716.790) = 2.792$, $p = .039$) was lowest when around people and interacting with them ($M = -0.46$, 95% CI = -.113 to .021) and highest when around people but not interacting ($M = .044$, 95% CI = -.017 to .15). Finally, "Sensory Engagement" ($F(3, 6619.466) = 5.289$, $p = .001$) was highest when alone ($M = .029$, 95% CI = -.084 to .026). A broadly similar patterns was found for our analysis of the consequence of virtual environments. "Detailed Task Focus" ($F(3, 6705.721) = 2.672$, $p = .046$) was higher when around people and not interacting ($M = .053$, 95% CI = -.032 to .137) and lowest when alone ($M = -.032$, 95% CI = -.83 to .02). "Intrusive Distraction" ($F(3, 6695.698) = 11.528$, $p < .001$) was least prevalent when participants were around people and interacting virtually ($M = -.108$, 95% CI = -.185 to -.032) and highest when

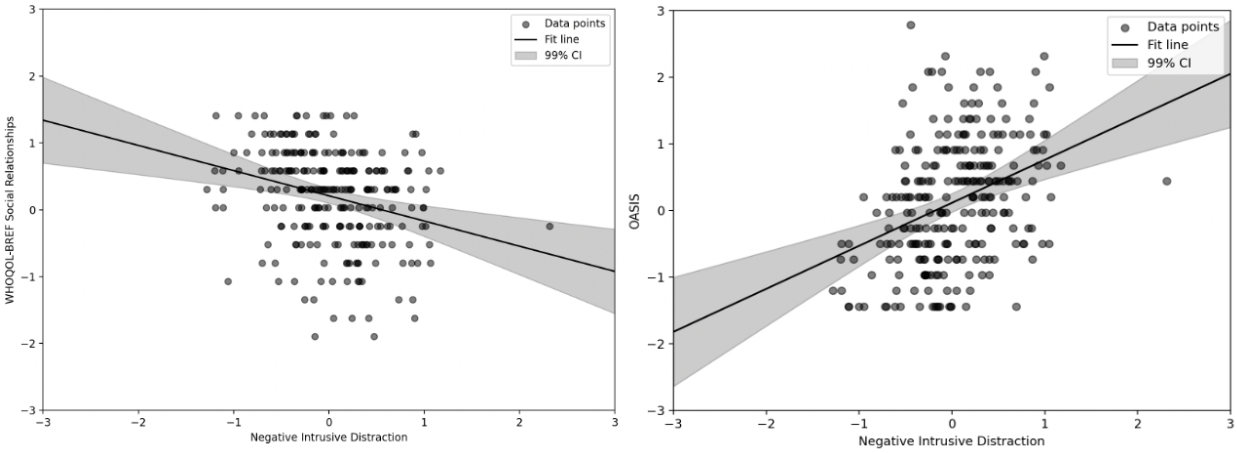
around people but not interacting virtually (*M* = .070, 95% CI = -.02 to .159). “Episodic Social Cognition” (*F*(3, 6715.537) = 39.365, *p* <.001) was highest when around people and interacting virtually (*M* = .266, 95% CI = .194 to .337) and lowest when alone (*M* = -.07, 95% CI = .19 to .33). “Future Problem-Solving” (*F*(3, 6709.599) 9.546, *p* <.001) was highest when around people but not interacting (*M* = .149, 95% CI = .07 to .22) and lowest when around people but not interacting virtually with another person (*M* = -.032, 95% CI = -.117 to .05). Finally, “Sensory Engagement” (*F*(3, 6663.163) = 2.889, *p* = .034) was highest when alone (*M* = .01, 95% CI = -.05 to .08) and lowest around people but not interacting virtually (*M* = -.003, 95% CI = -.09 to .09).

