From Context to Connectomes: Understanding Differences in Ongoing Thought in the Laboratory and Daily life

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Abstract

Previous work indicates that ongoing thought varies between contexts and that the adaptive nature of different features of thought depends on the context in which they emerge. However, prior investigations have primarily examined specific features of thought in a limited range of laboratory tasks. In doing so, they do not consider the multidimensional and heterogeneous nature of thought, nor reflect the many and varied situations we encounter in everyday life. Accordingly, a core aim of this thesis was to use Multidimensional Experience Sampling (MDES) to empirically map different patterns of thought across a wider range of situations to build a more comprehensive account of context-dependent cognition. In parallel, this thesis capitalises on contemporary methods to map differences in thought to differences in neural architecture to understand the distributed mechanisms supporting different forms of thought, allowing us to go beyond describing experiences. By examining MDES data collected before and during the UK's first COVID-19 lockdown, Study 1 highlights that daily activities play an important role in shaping patterns of thought and that differences in age moderate thought-situation relationships. By examining MDES data collected in the laboratory while watching videos and in daily life during the COVID-19 pandemic, Study 2 identified a generalisable pattern of socio-emotional and future-directed problem-solving that consistently emerges under conditions of uncertainty. Finally, Study 3 suggests that past-related thought and problem-solving at rest differentially predict the relative functional integration and segregation of unimodal systems (visual and sensorimotor). This thesis, therefore, demonstrates the utility of MDES for building a comprehensive account of cognition since it can be used to understand between- and within-person differences in ongoing thought across a wide range of situations, understanding that can be leveraged in the future to understand how thought-situation relationships contribute to aspects of wellbeing and how the brain supports these experiences.

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Author's Declaration

I, Brontë Mckeown, declare that this thesis is a presentation of original work, and I am the sole author, under the primary supervision of Dr Cade McCall. This work has not previously been presented for an award at this, or any other, university. All sources are acknowledged as References.

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Supervisor's Declaration

As the primary supervisor of Brontë Mckeown, I, Dr Cade McCall, confirm that this thesis is the work of the candidate. Where I am named as co-author, this is due to my role in editing and supervising. The roles of other collaborators have been detailed in the acknowledgements section for each empirical chapter.

Chapter 1- Introduction and Review of the Literature

Our train of conscious thought is an integral feature of the human experience, and the contents of these ongoing thoughts vary substantially between different situations, people, and over time (Smallwood et al., 2021). In some moments, our thoughts are closely tied to the situation we are in, or the task we are performing. For example, evaluating an author's point of view while reading an article, or pondering over the beauty of the sun as it rises. However, in other moments, our minds wander further away to events, people, and places that extend beyond the physical here-and-now (Smallwood & Schooler, 2006). For instance, anticipating future scenarios for an upcoming work meeting while getting ready for the day, or reflecting on a recent social interaction while lying in bed at night.

Prior work indicates that our ongoing thoughts change substantially between different contexts and that the costs and benefits associated with different features of thought depend on the context in which they are experienced (Smallwood & Andrews-Hanna, 2013). Contexts can be both internal and external. Internal contexts refer to elements of our internal experience, including cognitive, emotional, and physiological states, while external contexts refer to elements of our external environment, including locations, social environments, and activities. Historically, previous research has focused on investigating specific dimensions of thought (e.g., task focus; Giambra, 1989) in a limited range of task contexts in the laboratory (e.g., sustained-attention-to-response tasks; McVay & Kane, 2009). In doing so, these investigations do not consider the multidimensional and heterogeneous nature of thought, nor reflect the many and varied situations we encounter in our daily lives. Consequently, our understanding of how our ongoing thoughts are influenced by changes in context, particularly those that are demanding, personally-meaningful, and naturally-occurring, remains limited. In turn, this limits our understanding of the psychological nature of different patterns of thought experienced in day-to-day life.

Accordingly, empirically mapping different patterns of thought across a wider range of contexts—in both controlled laboratory and naturalistic real-world settings—is an important step for ultimately understanding how individual differences in 'thought-situation' relationships contribute to aspects of health and wellbeing in the future (Smallwood et al., 2021). In parallel, capitalising on contemporary methods to map individual differences in thought content to individual differences in neural architecture provides valuable insights into the neural mechanisms supporting different forms of thought—allowing us to go beyond simply describing experiences—and provides important validation of self-report methods used to sample ongoing thought (Martinon et al., 2019b).

The current thesis uses a technique known as Multidimensional Experience Sampling (MDES; Smallwood et al., 2016) to address these broad aims. MDES asks participants to describe their experience by rating multiple items assessing different dimensions of thought (e.g., task focus, temporal orientation, self- and other-focus). Study 1 uses MDES to understand how changes to daily life activities during the UK's first COVID-19 lockdown related to changes in ongoing thought patterns and examines how thought-situation relationships in daily life vary between younger and older individuals. Study 2 uses MDES to understand how people think when they are uncertain —and how this varies according to trait anxiety—under controlled laboratory conditions and in daily life during the COVID-19 pandemic. Finally, Study 3 uses MDES to understand how individual differences in ongoing thought content at rest relate to individual differences in neural architecture. The theoretical insights and methodological advancements emerging from these complementary avenues of research can ultimately be leveraged in the future to improve our understanding of *how, when, and for whom* thought patterns are helpful or detrimental and how the brain supports these experiences.

1.1 Outline

This introductory chapter will first provide a conceptual framework and a set of methodological criteria necessary for understanding differences in ongoing thought, and explain how MDES can address these criteria (section 1.2). It will then discuss the value of using naturalistic viewing paradigms in the laboratory, but also highlight the importance of sampling experience in daily life and the need for methods that assess the generalisability of MDES findings in real-world situations (section 1.3). Next, it will consider how sampling ongoing thought in neuroimaging contexts offers valuable insights into these experiences by providing insight into the neural mechanisms as well as important validation of self-report methods used to sample ongoing thought (section 1.4). Finally, it will summarise the aims of each empirical study presented in the current thesis (section 1.5).

1.2 Ongoing Thought is Multidimensional and Heterogeneous

Contemporary accounts of cognition highlight that ongoing thought is multidimensional since it varies in focus, form, and content (Mildner & Tamir, 2019; Seli et al., 2018; Smallwood & Andrews-Hanna, 2013; Smallwood et al., 2016; Smallwood et al., 2021). It is also heterogeneous because not all individuals experience the same patterns of thoughts in all situations. For example, individuals scoring higher in autistic traits show a tendency to think more in words than in images (Turnbull et al., 2020a), while unhappy individuals tend to focus on the past (Smallwood & O'Connor, 2011). Despite both the multidimensionality and the heterogeneity, scientific investigations have often focused on examining specific dimensions of thought in isolation. For example, significant advancements have been made in understanding the functional outcomes associated with ‘mind-wandering’ (e.g., Killingsworth & Gilbert, 2010; Mrazek et al., 2012; Smallwood et al., 2008b) and the variables that determine the prevalence of mind-wandering (e.g., Giambra, 1989; Smallwood et al., 2002). For instance, the prevalence of mind-wandering increases as task block duration increases in tasks that do not require controlled processing, while this effect is not observed in tasks that require controlled processing (Smallwood et al., 2002). Similarly, substantial progress has been made in understanding the role that mental time travel (MTT; Suddendorf & Corballis, 2007; Tulving & Kim, 2007) plays in our everyday lives (e.g., D'Argembeau et al., 2011), the frequency and phenomenological characteristics of voluntary and involuntary MTT (Berntsen, 2021; Cole et al., 2016; Rubin & Berntsen, 2009; Schlagman & Kvavilashvili, 2008), and how these experiences are supported by the brain (Schacter et al., 2017). For example, compared to their voluntary equivalents, involuntary future- and past-oriented thoughts emerge faster, are more specific, and have a stronger impact on mood (Cole et al., 2016). Although valuable, by focussing on specific dimensions of thought in isolation, these investigations do not adequately capture the complex, multidimensional and heterogeneous features of ongoing thought, leading to two important consequences.

First, assessing only a limited range of cognitive dimensions of experience can make it ambiguous whether participants’ responses capture the most salient aspect of their experience. This ambiguity makes it harder to draw firm conclusions regarding the psychological consequences of cognitive experiences and the neural mechanisms underpinning these states. For example, initial investigations in the mind-wandering literature found that mind-wandering is associated with subsequent negative mood, leading to the conclusion that mind-wandering represents a maladaptive cognitive process contributing to unhappiness (Killingsworth & Gilbert, 2010). However, subsequent studies suggest that the association between mind-wandering and subsequent negative mood is driven by the heterogeneous contents of these experiences rather than the occurrence of mind-wandering itself (Poerio et al., 2013; Ruby et al., 2013a). For example, Poerio et al. (2013) found no relationship between instances of mind-wandering and subsequent feelings of sadness or anxiety. However, they found that mind-wandering with negative affective content predicted sadness while mind-wandering with anxious content predicted anxiety. This study suggests that it was features of the content of these experiences, not mind-wandering itself, that determined how these experiences related to mood. However, the absence of questions relating to these features in the study by Killingsworth and Gilbert (2010) meant that this association was impossible to identify. Accordingly, unless we adequately map multiple features of ongoing thought, it is unclear whether we have captured the unique contributions of distinct aspects of thought to other features of experience.

Similar to work on mood, failure to adequately map multiple dimensions of thought can make it difficult to determine the unique neural mechanisms underlying distinct aspects of cognition. For example, initial work examining the neural correlates of mind-wandering found that the default mode network (DMN; Raichle et al., 2001) was consistently recruited during these experiences (Christoff et al., 2009; Fox et al., 2015; Mason et al., 2007). However, subsequent studies assessing different dimensions of these experiences highlight that distinct dimensions of mind-wandering have unique neural correlates. For example, O'Callaghan et al. (2015) found that memory-based construction/simulation mind-wandering was associated with increased functional connectivity between the bilateral temporal pole and bilateral hippocampal formation. In contrast, metacognitive/introspective mind-wandering was associated with increased connectivity between the right hippocampal formation and bilateral posterior cingulate cortex (pCC), suggesting that distinct dimensions of mind-wandering experiences are associated with unique patterns of neural activity. Similarly, Smallwood et al. (2016) found that functional connectivity between different regions of the DMN and pCC was associated with a range of different features of ongoing thoughts. As with investigations of affect, therefore, investigations of brain function demonstrate the need to examine multiple dimensions of experience in order to accurately establish the thought-brain relationships that underpin different features of ongoing experience.