Thought Dimensions and Traits

Having established a mapping between the current study and prior studies, the final goal of our study was to investigate whether mDES dimensions can differentiate people based on certain underlying traits associated with mental health and well-being. To do so, we performed a series of multiple regression with PCA component scores as dependent variables and trait questionnaires as explanatory variables. Results indicated the negative intrusive distracting thought component (*F*(8, 252) = 8.348, *p* = <.001; see Table 10 for results for each component) could be predicted based on high levels of anxiety (Beta = 0.226, *p* = .003) and low levels of social well-being (Beta = -0.171, *p* =.010). This analysis shows a clear mapping between patterns of “Negative Intrusive Distraction” with higher levels of anxiety and lower social well-being.

Figure 4

mDES Questionnaire Data and Trait Data Multiple Regression Results



Note. Left panel: Scatterplot with WHOQOL-BREF social relationships (z-scored) on the y-axis and “Negative Intrusive Distraction” PCA component scores on the x-axis. Right panel: Scatterplot with OASIS (z-scored) on the y-axis and “Negative Intrusive Distraction” PCA component scores on the x-axis. For both scatterplots, all values were mean z-scored per participant.

Table 10

Mental Health and Well-Being Multiple Regression Results Per PCA Component Scores

Component	Model	Sum of Squares	df	Mean Square	F	Sig.
Detailed Task Focus	Regression	.660	8	.083	.444	.894
	Residual	46.866	252	.186		
	Total	47.526	260			
Negative Intrusive Distraction	Regression	15.071	8	1.884	8.348	<.001
	Residual	56.869	252	.226		
	Total	71.940	260			
Episodic Social Cognition	Regression	2.127	8	.266	1.085	.374
	Residual	61.773	252	.245		
	Total	63.900	260			
Future Problem-Solving	Regression	3.129	8	.391	1.806	.076
	Residual	54.569	252	.217		
	Total	57.698	260			
Sensory Engagement	Regression	1.248	8	.156	.415	.911
	Residual	94.767	252	.376		
	Total	96.015	260			

Discussion

Our study set out to investigate the underlying relationships between patterns of thought, behaviour, and traits in daily life. First, we investigated the reproducibility of previously discovered patterns of thought and thought-activity mappings found in daily-life. The thought patterns generated via mDES were similar to the thought patterns described by Mulholland and colleagues (Mulholland et al., 2023; Figure 2) and had reasonable similarity in the way they were associated with ongoing activities (Figure 2). It is important to note that populations in both studies are undergraduate students so this reproducibility highlights that if mDES is employed within a similar group of individuals then it captures thought patterns that are reasonably consistent in their profile and their associations with activities. We also replicated prior studies that show that patterns of episodic social cognition are higher when individuals are interacting either physically or virtually observed in both our prior study (Mulholland et al., 2022), a pattern of thought that was also absent during COVID lockdowns in the United Kingdom (McKeown et al., 2021). However, it is possible that the observed thought patterns, as well as their links to activities or social situations could conceivably change if they were measured in different cultures or age groups. Nonetheless, at the most general level the pattern of data are consistent with prior studies conducted in both daily and in the lab (e.g., Turnbull et al., 2019, Mckeown et al. 2021, and Konu et al. 2021) that highlight that ongoing activities play an important role in determining the thought patterns we experience as measured using mDES.

Links Between Thought Patterns in Daily Life and Psychological Well-Being

The main goal of the study was to understand the links between patterns of thought in daily life and an individual's mental health. In this study we found a relationship between how people describe their thoughts such that greater levels of anxiety and less social support were

correlated with thought patterns emphasizing “Negative Intrusive Distraction”. This pattern of thought showed a reasonable degree of consistency in terms of how it mapped onto activities within this sample (r = .77) and with our prior study (r = .73).

Contemporary perspectives that emphasize patterns of thought have an important social component (e.g., Poerio & Smallwood, 2016; McKeown et al., 2021). Consistent with these views our analysis suggests that higher levels of intrusive distraction are linked to social processes. First, our analysis shows that this pattern of thought tends to dominate solo activities (such as exercise, doing nothing, and homework) and are least present during social interactions either virtually or in person. Interestingly, this component is negatively anchored by sports suggesting that when exercise occurs in a social context, the level of negative intrusive distracting experienced may be reduced. Furthermore, the “Negative Intrusive Distraction” thought component was also associated with higher levels of anxiety. Prior studies have shown links between anxiety and increased levels of mind-wandering (e.g., Fell et al., 2023), a self-generated state that is likely to have distracting features (Smallwood & Schooler, 2015). “Negative Intrusive Distraction” was also linked to less social well-being. Altogether these data suggest that states of intrusive distraction may have an important relationship to social cognition, possibly reflecting personal worries related to social concerns (i.e., anxiety in relation to body image or weight loss, etc.). In this way our study highlights the importance of current concerns as an important determining feature of an individual’s conscious experience (Smallwood & Schooler, 2006; Smallwood & Schooler, 2015; McVay & Kane, 2010; Klinger & Cox, 2004).

Open Questions

As well as detailing links between thinking in daily life and well-being, our study also raises a number of important open questions. For example, the consistency of the thought-

activity mappings suggests that in any given population, there may be systematic relationships between what people think and what they do in daily life. Based on these results, it may be possible to develop an understanding of the activities in daily life that are most relate to different features of a person's thought content, a taxonomy of mappings between thoughts and activities which as a discipline we currently lack. It is worth noting that the capacity for mDES to map thoughts in the lab and in daily life (Chitiz et al., 2024) makes mDES a useful tool for this endeavor. It is important to note that to achieve this goal a more diverse, representative population will be needed since this would allow researchers to understand whether in different populations (e.g. older adults or individuals from a different culture) thought patterns change their features or their relationship to ongoing tasks or activities. We used a population that, while convenient, lacked diversity, especially when compared alongside previous populations used in similar and adjacent studies (e.g. Konu et al., 2021 and Mulholland et al., 2023). Fortunately, our methodology of smartphone sampling is free and easy to use, so future studies can address this gap by broadening the scope of their sampling population in a fairly accessible manner.

The value of a taxonomy of thought-activity associations could ultimately eliminate uncertainty surrounding the influence of activities and traits on mental health and well-being. Specifically, it might help researchers understand when individual traits or selected activity primarily influences reported measures of mental health and well-being. For example, based on our result a failure to account for the external context may make it unclear whether measures of anxiety (i.e., reports of intrusive distraction) are a product of an individual's internal trait (i.e. an anxious individual might report anxious thoughts in spaces where non-anxious individuals do not report anxious thoughts) or the activity they are engaged in (i.e., regardless of internal traits, individuals may experience more intrusive thoughts when they are alone). In other words, it may

be possible to quantify for a given individual in a specific situation that relative contribution of an internal trait and the external context.

It is also likely that the battery of questions we used in our study could be improved. In our study we used a combination of mDES questions that had been used previously in both lab-based and daily-life-based settings, as well as new mDES questions based on previously identified limitations. Mulholland et al. (2023) noted that including a single modality question does not allow participants to describe their conscious experience of an activity fully. In light of this discovery, we decided to replace the modality probe with three questions relating to an individual's sensory experience (i.e., images, words, and sounds). The inclusion of these three questions most likely led to the discovery of the sensory engagement component in the current study. It is important to note that a similar component was observed by Wallace and colleagues (2024) in the context of movie watching (using the same set of items as was applied in the current study) and was associated with periods of films when brain activity was higher in sensory systems (both auditory and visual). This demonstrates that it is possible to optimize the questions included in mDES approaches that would provide more accurate ways for participants to describe their conscious experience. In the same vein there are likely to be ways to improve the measures of mental health we employed in this analysis. The health and wellness surveys were selected based on a widespread, general approach to health and wellness. In the future more accurate or informative questionnaires could be selected that would provide a better understanding of how our thoughts in daily life impact upon our mental health.