A second consequence of assessing specific dimensions of thought in isolation is that it precludes examining the covariation between different dimensions to characterise common 'patterns of thought'. For example, prior work highlights that multiple dimensions of thought often emerge simultaneously and that the same dimensions of thought can emerge in seemingly opposing states (Smallwood et al., 2021). For instance, when people report being 'off-task', they are often also thinking about the future and other people (Baird et al., 2011;

Konu et al., 2020), and off-task thoughts can emerge in both deliberate and spontaneous cognitive states (Seli et al., 2017b). Therefore, studies suggest that ongoing thought is often multidimensional, and so characterising ‘patterns of thought’ allows us to describe cognition in its’ complexity and may better reflect how it is actually experienced. In MDES studies, this is typically achieved using decomposition techniques like Principal Components Analysis (PCA) that quantify the covariation between questions assessing different dimensions of thought and describe the data in a smaller number of dimensions. For example, using PCA, Ruby et al. (2013a) identified two patterns of off-task thinking that varied in their temporal and social focus (future-directed and self-related vs past- and other-focused). Notably, patterns of future-directed and self-related off-task thought predicted subsequent positive mood, while patterns of past- and other-focused off-task thought predicted subsequent negative mood. This study highlights the possibility that there are (at least) two patterns of off-task thinking and that they may not have the same psychological associations. Therefore, when multiple features of thought are measured, the statistical covariation between different dimensions of thought may be used to estimate features of common ‘patterns of thought’ that people experience. By studying these thought patterns, we may be able to study cognition in a way that better reflects ongoing thought as it actually happens.

In summary, the multidimensional and heterogeneous nature of thought requires it to be described along multiple dimensions since this allows us to (a) better understand the causal mechanisms linking cognition to other attributes (e.g., mood or brain) in a way that is more accurate than unidimensional accounts would allow and (b) characterise the complex features that ongoing thought has by examining the covariation between different dimensions (e.g., the identification that there may be multiple patterns of off-task thinking with different features).

1.2.1 Context and Individual Differences

As well as mapping the multidimensionality and heterogeneity of thought, understanding the psychological nature of different features of thought requires that we can map thought content in a situation-specific manner and that we sample experience across a wide range of situations. Prior work highlights that ongoing thought varies substantially between different external contexts. For example, Barsics et al. (2016) found that the prevalence of emotional future thinking in daily life varied according to ongoing activities, such that working was associated with the most (29%) and leisure activities were associated with the least (3%). Furthermore, Sellen et al. (1997) reported that participants thought more about an upcoming task in daily life in ‘transitional’ locations, including staircases and corridors, compared to their offices where they would be engaged in more cognitively demanding activities. Similarly, Kvavilashvili and Fisher (2007) found that thinking about an upcoming task was more common during habitual, automatic activities (62%), such as having a shower or brushing teeth, compared to demanding, controlled activities (38%), such as being in a lecture or reading a book. In addition, laboratory evidence suggests that the prevalence of spontaneous social thought is closely linked to the availability of social interactions, such that social thinking reduces following periods of solitude and increases following periods of social interaction (Mildner & Tamir, 2021). Accordingly, previous research highlights that different situations and activities (i.e., external contexts) are associated with differences in ongoing thought content.

Accounting for the context within which ongoing thoughts emerge has important explanatory power when investigating the psychological nature of different forms of thought (Smallwood & Andrews-Hanna, 2013). For example, in the mind-wandering literature, conflicting findings led some to conclude that mind-wandering is simply a failure of executive control (McVay & Kane, 2010), while others argued that mind-wandering depends on working memory to provide a workspace for the experience to emerge (Smallwood & Schooler, 2006). However, as formalised under the content- and context-regulation hypotheses (Smallwood & Andrews-Hanna, 2013), adaptive cognition depends on regulating ongoing thought content to match the specific demands of different contexts. For example, while allowing one’s mind to wander during complex, demanding tasks detracts from concentration and impairs performance (Mooneyham & Schooler, 2013; Smallwood et al., 2003; Smallwood et al., 2008b), doing so during less demanding conditions is associated with beneficial features of behaviour including lower impulsivity when making economic choices (Smallwood et al., 2013) and greater fluid intelligence (Turnbull et al., 2019a). Therefore, understanding the psychological nature of different forms of thought requires that we consider the context in which experience unfolds and that we can map multiple features of thought in a situation-specific manner. Moreover, since prior work has primarily focused on assessing a limited range of cognitive features (e.g., task focus or future thinking) in a limited range of controlled task contexts (e.g., working memory), an important goal of the current thesis is to map multiple patterns of thought across a wide range of naturalistic contexts that better reflect the many and varied situations we encounter in our day-to-day lives. For example, Study 1 examines how social interactions and working influence the prevalence of patterns of ongoing thought in daily life.

Relatedly, prior work highlights important links between changes in internal contexts and differences in ongoing thought. Internal contexts include changes in emotional, cognitive, and physiological states. For example, inducing negative affect in the laboratory is associated with an increase in mind-wandering generally (Seibert & Ellis, 1991; Smallwood et al., 2009) and, in particular, mind-wandering with a focus on the past (Smallwood & O'Connor, 2011; Stawarczyk et al., 2013b). In daily life, Poerio et al. (2013) found that sadness—but not anxiety—predicted subsequent increases in mind-wandering frequency. In addition, they found that sadness and anxiety predicted mind-wandering with sad and anxious content, respectively, and sadness predicted more retrospective mind-wandering while anxiety marginally predicted more future-directed mind-wandering. Finally, physiological needs such as nicotine cravings (Sayette et al., 2010) and hunger (Rummel & Nied, 2017) are associated with increased rates of mind-wandering. Accordingly, prior work suggests that our ongoing thoughts are influenced by changes in internal context and therefore highlights the need for methods that can map multiple features of thought according to changes in internal experience. In addition, since prior investigations have predominantly focused on examining how negative versus positive internal contexts relate to specific features of thought, our understanding of how common patterns of thought change in response to other important features of internal experience remains limited. Accordingly, an important contribution of the current thesis is that it explores how the prevalence of different thought patterns varies according to internal states of uncertainty, arousal, and threat across different external contexts (Study 2).

As well as being context-dependent, previous research highlights that ongoing thought varies substantially between individuals. For example, a large body of work suggests that older individuals report lower levels of mind-wandering compared to younger individuals (Diede et al., 2022; Frank et al., 2015; Jackson & Balota, 2012; Jordão et al., 2019a; Krawietz et al., 2012; Maillet et al., 2018; Maillet & Schacter, 2016; McVay et al., 2013; Seli et al., 2017a). In addition, there is some evidence to suggest that older adults report lower levels of spontaneous future thoughts compared to younger adults (Berntsen et al., 2015; Giambra, 2000; Irish et al., 2019). Although, it is worth noting that some studies have failed to detect age-related differences in ongoing thought. For example, Warden et al. (2019) found no age-related differences in the frequency of spontaneous future thoughts in daily life, Jordão et al.

(2019b) found no age-related differences in the frequency of either past- or future-directed spontaneous thoughts while completing a vigilance task in the laboratory, and Berntsen et al. (2017) found no age-related differences in the frequency of involuntary episodic memories in either the laboratory or daily life. In addition, variables such as task motivation (Frank et al., 2015) and reporting method (self-caught versus probe-caught; Jordão et al., 2019a) appear to contribute to some of the observed age-related differences in ongoing thought. Nonetheless, meta-analyses suggest mind-wandering is reliably reduced in older adults (Jordão et al., 2019a; Maillet & Schacter, 2016) and mixed evidence regarding age differences in future thinking warrants further investigation across a wider range of contexts to understand the situations in which younger and older adults think differently (Berntsen et al., 2015; Cole & Kvavilashvili, 2019; Floridou et al., 2019; Irish et al., 2019). As well as age-related differences, prior work suggests that individual differences in clinical disorder symptomology are associated with differences in ongoing thought. For example, attention-deficit hyperactivity disorder (ADHD) and obsessive-compulsive symptomology are associated with elevated levels of spontaneous mind-wandering (Cole & Tubbs, 2021; Seli et al., 2015). In addition, individual differences in neural structure and function are associated with individual differences in ongoing thought. For example, Golchert et al. (2017) found that greater cortical thickness in the retrosplenial cortex and lingual gyrus in the left hemisphere was associated with an increased trait-level tendency to engage in spontaneous mind-wandering, while less cortical thickness in these regions in the right hemisphere was associated with a greater tendency to engage in deliberate mind-wandering. Accordingly, prior work highlights the importance of using methods that are sensitive to individual variation in ongoing thought content and can map individual differences in thought content to differences in individuals' traits and neural architecture. The current thesis examines how ongoing thought patterns and thought-situation relationships vary according to individual differences in age (Study 1) and trait anxiety (Study 2) and how individual differences in ongoing thoughts at rest relate to individual differences in whole-brain functional organisation (Study 3).

1.2.2 Multidimensional Experience Sampling (MDES)

The literature reviewed thus far highlights that building a comprehensive account of cognition requires that we sample experience across a wide range of situations and use methods that can (a) assess multiple features of thought simultaneously and (b) allow heterogeneous thought content to be compared between contexts and individuals. As described earlier, the current thesis uses Multidimensional Experience Sampling (MDES;

Smallwood et al., 2016) to achieve these goals (see Table 1.1). This experience sampling method asks participants to describe the focus, form, and contents of their thoughts by rating several items assessing different dimensions of ongoing thought (e.g., task focus, temporal orientation, valence, spontaneity, and relationship to self or others).

Since MDES allows cognition to be mapped in multiple dimensions, it can be used to (a) identify the dimensions of thought that are most related to the outcome measures of interest and (b) map the covariation between different items to identify common 'patterns of thought' across participants. First, the unique contributions that different dimensions make to other variables of interest can be identified by MDES when all items are used as predictors within the same statistical model. In the current thesis, Study 3 uses this approach to map the unique associations between MDES items and brain activity at rest. Second, by applying PCA to the MDES data, we can describe the covariation within the data to highlight 'patterns of thought'. In this thesis, Studies 1 and 2 will utilise PCA to characterise the MDES data to provide important insights into the patterns of thought experienced in the laboratory and real world.