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References

Asztalos, M., Wijndaele, K., De Bourdeaudhuij, I., Philippaerts, R., Matton, L., Duvigneaud, N., Thomis, M., Duquet, W., Lefevre, J., & Cardon, G. (2009). Specific associations between types of physical activity and components of mental health. *Journal of Science and Medicine in Sport*, *12*(4), 468-474. https://doi.org/10.1016/j.jsams.2008.06.009

Baron-Cohen, S., Wheelwright, S., Skinner, R., Martin, J., & Clubley, E. (2001). The Autism-Spectrum Quotient (AQ): Evidence from Asperger Syndrome/high-functioning autism, males and females, scientists and mathematicians. *Journal of Autism and Developmental Disorders*, *31*, 5-17. https://doi.org/10.1023/A:1005653411471

Chaieb, L., Hoppe, C., & Fell, J. (2022). Mind wandering and depression: A status report. *Neuroscience & Behavioral Reviews*, *133*, 104505. https://doi.org/10.1016/j.neubiorev.2021.12.028

Chitiz, L., Mckeown, B., Mulholland, B., Wallace, R. S., Goodall-Halliwell, I., Ho, N. S. P., Konu, D., Poerio, G., Wammes, J. D., Milham, M., Klein, A., Jefferies, B., Leech, R., & Smallwood, J. (2023). Mapping cognition across lab and daily life using experience-sampling. *PsyArXiv*. https://doi.org/10.31234/osf.io/yjqv2

Fell, J., Chaieb, L., & Hoppe, C. (2023). Mind wandering in anxiety disorders: A status report. *Neuroscience & Biobehavioral Reviews*, *155*, 105432. https://doi.org/10.1016/j.neubiorev.2023.105432

Forster, S. (2013). Distraction and mind-wandering under load. *Frontiers in Psychology*, *4*, 283. https://doi.org/10.3389/fpsyg.2013.00283

Forster, S., Nunez Elizalde, A. O., Castle, E., & Bishop, S. J. (2015). Unraveling the anxious mind: Anxiety, worry, and frontal engagement in sustained attention versus off-task processing. *Cerebral Cortex*, *25*(3), 609-618. https://doi.org/10.1093/cercor/bht248

Franklin, M. S., Mrazek, M. D., Anderson, C. L., Smallwood, J., Kingstone, A., & Schooler, J. W. (2013). The silver lining of a mind in the clouds: Interesting musings are associated with positive mood

while mind-wandering. *Frontiers in Psychology*, *4*, 583. https://doi.org/10.3389/fpsyg.2013.00583

Gable, S. L., Hopper, E. A., & Schooler, J. W. (2019). When the muses strike: Creative ideas of physicist and writers routinely occur during mind wandering. *Psychological Science*, *30*(3), 396-404. https://doi.org/10.1177/0956797618820626

Gaynor, N., & Fitzgerald, L. (2023). Mind-wandering and its relationship with psychology wellbeing and obsessive-compulsive symptomatology in the context of Covid-19. *Psychological Reports*, *0*(0), 1-28. https://doi.org/10.1177/00332941231203563

Ho, N. S. P., Poerio, G., Konu, D., Turnbull, A., Sormaz, M., Leech, R., Bernhardt, B., Jefferies, E., & Smallwood, J. (2020). Facing up to the wandering mind: Patterns of off-task laboratory thought are associated with stronger neural recruitment of right fusiform cortex while processing facial stimuli. *NeuroImage*, *214*, 116765. https://doi.org/10.1016/j.neuroimage.2020.116765

Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, *306*(5702), 1776-1780. https://doi.org/10.1126/science.1103572

Kane, M. J., Brown, L. H., McVay, J. C., Silvia, P. J., Myin-Germeys, I., & Kwapil, T. R. (2007). For whom the mind wanders, and when: An experience-sampling study of working memory and executive control and daily life. *Psychological Science*, *18*(7), 614-621. https://doi.org/10.1111/j.1467-9280.2007.01948.x