Importantly, previous studies demonstrate that the MDES approach is sensitive to changes in both external and internal contexts. For example, MDES studies indicate that low-demand task conditions are associated with elevated levels of off-task social and temporal thoughts, future-directed and self-relevant thoughts, imagery-based thoughts, and intrusive thoughts (Konishi et al., 2017; Sormaz et al., 2018; Turnbull et al., 2020a; Turnbull et al., 2019b). In contrast, patterns of detailed and deliberate task-focus are higher in high-demand conditions (Turnbull et al., 2020a). Similarly, deliberate, externally-focused, and goal-directed thought is more prevalent in daily life during demanding versus undemanding activities (Turnbull et al., 2021). In addition, MDES is sensitive to changes in physiological and subjective stress levels in the laboratory and in daily life (Engert et al., 2014; Linz et al., 2019).

Prior work further demonstrates that MDES is sensitive to individual differences. For example, Hoffmann et al. (2016) found that depressed individuals reported thoughts that were more negative, self-related, and past-focused compared to controls, while Turnbull et al. (2020a) found that autistic symptomology was associated with thinking more in words than images, particularly in individuals showing stronger functional connectivity between the lingual gyrus and motor cortex at rest. In addition, Turnbull et al. (2019b) found that individuals with greater executive control refrain from engaging in off-task social episodic thoughts until task demands are low. Furthermore, Karapanagiotidis et al. (2017) found that the extent to which individuals engage in patterns of mental time travel is associated with individual differences in the functional connectivity between the right hippocampus and a core region of the DMN, the dorsal anterior cingulate. Taken together, therefore, prior work demonstrates that MDES can be used to map multidimensional and heterogeneous thought content in a context-specific and person-specific manner.

Table 1.1. Methodological criteria for understanding differences in ongoing thought.

Criteria	How MDES addresses these criteria
Assess multiple features of thought simultaneously	MDES asks participants to describe their experience by rating multiple items assessing different dimensions of thought (e.g., temporal focus, self- and other- focus, valence)
Map multidimensional thought content within- and between individuals across situations	Dimension reduction techniques can be applied to MDES data to identify 'patterns of thought' to examine multidimensional thought within- and between individuals across situations (Studies 1 and 2)
Identify the unique contribution of different dimensions	MDES items can be used as simultaneous predictors within the same model to identify the unique contribution that specific experiential dimensions make to a given outcome (Study 3)

In the current thesis, Study 1 uses MDES and PCA in daily life to compare ongoing thought patterns between different social environments and activities, and understand how these relationships differ between younger and older individuals. Study 2 uses MDES and PCA in the laboratory and daily life to examine how ongoing thought patterns vary between different external contexts and internal emotional states, and how these relationships vary according to individual differences in trait anxiety. In these two studies, applying PCA to the thought data allows us to understand how common patterns of thought emerge within- and between individuals across different situations in both laboratory and daily life contexts. Finally, Study 3 capitalises on the sensitivity of functional magnetic resonance imaging (fMRI) to provide insights into the underlying mechanisms behind cognition and uses the

MDES data in a multivariate regression to isolate the unique relationships between distinct aspects of thought and patterns of whole-brain functional connectivity at rest.

1.3 MDES in the Laboratory and Daily Life

Since prior work highlights the importance of measuring cognition across multiple situations, a key advantage of MDES is that it can be used in the laboratory while participants complete a range of tasks *and* in the real world as participants go about their daily lives (using smartphones to gain in-the-moment reports). Examining ongoing thought in the laboratory is valuable because we have a high level of control over the environment in which experience is sampled, and we can directly manipulate variables of interest. For example, laboratory paradigms have been valuable for examining the similarities and differences between voluntary and involuntary mental time travel (Cole et al., 2016; Rubin & Berntsen, 2009; Schlagman & Kvavilashvili, 2008), for understanding the effect of cues on ongoing thought content (Kvavilashvili & Fisher, 2007; Vannucci et al., 2017), and for investigating how ongoing thought patterns vary according to changes in task difficulty (Konishi et al., 2017; Sormaz et al., 2018; Turnbull et al., 2020a; Turnbull et al., 2019b).

However, while controlled, laboratory investigations often suffer from low ecological validity since they do not reflect the many and varied situations that we encounter in daily life, and recent work highlights important differences between thinking in laboratory and daily life contexts (Ho et al., 2020; Kane et al., 2017; Linz et al., 2019). For example, Kane et al. (2017) examined personality factors associated with increased levels of mind-wandering in both the laboratory and daily life. They found that only neuroticism predicted the prevalence of off-task thoughts in the laboratory, while only openness predicted the prevalence of off-task thoughts in daily life. Therefore, this study suggests that associations identified in the laboratory between ongoing thought and other variables do not necessarily generalise to the real world. In addition, Ho et al. (2020) used the MDES approach to examine how patterns of thought differed between the laboratory and daily life. While their analyses indicated that laboratory and daily life patterns were broadly similar, laboratory off-task thoughts tended to be more social and occurred more spontaneously than daily life off-task thoughts. In addition, they found that daily life deliberate thoughts were more positive than laboratory deliberate thoughts. Accordingly, prior work highlights the importance of (a) developing more ecologically valid paradigms in the laboratory, (b) sampling experience in daily life, and (c) directly assessing the generalisability of laboratory findings in real-world situations.

In the laboratory, naturalistic viewing paradigms (Finn et al., 2020) offer a compromise between controlled laboratory conditions and ecological validity to examine context-dependent changes in thought. These paradigms typically present participants with film clips, TV shows, news items, or gaming environments. These naturalistic stimuli mimic the dynamic, rich, multimodal sensory and contextual features that make up our real-life experiences (Sonkusare et al., 2019), thereby maximising the generalisation of thinking between laboratory and daily life contexts. Importantly, however, they also allow for direct manipulation of variables of interest, including changes in external context, and the induction of specific internal contexts in controlled environments. For example, Antrobus et al. (1966) found that off-task thinking was higher during an ongoing task when participants had previously listened to a radio broadcast announcing that Communist China had declared war on the United States than when participants listened to music. This study highlights that naturalistic paradigms can successfully induce changes in context and thought in the laboratory. However, as with other studies in the literature, a limitation of this study is that it focused on a specific dimension of thought (off-task thinking) and did not examine how multiple dimensions of thought varied according to this manipulation. In the current thesis, Study 2 uses MDES alongside TV-watching paradigms in the laboratory to understand how people think under conditions of uncertainty.

While naturalistic paradigms are useful for overcoming issues with ecological validity, laboratory investigations are nevertheless limited because they place significant onus on the researcher to select relevant contexts that may not adequately reflect the many and varied situations we encounter in our day-to-day lives. Accordingly, examining ongoing thought in daily life is helpful for understanding how cognition emerges under real-world conditions that occur naturally, and are likely to be more personally-meaningful. The value of sampling experience in daily life to efficiently capture changes in context and thought is well illustrated by a study by Killingsworth and Gilbert (2010). This study examined the relationships between mind-wandering, mood, and daily activities in the real-world using smartphone technology. They found that mind-wandering was frequent (occurring in 47% of samples), but daily activities had only a relatively small effect on the prevalence of mind-wandering and almost no effect on the pleasantness of mind-wandering experiences. They also found that mind-wandering was associated with lower levels of happiness across all activities, and overall, mind-wandering was a better predictor of happiness than daily activities. The authors concluded that “a human mind is a wandering mind, and a wandering mind is an unhappy mind". However, as already discussed, this study only examined the pleasantness of mind-wandering experiences, and did not examine the contents of these thoughts (e.g., temporal focus or social content). Accordingly, there is a need to examine how multidimensional thought content emerges during different activities in daily life. In the current thesis, Study 1 uses MDES to understand how the prevalence of multiple thought patterns varies between social environments and daily activities such as work and leisure during the COVID-19 pandemic.

Although applying dimension reduction techniques to MDES data to identify patterns of thought is valuable, data-driven approaches make it difficult to assess the generalisability of laboratory findings in real-world situations since the thought patterns identified in each dataset will necessarily be different to a greater or lesser degree. Consequently, it becomes unclear whether discrepancies in how thoughts relate to other features of experience are driven by the thought patterns themselves being different, or by important differences in the context in which experience was sampled (i.e., naturally-occurring and personally-meaningful vs artificially induced). However, the current thesis employs a novel projection technique to overcome this limitation. In this context, projection involves computing the dot product between the component loadings from one dataset and the MDES items from another. Projecting patterns in this way allows us to examine patterns from different datasets in the same multidimensional space to understand how the same patterns of thought relate to other variables between different situations and samples. Study 2 uses this approach to understand how patterns of thought identified in the laboratory while watching videos relate to uncertainty experienced in both the laboratory and in daily life during the COVID-19 pandemic. While this statistical technique has been used in other research domains (e.g., Farah & McClelland, 1991), it has not been used to directly relate thought patterns between datasets. If the validity of this projection approach to relate thought patterns between datasets can be established, it will be useful for developing more ecologically valid accounts of cognition in the future (Kingstone et al., 2008; Kingstone et al., 2003).

1.4 MDES in Neuroimaging Contexts

MDES can also be used in neuroimaging contexts to investigate how differences in neural function and structure relate to differences in ongoing thought. While laboratory and daily life studies offer the opportunity to examine thought in more naturalistic conditions, relying solely on self-reports can be problematic since they are influenced by confounding variables, including contextual and motivational biases (Nisbett & Wilson, 1977; Vinski &

Watter, 2012). Moreover, self-reports primarily offer a description of ongoing experience and tell us little about the underlying mechanisms supporting these experiences (Martinon et al., 2019b). However, using neuroimaging techniques in combination with self-report measures allows us to overcome some of these limitations since measures of neural function provide objective indices for self-reported differences in experience and allow us to investigate the neural mechanisms underpinning these experiences (Martinon et al., 2019b). Across studies, if similar neural regions or systems are associated with the same types of thought, this (a) suggests that those systems play a key role in supporting these experiences and (b) provides further validity to the methods used to sample these experiences (Turnbull, 2020). In the current thesis, Study 3 uses MDES at the end of a resting-state fMRI scan to identify which dimensions of thought are most related to ongoing patterns of brain activity at rest. While retrospective sampling does not allow introspective reports to be linked to a specific point in time, an important advantage is that these approaches allow the contents of thoughts, and the dynamics of the brain, to unfold naturally since participants do not need to be interrupted (Martinon et al., 2019b; Smallwood & Schooler, 2015).

Contemporary views of cognition assume that complex mental states—such as thinking about the future or the past—rely on the flexible combination of multiple subprocesses supported by multiple systems across the cortex, and that different features of thought are supported by both unique and overlapping neural substrates (Fox et al., 2015; Moscovitch et al., 2016; Smallwood & Schooler, 2015; Smallwood et al., 2021). For example, activity in the DMN has been linked to various aspects of higher-order cognition, including mind-wandering (Fox et al., 2015; Smallwood et al., 2016), future- and past-oriented mental time travel (Addis et al., 2007; Konu et al., 2020; Spreng et al., 2009), and detailed task-relevant cognition during working memory maintenance (Sormaz et al., 2018). For instance, converging evidence indicates that a common 'core network' is recruited when participants remember the past (episodic memory) or imagine the future (episodic simulation) (Benoit & Schacter, 2015; Schacter et al., 2017). This core network shows substantial overlap with the DMN and includes regions in the medial temporal lobe, ventromedial prefrontal cortex (vmPFC), posterior cingulate, and lateral temporal and parietal regions (Benoit & Schacter, 2015). In addition, lesion studies indicate that damage to the vmPFC is associated with impairments in remembering the past and imagining the future (Bertossi et al., 2016) and a reduction in mind-wandering frequency (Bertossi & Ciaramelli, 2016). At the same time, these features of cognition are related to neural processing in other large-scale networks. For example, activity in the frontal parietal network (FPN) has been linked to mind-wandering (Christoff et al., 2009; Fox et al., 2015), episodic simulation (Benoit & Schacter, 2015), and planning of future events (Spreng et al., 2010). Indeed, damage to regions of the FPN is associated with a reduction in mind-wandering frequency (Philippi et al., 2021). Moreover, prior work indicates that the DMN and FPN contribute to different aspects of cognition through their interactions with other neural systems. For example, connectivity between the FPN and the right ventral visual cortex is linked to patterns of detailed thought when individuals complete a working memory task (Vatansever et al., 2019), while connectivity between the DMN and medial visual regions is associated with increased levels of mind-wandering when individuals are reading (Zhang et al., 2019). At the same time, regions outside the FPN and DMN are implicated in aspects of spontaneous thought, including the right secondary somatosensory cortex and left lingual gyrus (Fox et al., 2015). Accordingly, prior work highlights the importance of whole-brain analytical approaches to understand how interactions between large-scale systems relate to differences in ongoing thought.

Importantly, prior work using MDES (a) demonstrates that this approach is sensitive to individual variation in neural function, (b) highlights the mechanistic insights gained from investigating ongoing thought in neuroimaging contexts, and (c) provides further support for the idea that different features of ongoing thought are supported by a distributed set of regions across the cortex (Gorgolewski et al., 2014; Ho et al., 2020; Ho et al., 2019; Karapanagiotidis et al., 2017; Karapanagiotidis et al., 2021; Konu et al., 2020; Martinon et al., 2019a; Medea et al., 2018; Turnbull et al., 2020a; Turnbull et al., 2020b; Vatansever et al., 2020; Wang et al., 2018b). For example, Turnbull et al. (2019b) examined how individuals prioritise on- and off-task thoughts according to external demands. Their analyses indicated that the left dorsolateral prefrontal cortex (DLPFC) plays a key role in the prioritisation of off-task thoughts when external demands are low. Critically, this study demonstrates how the combination of self-report and neural measures allows researchers to go beyond describing experiences (i.e., off-task thoughts are more common under less-demanding conditions) to understand the mechanisms underlying differences in ongoing thought (i.e., DLPFC plays a common role in prioritisation of thought patterns based on their relevance to the context in which they occur). In addition, Wang et al. (2018a) simultaneously decomposed resting-state fMRI data and MDES data to identify whole-brain connectivity patterns associated with different types of thought at rest. This analysis identified four components, each describing unique patterns of variation in both the neural and thought data. For example, component one identified a pattern linking purposeful, temporal, and social thoughts with reduced connectivity between sensorimotor regions and all other networks, and a decoupling between the DMN and attentional networks. Therefore, this study demonstrates how using MDES in conjunction with whole-brain analysis techniques provides important insights into how macroscale features of the cortex relate to different types of ongoing thought.

In the current thesis, Study 3 adopts a 'gradient' approach to investigate which MDES items are most related to patterns of whole-brain function at rest. This approach applies dimension reduction techniques to resting-state fMRI data to identify patterns of whole-brain connectivity. These are often referred to as 'cortical gradients' (Margulies et al., 2016) and explain whole-brain connectivity variance in descending order. Along each gradient, brain regions with similar connectivity profiles (to the rest of the brain) fall close together, while regions with more distinct connectivity profiles fall further apart (Huntenburg et al., 2018). Importantly, this approach does not localise neural activity to specific regions, but instead describes similarities and differences in connectivity between large-scale functional networks across the cortex. Prior studies have highlighted three gradients that relate to important features of cognition (Hong et al., 2019; Murphy et al., 2018; Turnbull et al., 2020b). The first gradient describes the difference between regions of 'unimodal' (e.g., visual and sensorimotor regions) and 'transmodal' (e.g., DMN and limbic regions) cortex (Margulies et al., 2016). The second gradient describes the difference between unimodal regions, separating visual and sensorimotor systems. Finally, the third gradient describes the difference between DMN and task-positive systems (i.e., the FPN). Therefore, this gradient approach—coupled with MDES—allows for the investigation of how different features of ongoing thought relate to macroscale features of cortical organisation.

1.5 Summary and Aims of the Current Thesis

Contemporary accounts of cognition highlight that ongoing thought is multidimensional, varying in focus, form, and content, often in a heterogeneous manner. We can use MDES to capture this complexity and the current thesis uses this technique to address two broad aims. First, by mapping common 'patterns of thought' across a wide range of situations in both the laboratory and in daily life, it aims to improve our understanding of how context shapes our cognition and how this varies between individuals (Studies 1 and 2). Second, by capitalising on contemporary methods to map differences in ongoing thought content to differences in whole-brain functional organisation, it aims to improve our understanding of the neural mechanisms underlying distinct features of thought (Study 3). A high-level summary of the aims of each empirical study is shown in Table 1.2.

Table 1.2. A high-level summary of the aims of each empirical study included in the current thesis.

Study	Aims
Study 1	Map ongoing thought patterns to changes in external context and individual differences in age in daily life
Study 2	Map ongoing thought patterns to changes in external and internal context, and individual differences in trait anxiety in the laboratory and daily life
Study 3	Map individual differences in ongoing thought content to individual differences in whole-brain functional connectivity during resting-state fMRI scan

Study 1 uses MDES in daily life to compare ongoing thought patterns between different social environments and activities, and understand how individual differences in age moderate these relationships. Specifically, this study investigates how changes to daily life activities during the UK's first COVID-19 lockdown corresponded to changes in ongoing thought patterns observed during this time in younger and older individuals. Prior studies investigating the psychological impact of the COVID-19 pandemic have largely focused on mental health outcomes (e.g., Banks & Xu, 2020; O'Connor et al., 2020; White & Van Der Boor, 2020). However, several studies have also examined the impact of COVID-19 and its associated restrictions on individuals' cognition (Clayton McClure & Cole, 2022; Fiorenzato et al., 2021; Hart et al., 2022; Niziurski & Schaper, 2021; Öner et al., 2022). For example, Fiorenzato et al. (2021) found that for younger individuals (18-45 years), COVID-19 restrictions in Italy were associated with poorer subjective cognitive functioning in everyday tasks requiring attention and concentration, temporal orientation, and executive functions. However, COVID-19 restrictions were also associated with improved subjective memory functioning across age groups (i.e., reduced forgetfulness in daily activities), which the authors attribute to changes in daily routine during lockdown. Furthermore, Öner et al. (2022) found clear evidence of collective remembering and forecasting of national and global events during the COVID-19 pandemic. For example, they found that themes of infections and lockdowns dominated global and national past events, while themes of economy and a second wave dominated future events. In addition, Hart et al. (2022) found that during the early stages of the COVID-19 pandemic, consuming news related to COVID-19 was associated with greater task-unrelated thoughts in everyday life. Accordingly, Study 1 complements these studies by examining how changes to daily life activities during the UK's first COVID-19 lockdown corresponded to changes in ongoing thought patterns observed during this time. In doing so, this study improves our theoretical understanding of how naturally-occurring and personally-meaningful contexts shape our cognition in daily life and how this changes across the life span. This study was published in the *Proceedings of the National Academy of Sciences* (PNAS) in 2021.

Study 2 uses MDES in the laboratory and daily life to examine how ongoing thought patterns vary between external contexts and internal emotional states, and how these relationships vary according to individual differences in trait anxiety. Specifically, this study investigates how people think under conditions of uncertainty, arousal, and threat. In the laboratory, states of arousal and uncertainty are induced using TV-watching paradigms and ongoing thought patterns identified in the laboratory MDES data are related to changes in video condition (external context), differences in subjective arousal and uncertainty (internal context), and levels of trait anxiety. To assess the generalisability of our laboratory findings in a real-world situation, laboratory thought patterns are projected directly onto daily life data collected during the COVID-19 pandemic. These projected patterns are related to differences in subjective threat, subjective uncertainty, and levels of trait anxiety. In doing so, this study improves our theoretical understanding of how we think under conditions of uncertainty, arousal, and threat and how this differs between low- and high-trait-anxiety individuals. Moreover, this study establishes that projecting thought patterns between laboratory and daily life datasets allows us to directly assess the generalisability of laboratory MDES findings in real-world contexts. This study is currently under review (at the time of submission) at *PloS one.*

Finally, Study 3 investigates which features of thought assessed using MDES are most related to macroscale features of cortical organisation at rest. Specifically, this study explores whether individual variation along three reasonably well-explained 'cortical gradients'—describing whole-brain functional connectivity patterns—are related to individual differences in ongoing thought during a resting-state fMRI scan. In doing so, this study provides theoretical insights into how macroscale features of the cortex support different forms of thought. This study was published in *Neuroimage* in 2020.