Kane, M. J., Gross, G. M., Chun, C. A., Smeekens, B. A., Meier, M. E., Silvia, P. J., & Kwapil, T. R. (2017). From whom the mind wanders, and when, varies across laboratory and daily-life settings. *Psychological Science*, *28*(9), 1271-1289. https://doi.org/10.1177/0956797617706086

Kessler, R. C., Adler, L., Ames, M., Demler, O., Faraone, S., Hiripi, E., Howes, M. J., Jin, R., Secnik, K., Spencer, T., Ustun T. B., & Walters, E. E. (2005). The World Health Organization Adult ADHD Self-Report Scale (ASRS): A short screening scale for use in the general population. *Psychological Medicine*, *35*(2), 245-256. https://doi.org/10.1017/S0033291704002892

Killingsworth, M. A., & Gilbert, D. T. (2010). A wandering mind is an unhappy mind. *Science*, *330*(6006), 932. https://doi.org/10.1126/science.1192439

Klinger, E., & Cox, W. M. (Ed.). (2004). Motivation and theory of current concerns. *Handbook of Motivational Counseling: Concepts, Approaches, and Assessment.* John Wiley & Sons Ltd. https://doi.org/10.1002/9780470713129

Konu, D., Turnbull, A., Karapanagiotidis, T., Wang, H. T., Brown, L. R., Jeffries, E. & Smallwood, J. (2020). A role for the ventromedial prefrontal cortex in self-generated episodic social cognition. *NeuroImage*, *218*, 116977. https://doi.org/10.1016/j.neuroimage.2020.116977

Konu, D., Mckeown, B., Turnbull, A., Ho, N. S. P., Karapanagiotidis, T., Vanderwal, T., McCall, C., Tipper, S. P., Jefferies, E., & Smallwood, J. (2021). Exploring patterns of ongoing thought under naturalistic and conventional task-based conditions. *Consciousness and Cognition*, *93*, 103139. https://doi.org/10.1016/j.concog.2021.103139

Kucyi, A., Kam, J. W. Y., Andrews-Hanna, J. R., Christoff, K., & Whitfield-Gabrieli, S. (2023). Recent advances in the neuroscience of spontaneous and off-task thought: Implications for mental health. *Nature Mental Health*, *1*, 827-840. https://doi.org/10.1038/s44220-023-00133-w

Lorenz, R., Hampshire, A., & Leech, R. (2017). Neuroadaptive Bayesian optimization and hypothesis testing. Trends in Cognitive Sciences, 21(3), 155-167. https://doi.org/10.1016/j.tics.2017.01.006

Mason, A. F., Brown, K., Mar, R. A., Smallwood, J. (2013). Diver of discontent or escape vehicle: The affective consequence of mindwandering. *Frontiers in Psychology*, *4*, 477. https://doi.org/10.3389/fpsyg.2013.00477

Mckeown, B., Poerio, G. L., Strawson, W. H., Martinon, L. M., Riby, L. M., Jefferies, E., McCall, C., & Smallwood, J. (2021). The impact of social isolation and changes in work patterns on ongoing thought during the first COVID-19 lockdown in the United Kingdom. *Proceedings of the National Academy of Sciences*, *118*(40), e2102565118. https://doi.org/10.1073/pnas.2102565118

Mckeown, B., Strawson, W. H., Zhang, M., Turnbull, A., Konu, D., Karapanagiotidis, T., Wang, H. T., Leech, R., Xu, T., Hardikar, S., Bernhardt, B., Margulies, D., Jefferies, E., Wammes, J., &

Smallwood, J. (2023). Experience sampling reveals the role that covert goal states play in task-relevant behaviour. *Scientific Reports*, *13*, 21710. https://doi.org/10.1038/s41598-023-48857-0