Chapter 2- The impact of social isolation and changes in work patterns on ongoing thought during the first COVID-19 lockdown in the United Kingdom

This chapter is adapted from:

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).

Acknowledgements and authors' contributions:

Brontë Mckeown designed the lockdown study, prepared the lockdown study materials, collected the lockdown data, performed the statistical analyses, interpreted the results, prepared visualisation of results, and wrote the manuscript for publication under the supervision of Dr Cade McCall, Prof. Elizabeth Jefferies, and Prof. Jonathan Smallwood. Dr Giulia Poerio and Will Strawson also provided feedback on the design of the lockdown study and helped prepare lockdown study materials. Prior to the start of Brontë Mckeown's research degree, Prof. Jonathan Smallwood, Prof. Elizabeth Jefferies, Prof. Leigh Riby, and Dr Giulia Poerio designed the pre-lockdown study, and Dr Giulia Poerio and Dr Lea Martinon collected the pre-lockdown data. All co-authors contributed to reviewing and editing the manuscript for publication.

2.1 Abstract

The COVID-19 pandemic led to lockdowns in countries across the world, changing the lives of billions of people. The United Kingdom's first national lockdown, for example, restricted people's ability to socialize and work. The current study examined how changes to socializing and working during this lockdown impacted ongoing thought patterns in daily life. We compared the prevalence of thought patterns between two independent real-world, experience-sampling cohorts, collected before and during lockdown. In both samples, young (18 to 35 y) and older (55+ y) participants completed experience-sampling measures five times daily for 7 d. Dimension reduction was applied to these data to identify common "patterns of thought." Linear mixed modeling compared the prevalence of each thought pattern 1) before and during lockdown, 2) in different age groups, and 3) across different

social and activity contexts. During lockdown, when people were alone, social thinking was reduced, but on the rare occasions when social interactions were possible, we observed a greater increase in social thinking than prelockdown. Furthermore, lockdown was associated with a reduction in future-directed problem solving, but this thought pattern was reinstated when individuals engaged in work. Therefore, our study suggests that the lockdown led to significant changes in ongoing thought patterns in daily life and that these changes were associated with changes to our daily routine that occurred during lockdown.

2.2 Introduction

On March 23, 2020, the United Kingdom entered a nationwide lockdown to curb the spread of COVID-19. This first national lockdown required people to stay at home and not meet with anyone outside their household. Social gatherings were banned, and “nonessential” industries were closed, reducing opportunities for work (Chiripanhura et al., 2020). There were also large economic changes (Stephens et al., 2020), and death rates increased substantially (Campbell & Caul, 2020). Studies show the lockdown had widespread psychological and behavioral consequences including elevated anxiety and depression levels (White & Van Der Boor, 2020), overall deterioration of mental health (Banks & Xu, 2020), changes to diet and physical activity (Giuntella et al., 2021; Huckins et al., 2020; Robinson et al., 2020), high levels of loneliness (Groarke et al., 2020), and increasing suicidal ideation (O'Connor et al., 2020). Our study used experience sampling to measure patterns of ongoing thoughts before and during lockdown in the United Kingdom, with the aim of understanding how specific features of the stay-at-home order impacted people’s thinking in daily life, and to use this data to inform contemporary theoretical views on ongoing thought.

Our investigation served three broad goals. First, the lockdown led to changes in opportunities for socializing, and contemporary theories of ongoing thought suggest that social processing is an important influence on our day-to-day thinking (Mildner & Tamir, 2021; Poerio & Smallwood, 2016). For example, previous research indicates that individuals spend a lot of time thinking about other people in daily life (Mar et al., 2012; Song & Wang, 2012) or when performing tasks dependent on social cognition in the laboratory (Konu et al., 2021). Importantly, spontaneous social thoughts decline following periods of solitude and increase following periods of social interaction in the laboratory (Mildner & Tamir, 2021). They can also facilitate socioemotional adjustment during important life transitions, such as starting university (Poerio et al., 2016). Furthermore, ongoing thought patterns with social features are associated with increased neural responses to social stimuli (in this case, faces)

(Ho et al., 2020). Such evidence suggests that the social environment can shape ongoing thought, leading to the possibility that changes in opportunities for socialization following the stay-at-home order could have changed the expression of social thinking in daily life.

Second, lockdowns also disrupted individuals' normal working practices, forcing people to reassess their goals. Prior work highlights that ongoing thought content is linked to an individual's current concerns and self-related goals (Baird et al., 2011; Gold & Reilly III, 1985; Klinger et al., 1980; Stawarczyk et al., 2011) and that experimentally manipulating an individual's goals can prime ongoing thought to focus on these issues (Antrobus et al., 1966; Kappes et al., 2012; Stawarczyk et al., 2011). In particular, a substantial proportion of ongoing thoughts are future directed (Baird et al., 2011; D'Argembeau et al., 2011; Ruby et al., 2013a; Song & Wang, 2012; Stawarczyk et al., 2013a; Stawarczyk et al., 2011), and this "prospective bias" is thought to support the formation and refinement of personal goals for future behavior (Baird et al., 2011; Klinger et al., 2018; Medea et al., 2018; Stawarczyk et al., 2011). Notably, this type of thought is also important in maintaining mental health through associations with improved subsequent mood (Ruby et al., 2013a) and reduced suicidal ideation (Hunter & O'Connor, 2003; O'Connor et al., 2004). Changes to opportunities for working during the lockdown, therefore, provide a chance to understand whether prospective features of ongoing thought are altered when important external commitments change.

Third, previous work indicates that the contents of thought vary across the life span. For example, during periods of low cognitive demand, younger adults report significantly more future-directed thoughts, while older adults report significantly more past-related thoughts (Irish et al., 2019). At rest, older adults report more "novel" and present-oriented thoughts compared to younger adults (Maillet et al., 2019). In daily life, older adults tend to report fewer "off-task" thoughts than younger adults, and their thoughts are rated as more "pleasant," "interesting," and "clear" (Maillet et al., 2018). Finally, aging is associated with a decline in daydreaming, particularly a reduction in topics such as the future, fear of failure, or guilt (Giambra, 1974). However, the degree to which these age-related changes are explained by lifestyle differences between young and older individuals is unclear. The lockdown may have altered key contextual factors that, under normal circumstances, differ systematically between younger and older adults. For example, increasing age is associated with more interactions with family members and fewer with "peripheral partners" (e.g., coworkers, acquaintances, and strangers) (Zhaoyang et al., 2018), a pattern that may be common in younger people during lockdown. With all this in mind, the lockdown provided an opportunity to examine whether changes to daily life during the lockdown differentially impacted ongoing thought patterns in younger and older individuals.

Our study used an experience-sampling methodology in which people are signaled at random times in their daily lives to obtain multiple reports describing features of their ongoing thoughts and the context in which they occur (e.g., social environment, activity, and location) (Larson & Csikszentmihalyi, 2014). To examine the contents of people's thoughts, we used multidimensional experience sampling (MDES) (Smallwood et al., 2016). In this method, participants describe their in-the-moment thoughts by rating their thoughts on several dimensions (e.g., temporal focus or relationship to self and others) (Martinon et al., 2019b). Dimension reduction techniques can then be applied to use covariation in the responses to different questions to identify "patterns of thought" (Smallwood et al., 2016; Smallwood et al., 2021). Previous studies have used MDES to identify common patterns of ongoing thought, varying in both form and content, often with distinct neural correlates (Karapanagiotidis et al., 2020; Konu et al., 2020; Medea et al., 2018; Smallwood et al., 2016; Smallwood et al., 2021; Turnbull et al., 2019b; Wang et al., 2018b). For example, a pattern of episodic social cognition is associated with increased activity within regions of the ventromedial prefrontal cortex associated with memory and social cognition (Konu et al., 2020), while a pattern of external task focus is associated with increased activity in the intraparietal sulcus (Turnbull et al., 2019b). In addition, at rest, visual imagery is associated with stronger interactions between the precuneus and lateral frontotemporal network (Karapanagiotidis et al., 2021), while detailed task focus is high during working memory tasks (Konu et al., 2021) and other complex tasks (Turnbull et al., 2019a) and linked to activity in the default mode network during working memory maintenance (Sormaz et al., 2018).

In summary, our study set out to examine whether ongoing thought patterns experienced during lockdown differed from those normally reported in daily life, focusing on the consequences of changes in opportunities for socialization and work. The prelockdown sample was an existing dataset used to provide a baseline for ongoing thought patterns in daily life before lockdown restrictions. In both samples, young (18 to 35 y) and older (55+ y) participants completed surveys five times daily over 7 d. Each sampling point obtained in the moment measured key dimensions of ongoing thought using MDES (Smallwood et al., 2016). Participants also provided information regarding the social environment in which the experience occurred. Dimension reduction was applied to both samples' thought data to identify common patterns of thought. We then used linear mixed modeling (LMM) to explore the prevalence of each thought pattern 1) before and during lockdown, 2) in different age groups, and 3) across social contexts. In the lockdown sample, participants provided additional information regarding their current activity (e.g., working or leisure activities) and virtual social environment, which we used to explore how specific features of daily life during lockdown corresponded with patterns of thought.

2.3 Results

2.3.1 Changes to Daily Life during Lockdown

In both samples, after first assessing the contents of their thoughts, participants were asked about their social environment immediately before being signaled. We expected that the percentage of responses for which participants reported being alone would be higher in the lockdown sample than the prelockdown sample. To test this, we calculated the percentage of each participant's responses in which they said they were 1) alone, 2) around people but not interacting, and 3) around people and interacting. Sample means for each of the three percentages, for young and older participants, are shown in Figure 2.1A. A two-way ANOVA confirmed that during lockdown, the "alone" percentage was significantly higher compared to prelockdown [$F(1, 191) = 12.03$, $P < 0.001$, $\eta p^2 = 0.06$] and significantly higher for younger compared to older participants across both samples (pre- and during lockdown) [$F(1, 191) = 13.25$, $P < 0.001$, $\eta p^2 = 0.06$]. Participants in the lockdown sample also reported their location immediately before completing the survey. Overall percentages for each option are shown in Figure 2.1B, revealing that 85% of responses were "inside at home." These analyses establish that people spent more time alone during lockdown and most of their time inside at home.

2.3.2 Patterns of Thought

To identify common patterns of thought across both samples, we combined the thought data from both samples (*SI Appendix*, Table S1) and decomposed these in a single principal components analysis (PCA). Based on eigenvalues >1, five components—accounting for 53% of the total variance—were retained for further analysis (see *SI Appendix*, Fig. S1 for scree plot): 1) "future-directed problem solving"— describing patterns of thought with the highest loadings on "problem solving," "future goals," "controlled," and "rehearsing future"; 2) "pleasant engagement"—with the highest loadings on "positive," "wanted," "current goals," and "task"; 3) "episodic social cognition"—with the highest loadings on "close others," "important," "self," and "future"; 4) "imagery"—with the highest loadings on "vivid," "images," and "detailed"; and 5) "detailed task focus"—with the highest loadings on "words," "task," "detailed," and "current goals." Item loadings on these components are presented as word clouds in Figure 2.1C (see *SI Appendix*, Table S2 for exact component loadings). To ensure that the thought patterns identified across samples were present in both samples, we ran a PCA on each sample separately (specifying five components for extraction) and correlated each participant's PCA score from this analysis with their PCA score from the combined analysis, revealing a high correspondence between patterns seen in the two samples (see *SI Appendix*, Fig. S2 for scatterplots).

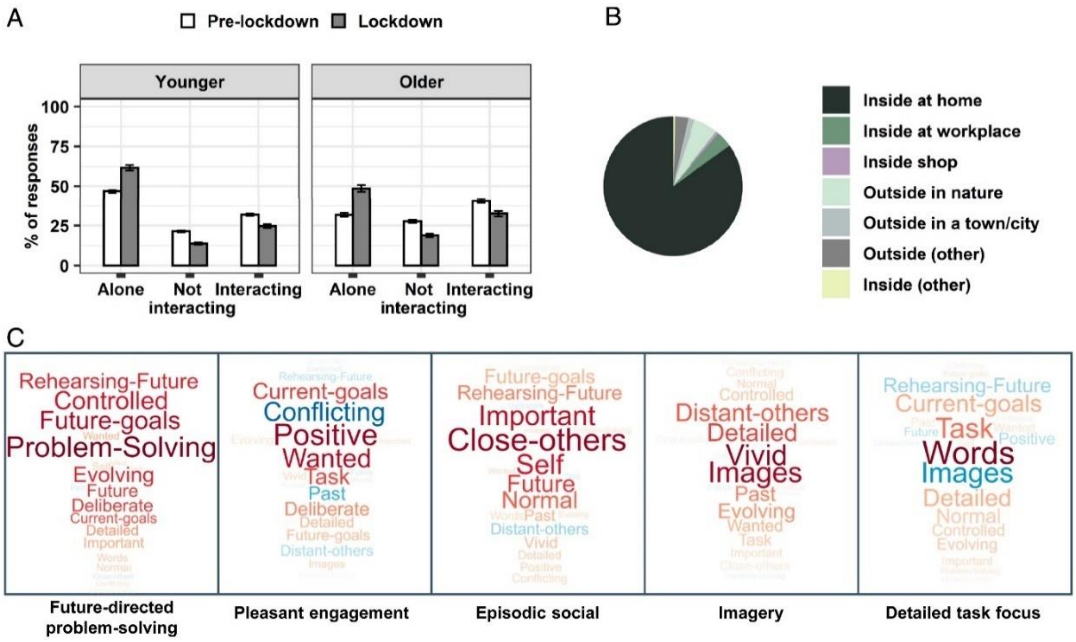

Figure 2.1. Changes to daily life during lockdown and patterns of ongoing thought identified across both experience-sampling datasets (pre- and during lockdown). (A) Bar chart comparing the mean percentage of experience-sampling responses in which participants said they were 1) alone, 2) around other people but not interacting, or 3) around people and interacting, between age groups and samples, demonstrating that during lockdown, both age groups reported being alone more than prelockdown. Error bars represent 95% CIs (N observations = 4,955). (B) The pie chart shows the percentage of responses for each location option in the lockdown sample, demonstrating that the majority (85%) of responses were "inside at home" (N observations = 1,865). (C) Word clouds representing the item loadings on the five patterns of thought identified in the thought data from both samples (pre- and during lockdown) (N observations = 4,876) using PCA. Each word represents an experience-sampling item (22 items; *SI Appendix,* Table S1). Font size represents the magnitude of the loading, and the color describes the direction. Warm colors reflect positive loadings, while cool colors reflect negative loadings (see *SI Appendix*, Table S2 for exact component loadings).

2.3.3 Comparing Thought Patterns between 1) Pre- and during Lockdown Samples, 2) Age Groups, and 3) Social Environments

Having identified five patterns of thought, we examined the influence that lockdown, and changes to social interactions during lockdown, had on ongoing thought by comparison with the baseline group. We performed a series of LMMs in which each of the five thought patterns was the outcome measure (see *Materials and Methods*). These models included three explanatory variables and their interactions: 1) whether the sample was pre- or during lockdown, 2) whether the individual was young or older, and 3) the nature of the social environment in which the experience occurred (alone, with others not interacting, or with others and interacting). For each model, alpha was set to <0.01 (two tailed) to account for family-wise error emerging from conducting five models (i.e., 0.05/5). The reported alpha levels in our paper are unadjusted; main effects and interactions are considered significant only at the $P < 0.01$ level. When probing these significant main effects and interactions using pairwise comparisons, the alpha level was Bonferroni adjusted to account for the number of tests being conducted; here, the adjusted alpha levels are reported in parentheses. Estimates are unstandardized and reflect the difference between each factor level and the intercept (grand mean of all conditions). These results are summarized in Figure 2.2 (see *SI Appendix*, Tables S3–S5 for ANOVA output, parameter estimates, and the variance explained by random effects).

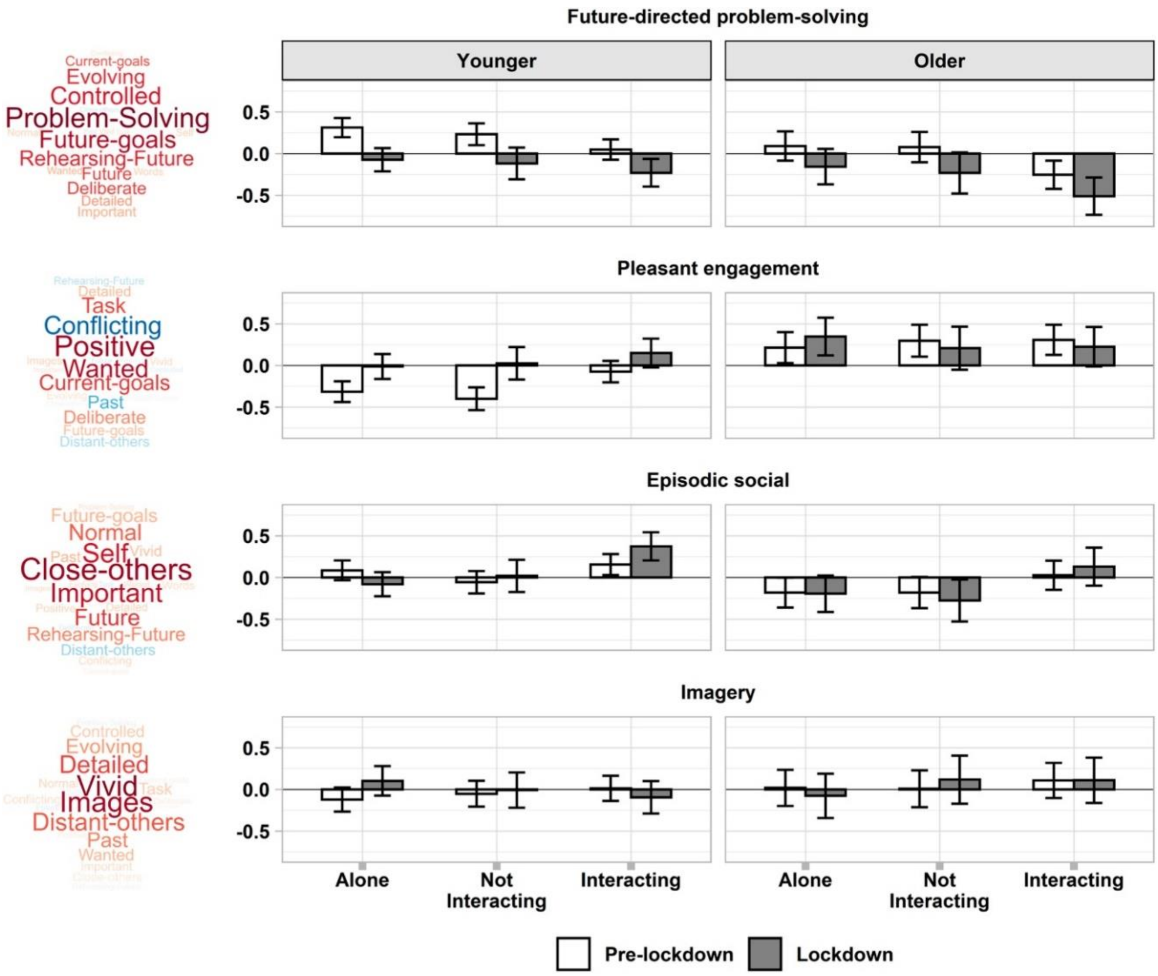

Figure 2.2. A summary of the LMMs' results comparing the prevalence of each thought pattern between 1) pre- and during-lockdown samples, 2) age groups, and 3) social environments. On the left-hand side, there are the word clouds representing each thought pattern. Each word represents an experience-sampling item (*SI Appendix*, Table S1). Font size represents the magnitude of the loading, and the color describes the direction. Warm colors reflect positive loadings, while cool colors reflect negative loadings. The y-axis of each graph shows the predicted means for each thought pattern. The x-axis shows the social environment options: 1) alone, 2) around people but not interacting, and 3) around people and interacting. White bars represent the prelockdown sample, and gray bars represent the lockdown sample. Each bar graph is split by age group, with young participants on the left and older on the right. Error bars represent the 95% CIs for each predicted mean. In total, 195 participants (4,870 observations) were included in this analysis.