Montgomery, S. A., & Asberg, M. (1979). A new depression scale designed to be sensitive to change. *British Journal of Psychiatry*, *134*, 382-389. https://doi.org/10.1192/bjp.134.4.382

Mulholland, B., Goodall-Halliwell, I., Wallace, R., Chitiz, L., Mckeown, B., Rastan, A., Poerio, G. L., Leech, R., Turnbull, A., Klein, A., Milham, M., Wammes, J. D., Jefferies, E., & Smallwood, J. (2023). Patterns of ongoing thought in the real world. *Consciousness and Cognition*, *114*, 103530. https://doi.org/10.1016/j.concog.2023.103530

McVay, J. C., & Kane, M. J., (2010). Does mind wandering reflect executive function or executive failure? Comment on Smallwood and Schooler (2006) and Watkins (2008). *Psychological Bulletin*, *136*(2), 188-197. https://doi.org/10.1037/a0018298

Norman., S. B., Cissell, S. H., Means-Christensen, A. J., & Stein, M. (2006). Development and validation of an Overall Anxiety Severity and Impairment Scale (OASIS). *Depression and Anxiety*, *23*(4), 245-249. https://doi.org/10.1002/da.20182

Poerio, G. L., & Smallwood, J. (2016). Daydreaming to navigate the social world: What we know, what we don't know, and why it matters. *Social and Personality Psychology Compass*, *10*, 605-618. https://doi.org/10.1111/spc3.12288

Reiss, S., Peterson, R. A., Gursky, D. M., & McNally, R. J. (1986). Anxiety sensitivity, anxiety frequency and the prediction of fearfulness. *Behaviour Research and Therapy*, *24*(1), 1-8. https://doi.org/10.1016/0005-7967(86)90143-9

Rush, A. J., Trivedi, M. H., Ibrahim., H. M., Carmody, T. J., Arnow, B., Klein, D. N., Markowitz. J. C., Ninan, P. T., Kornstein, S., Manber, R., Thase, M. E., Kocsis, J. H., & Keller, M. B. (2003). The 16-Item Quick Inventory of Depressive Symptomatology (QIDS), clinician rating (QIDS-C), and self-report (QIDS-SR): A psychometric evaluation in patients with chronic major depression. *Biological Psychiatry*, 54(5), 573-583. https://doi.org/10.1016/S0006-3223(02)01866-8

Sheehan, D. V. (1983). The Anxiety Disease. Scribner, New York.

Shevchenko, Y. (2020). *Samply Research* (Version 1.6.4) [Mobile app]. App Store. https://apps.apple.com/us/app/samply-research/id1511062019

Smallwood, J., Fitzgerald, A., Miles, L. K., & Philips, L. H. (2009). Shifting moods, wandering minds: Negative moods lead the mind to wander. *Emotion*, *9*(2), 271-276. https://doi.org/10.1037/a0014855

Smallwood, J., & O'Connor, R. C. (2011). Imprisoned by the past: Unhappy moods lead to a retrospective bias to mind wandering. *Cognition and Emotion*, *25*(8), 1481-1491. https://doi.org/10.1080/02699931.2010.545263

Smallwood, J., Karapanagiotidis, T., Ruby, F., Medea, B., de Caso, I., Konishi, M., Wang, H. T., Hallam, G., Margulies, D. S., & Jefferies, E. (2016). Representing representation: Integration between the temporal lobe and the posterior cingulate influences the content and form of spontaneous thought. *PLoS ONE*, *11*(4), e0152272. https://doi.org/10.1371/journal.pone.0152272

Smallwood, J. & Schooler, J. W. (2006). The restless mind. *Psychological Bulletin*, *132*(6), 946-958. https://doi.org/10.1037/0033-2909.132.6.946

Smallwood, J., & Schooler, J. W. (2015). The science of mind wandering: Empirically navigating the stream of consciousness. *Annual Review of Psychology*, *66*, 487-518. https://doi.org/10.1146/annurev-psych-010814-015331