2.3.3.1 Model 1: Future-directed problem solving

There was a significant main effect of sample (pre- versus during lockdown) [$F(1, 191) = 16.19$, $P < 0.001$]. Future-directed problem solving was lower in the lockdown sample [$b = -0.15$, 95% CI (−0.23, −0.08), $t(191) = -4.02$, $P < 0.001$]. There was also a significant main effect of age group [$F(1, 188) = 6.33$, $P = 0.013$], with future-directed problem solving higher in younger participants [$b = 0.10$, 95% CI (0.02, 0.17), $t(188) = 2.52$, $P = 0.012$]. There was also a significant main effect of social environment [$F(2, 4824) = 31.36$, $P < 0.001$], with future-directed problem solving lower when interacting with other people [$b = -0.17$, 95% CI $(-0.21, -0.12)$, $t(4850) = -7.52$, $P < 0.001$]. Therefore, the lockdown was associated with a reduction in future-directed problem solving regardless of social environment or age group.

2.3.3.2 Model 2: Pleasant engagement

Levels of pleasant engagement significantly varied by age group [$F(1, 191) = 19.82$, $P < 0.001$] and were lower in younger participants [$b = -0.19$, 95% CI $(-0.27, -0.10)$, $t(191) = -4.45$, $P < 0.001$). There was a significant main effect of social environment [$F(2, 4823) = 5.43$, $P = 0.004$], with pleasant engagement highest when participants were interacting with others [$b = 0.07$, 95% CI $(0.03, 0.11)$, $t(4833) = 3.29$, $P < 0.001$] and lowest when around people but not interacting [$b = -0.05$, 95% CI $(-0.10, -0.00)$, $t(4802) = -1.99$, $P = 0.046$]. There was also a significant interaction between age group and social environment [$F(2, 4823) = 5.60$, $P = 0.004$]. Pairwise comparisons at each level of social environment split by age group (Bonferroni adjusted for six tests) revealed that for younger participants, pleasant engagement was significantly higher when interacting with other people compared to when alone [$b = 0.20$, 95% CI $(0.09, 0.31)$, $t(4808) = 4.90$, $P < 0.001$] or when around other people but not interacting [$b = 0.22$, 95% CI $(0.09, 0.36)$, $t(4786) = 4.43$, $P < 0.001$]. For older participants, however, pleasant engagement did not significantly vary across social environments ($P > 0.05$). Regardless of the lockdown, therefore, social situations were characterized by higher levels of pleasant engagement for younger individuals.

2.3.3.3 Model 3: Episodic social cognition

There was a significant main effect of social environment [$F(2, 4827) = 35.20$, $P < 0.001$] with episodic social cognition highest when interacting with others [$b = 0.19$, 95% CI $(0.14, 0.23)$, $t(4840) = 8.37$, $P < 0.001$] and lowest when around people but not interacting [$b = -0.11$, 95% CI $(-0.16, -0.06)$, $t(4815) = -4.35$, $P < 0.001$). There was a significant main effect of age group [$F(1, 193) = 6.10$, $P = 0.014$]. Episodic social cognition was higher in younger participants [$b = 0.10$, 95% CI $(0.02, 0.18)$, $t(193) = 2.47$, $P = 0.014$]. There was also a significant interaction between sample (pre- versus during lockdown) and social environment [$F(2, 4826) = 6.06$, $P = 0.002$]. This interaction indicated that although episodic social cognition was most prevalent when interacting with others in both samples, the increase in episodic social cognition between "interacting" with both "alone" [unadjusted, $b = 0.25$, 95% CI $(0.11, 0.39)$, $t(4844) = 3.44$, $P < 0.001$] and "not interacting" [unadjusted, $b = 0.17$, 95% CI $(0.01, 0.34)$, $t(4795) = 2.03$, $P = 0.042$] was greater in the lockdown sample.

During lockdown, therefore, although social interactions were less frequent, when they did occur, they were associated with greater evidence of episodic social cognition.

2.3.3.4 Model 4: Imagery

There was a significant three-way interaction between sample, age group, and social environment [$F(2, 4778) = 5.85$, $P = 0.003$]. Pairwise comparisons at each level of social environment, split by sample and age group (Bonferroni adjusted for 12 tests), revealed that for younger participants, the direction of the effect of social environment on levels of imagery differed between samples. Prelockdown, younger participants reported *less* imagery when they were alone compared to when they were interacting with others [$b = -0.14$, 95% CI (−0.27, −0.01), $t(4745) = -2.98$, $P = 0.035$], and during lockdown, younger participants reported *more* imagery when they were alone compared to when they were interacting with others [$b = 0.20$, 95% CI (0.01, 0.38), $t(4855) = 3.05$, $P = 0.028$]. A comparison of these contrasts confirmed that this difference was significant [unadjusted, $b = -0.33$, 95% CI (−0.49, −0.18), $t(4845) = -4.21$, $P < 0.001$]. Therefore, during lockdown, younger participants reported more imagery when they were alone compared to when interacting with others.

2.3.3.5 Model 5: Detailed task focus

There were no significant main effects or interactions ($P > 0.05$). Therefore, the lockdown had no significant impact on the overall prevalence of detailed task focus.

2.3.4 Comparing Thought Patterns between 1) Current Activities and 2) Age Groups during Lockdown

To understand how changes to people's daily routine, including changes to working, influenced patterns of ongoing thought during lockdown, we next explored the links between ongoing thought patterns and ongoing activities. In the baseline sample, we had not obtained information about concurrent activities; however, in the lockdown sample, we asked participants to describe the primary activity they were performing (see *Materials and Methods*). The 24 options were condensed into five categories for analysis: 1) working, 2) leisure activities, 3) social interactions, 4) media consumption, and 5) essential tasks (*SI Appendix*). We conducted a series of models examining whether patterns of thought varied significantly between activity categories and whether there were age-related differences (see *Materials and Methods*). As before, the alpha level was set to <0.01 (two tailed) to account for family-wise error emerging from conducting five models. These results are summarized in Figure 2.3 (see *SI Appendix*, Tables S7–S9 for ANOVA output, parameter estimates, and the variance explained by random effects).

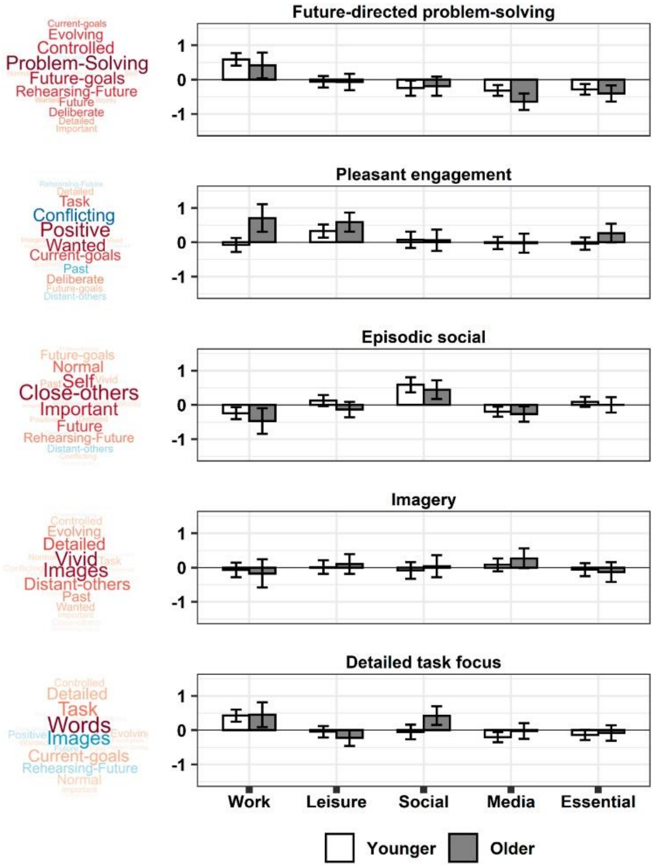

Figure 2.3. A summary of the LMMs' results comparing the prevalence of each thought pattern between 1) current activities and 2) age groups in the lockdown sample. On the left-hand side, there are the word clouds representing each thought pattern. Each word represents an experience-sampling item (*SI Appendix*, Table S1). Font size represents the magnitude of the loading, and the color describes the direction. Warm colors reflect positive loadings, while cool colors reflect negative loadings. The y-axis of each graph shows the predicted means for each thought pattern. The x-axis shows the five activity categories: 1) working, 2) leisure activities, 3) social interactions, 4) media consumption, and 5) essential tasks (see *SI Appendix* for details). White bars represent young participants, and gray bars represent older participants. Error bars represent the 95% CIs for each predicted mean. In total, 81 participants (1,777 observations) were included in this analysis.

2.3.4.1 Model 1: Future-directed problem solving

There was a significant main effect of activity [$F(4, 1712) = 33.67$, $P < 0.001$]. Future-directed problem solving was higher when participants were working during lockdown [$b = 0.62$, 95% CI (0.48, 0.77), $t(1689) = 8.62$, $P < 0.001$] and lower when consuming media [$b = -0.36$, 95% CI (−0.44, −0.28), $t(1743) = -8.92$, $P < 0.001$] or engaging in essential tasks [$b = -0.22$, 95% CI (−0.30, −0.14), $t(1727) = -5.59$, $P < 0.001$]. Therefore, while future-directed problem solving was significantly lower in the lockdown sample, this pattern of thought was reinstated when individuals engaged in work.

2.3.4.2 Model 2: Pleasant engagement

There was a significant main effect of activity [$F(4, 1699) = 18.93$, $P < 0.001$]. Pleasant engagement was higher during leisure activities [$b = 0.27$, 95% CI (0.19, 0.36), $t(1712) = 6.36$, $P < 0.001$] and lower when participants consumed media [$b = -0.21$, 95% CI (−0.29, −0.13), $t(1730) = -5.14$, $P < 0.001$] or during social interactions [$b = -0.12$, 95% CI (−0.23, −0.00), $t(1719) = -2.03$, $P = 0.043$]. There was also a significant interaction between activity and age group [$F(4, 1699) = 5.71$, $P < 0.001$]. Pairwise comparisons at each level of age group split by activity (Bonferroni adjusted for five tests) revealed that pleasant engagement was higher for older participants when working compared to younger participants [$b = 0.78$, 95% CI (0.19, 1.37), $t(350) = 3.43$, $P = 0.003$].