Smallwood, J., Turnbull, A., Wang, H. T., Ho, N. S. P., Poerio, G. L., Karapanagiotidis, T., Konu, D., Mckeown, B., Zhang, M., Murphy, C., Vatansever, D., Bzdok, D., Konishi, M., Leech, R., Seli, P., Schooler, J. W., Bernhardt, B., Margulies, D. S., & Jefferies, E. (2021). The neural correlates of ongoing conscious thought. *iScience*, *24*(3), 102132. https://doi.org/10.1016/j.isci.2021.102132

Sormaz, M., Murphy, C., Wang, H. T., Hymers, M., Karapanagiotidis, T., Poerio, G., Margulies, D. S., Jefferies, E., & Smallwood, J. (2018). Default mode network can support the level of detail in experience during active task states. *Proceedings of the National Academy of Sciences*, *115*(37), 9318-9323. https://doi.org/10.1073/pnas.1721259115

The WHOQOL Group. (1998). Development of the World Health Organization WHOQOL-BREF quality of life assessment. *Psychological Medicine*, *28*(3), 551-558. https://doi.org/10.1017/S0033291798006667

Turnbull, A., Wang, H. T., Murphy, C., Ho, N. S. P., Wang, X., Sormaz, M., Karapanagiotidis, T., Leech, R., M., Bernhardt, B., Margulies, D. S., Vatansever, D., Jefferies, E., & Smallwood, J. (2019). Left dorsolateral prefrontal cortex supports context-dependent prioritization of off-task thought. *Nature Communications*, *10*, 3816. https://doi.org/10.1038/s41467-019-11764-y

Turnbull, A., Garfinkel, S. N., Ho, N. S. P., Critchley, H. D., Bernhardt, B. C., Jefferies, E., & Smallwood, J. (2020). Word up – Experiential and neurological evidence for associations between autistic symptomology and a preference for thinking in the form of words. *Cortex*, *128*(0), 88-106. https://doi.org/10.1016/j.cortex.2020.02.019

Turnbull, A., Poerio, G. L., Ho, N. S. P., Martinon, L. M., Riby, L. M., Lin, F. V., Jefferies, E., & Smallwood, J. (2021). Age-related changes in ongoing thought relate to external context and individual cognition. *Consciousness and Cognition*, *96*, 103226. https://doi.org/10.1016/j.concog.2021.103226

Vatansever, D., Bozhilova, N., Asherson, P., & Smallwood, J. (2019). The devil is in the detail: Exploring the intrinsic neural mechanisms that link attention-deficit/hyperactivity disorder symptomatology to ongoing cognition. *Psychological Medicine*, *49*(7), 1185-1194. https://doi.org/10.1017/S0033291718003598

Vatansever, D., Karapanagiotidis, T., Margulies, D. S., Jefferies, E., & Smallwood, J. (2020). Distinct patterns of thought mediate the link between brain functional connectomes and well-being. *Network Neuroscience*, *4*(3), 637-657. https://doi.org/10.1162/netn_a_00137

Wallace, R. S., Mckeown, B., Goodall-Halliwell, I., Chitiz, L., Forest, P., Karapanagiotidis, T., Mulholland, B., Turnbull, A. G., Vanderwal, T., Hardikar, S., Alam, T. G., Bernhardt, B., Wang, H. T., Strawson, W., Milham, M., Xu, T., Margulies, D., Poerio, G. L., Jefferies, E. S., Skipper, J.

I., Wammes, J., Leech, R., & Smallwood, J. (2024). Mapping patterns of thought onto brain activity during movie-watching. *eLife*, *13*, RP97731. https://doi.org/10.7554/eLife.97731.1

Ware, J. E., & Sherbourne, C. D. (1992). The MOS 36-item short-form health survey (SF-36): I. Conceptual framework and item selection. *Medical Care*, *30*(6), 473-483. https://www.jstor.org/stable/3765916