2.3.4.3 Model 3: Episodic social cognition

There was a significant main effect of activity [$F(4, 1718) = 25.58$, $P < 0.001$]. Episodic social cognition was higher during social interactions [$b = 0.52$, 95% CI (0.40, 0.64), $t(1738) = 8.72$, $P < 0.001$] and lower when consuming media [$b = -0.23$, 95% CI (−0.31, −0.14), $t(1752) = -5.42$, $P < 0.001$] or working [$b = -0.35$, 95% CI (−0.50, −0.20), $t(1696) = -4.68$, $P < 0.001$].

2.3.4.4 Model 4: Imagery

There was a significant main effect of activity [$F(4, 1690) = 6.52$, $P < 0.001$]. Imagery was higher when participants consumed media [$b = 0.17$, 95% CI (0.09, 0.26), $t(1719) = 4.21$, $P < 0.001$] and lower when engaging in essential tasks [$b = -0.09$, 95% CI (−0.17, −0.01), $t(1{,}700) = -2.30$, $P = 0.022$].

2.3.4.5 Model 5: Detailed task focus

There was a significant main effect of activity [$F(4, 1713) = 13.38$, $P < 0.001$]. Detailed task focus was higher when working [$b = 0.39$, 95% CI (0.25, 0.53), $t(1{,}656) = 5.44$, $P < 0.001$] or during social interactions [$b = 0.13$, 95% CI (0.02, 0.24), $t(1730) = 2.30$, $P = 0.021$] and lower when engaging in essential tasks [$b = -0.16$, 95% CI (−0.24, −0.09), $t(1{,}733) = -4.13$, $P < 0.001$], leisure activities [$b = -0.19$, 95% CI (−0.27, −0.11), $t(1{,}731) = -4.48$, $P < 0.001$), or when consuming media ($b = -0.17$, 95% CI (−0.25, −0.09), $t(1{,}741) = -4.23$, $P < 0.001$). There was also a significant interaction between activity and age group [$F(4, 1713) =$

5.04, $P < 0.001$]. Pairwise comparisons at each level of age group split by activity (Bonferroni adjusted for five tests) revealed that detailed task focus was higher when older participants engaged in social interactions compared to younger participants [$b = 0.48$, 95% CI (0.02, 0.93), $t(308) = 2.72$, $P = 0.034$].

2.3.5 Comparing Thought Patterns between 1) Virtual and Physical Social Interactions and 2) Age Groups during Lockdown

During lockdown, while people were unable to socialize in person with people outside of their household, they could still interact virtually. In the baseline group, we did not collect information regarding whether social interactions were virtual. However, in the lockdown sample, participants reported on both their physical and virtual interactions. To examine the effects of virtual social interaction on thoughts in the lockdown sample, we conducted a series of models in which each thought pattern was the outcome measure, and interaction type and age group were the explanatory variables (*SI Appendix*). Interaction type had four levels: 1) no interaction at all, 2) virtual interaction only, 3) physical interaction only, and 4) both virtual and physical interaction (see *SI Appendix*, Table S10 for how this variable was coded). As before, the alpha level was set to <0.01 (two tailed) to account for family-wise error emerging from conducting five models. These results are summarized in *SI Appendix*, Fig. S3; see *SI Appendix*, Tables S11–S13 for ANOVA output, parameter estimates, and variance explained by random effects.

We found that future-directed problem solving was less prevalent when participants were physically compared to virtually interacting, while episodic social cognition was more prevalent across all forms of interaction when compared to not interacting at all. In addition, although the effects did not pass the Bonferroni correction, patterns of imagery were less prevalent when physically interacting compared to virtually interacting, particularly for younger participants. Finally, detailed task focus was more prevalent when virtually interacting compared to when interacting both virtually and physically and not interacting at all. Notably, for older participants, detailed task focus was more prevalent during virtual interactions compared to all other forms of interaction and when not interacting at all. However, it is worth noting that the cells of this analysis were unbalanced, with fewer observations for interacting—particularly virtually—compared to not interacting at all (see *SI Appendix*, Table S14 for number of observations per factor level by age group), so these results should be interpreted with caution.

2.3.6 Relationship to Affect

Finally, we conducted an exploratory analysis to understand whether the lockdown-related changes in ongoing thought identified in our prior analysis were independent of changes in affect (*SI Appendix*). Importantly, including affect did not substantially change the lockdown-related results reported in models 1, 3, and 4 comparing thought patterns between samples, age groups, and social environments. However, the main effects of age group for models 1 through 3 no longer reached significance (*SI Appendix*). In addition, we ran a parallel analysis in which we compared the prevalence of negative and positive affect between samples, social environments, and age groups to examine how state affect may have changed during lockdown (see *SI Appendix* for further details).

2.4 Discussion

Our study set out to determine how specific features of the United Kingdom's first lockdown corresponded with changes in ongoing thought patterns in daily life, focusing on changes to socializing and working. The contents of ongoing thoughts were assessed using MDES (Smallwood et al., 2016), an established method with documented neural (e.g., Karapanagiotidis et al., 2020; Konu et al., 2020; Sormaz et al., 2018; Wang et al., 2018b) and behavioral correlates (e.g., Medea et al., 2018; Turnbull et al., 2020b). Our analysis identified five thought patterns: future-directed problem solving, pleasant engagement, episodic social cognition, imagery, and detailed task focus. Importantly, these five thought patterns are consistent with previous research using this method (Ho et al., 2020; Karapanagiotidis et al., 2020; Konu et al., 2021; Konu et al., 2020; Sormaz et al., 2018; Turnbull et al., 2019a).

One goal of our study was to assess how changes in socialization during lockdown impacted patterns of social thought in daily life. Across both samples, in-person social interaction was associated with increased episodic social cognition, reduced future-directed problem solving, and greater pleasant engagement in younger individuals. During lockdown, opportunities for social interactions were reduced, but when social interactions did occur, episodic social cognition was especially prevalent. So, although participants were less able to engage in in-person social interactions during lockdown, when those interactions were possible, they promoted greater increases in social thinking than would normally occur. Furthermore, during lockdown, all types of interaction—both virtual and in person—were associated with increased episodic social cognition, suggesting that online interactions may partly ameliorate the consequences of lockdown on social cognition. Importantly, since the lockdown was a natural experiment in how changes in socialization affect our thinking in daily life, our findings provide real-world confirmation of laboratory evidence linking social thinking to the availability of social interactions (Mildner & Tamir, 2021) and are consistent with the possibility that ongoing thought helps facilitate interactions either in the moment or in the future (Meyer, 2019; Mildner & Tamir, 2021). Our study, therefore, provides ecologically valid evidence to support theoretical perspectives that highlight how social interactions shape social thought patterns in daily life (Mildner & Tamir, 2021; Poerio & Smallwood, 2016).

The second goal of our study was to understand how changes in opportunities for working during lockdown influenced ongoing thought patterns in daily life. Future-directed problem solving, something generally prevalent in younger individuals, was 1) significantly reduced during lockdown relative to prelockdown but 2) was highest during lockdown when individuals were working. Our results, therefore, suggest that when external commitments are disrupted (in this case, via lockdown), future-directed problem solving is reduced unless people are working. Thus, our data support theories suggesting that the "prospective bias" in ongoing thought is related to goal-related processes, since it was disrupted by lockdown unless people were actively engaged in work (Baird et al., 2011; D'Argembeau et al., 2011; Klinger et al., 2018; Kvavilashvili & Rummel, 2020; Medea et al., 2018; Stawarczyk et al., 2013a). Moreover, given research showing goal-directed planning is reduced in dysphoric individuals (Plimpton et al., 2015) and that future thinking is important for maintaining mental health (Hunter & O'Connor, 2003; O'Connor et al., 2004; Ruby et al., 2013a), our study raises the possibility that reduced opportunities for work may contribute to the negative emotional changes documented during lockdown (Banks & Xu, 2020; O'Connor et al., 2020; White & Van Der Boor, 2020) via a reduction in future-related thinking—an important question for future work to explore.

Our final goal was to understand whether lockdown differentially impacted thinking patterns in older and young individuals. Consistent with prior research (Irish et al., 2019; Maillet et al., 2019; Maillet et al., 2018), we found evidence for age differences in ongoing thought patterns. For example, younger individuals reported higher levels of future-directed problem solving and episodic social cognition and lower levels of pleasant engagement during activities than older adults. We also found that before lockdown, younger individuals reported more imagery when interacting with others, whereas during lockdown, imagery was higher when younger individuals were alone. This thought pattern was associated with media consumption during lockdown, so it is plausible that this increased imagery in younger adults when alone was related to an increase in media usage (Vassilev, 2020). Finally, for older participants, virtual interactions during lockdown were linked to increased detailed task focus, a pattern that might reflect the effort required when interacting online, possibly capturing the phenomenon of "Zoom fatigue" (Cranford, 2020).

In summary, the restrictions introduced during the United Kingdom's first national lockdown brought reduced opportunities for socialization and working. In parallel with these changes in daily routine, we found changes in the patterns of thinking associated with these activities. Specifically, during lockdown, social interactions promoted a greater increase in episodic social thinking than prelockdown and while future-directed problem solving was significantly reduced during lockdown, this thought pattern increased when individuals engaged in work. Therefore, on the limited occasions that individuals were able to socialize or work during lockdown, these activities had a significant effect on relevant thought patterns, highlighting the important role that our daily routine has in shaping our thinking.

Although our study sheds light on how lockdown changed ongoing thought patterns in daily life, several limitations should be considered when interpreting these results. First, our study capitalized on an existing dataset to provide a baseline to understand how thought patterns changed during lockdown. While this design feature was unavoidable given the pandemic's unforeseen nature, conclusions regarding the impact of lockdown would have been stronger if we could have examined within-person changes in the same participants over time. Importantly, however, we established that the underlying structure of ongoing thought was almost identical in both samples (*SI Appendix*, Fig. S2), supporting the validity of the prelockdown sample as a baseline. Future work should aim to track people's thoughts in the moment longitudinally, through periods of lockdown and during periods of lockdown relaxation. Second, our analyses of the relationship between current activities (e.g., working) and ongoing thought are based only on the lockdown sample. Therefore, while our data allow the determination of how changes in working opportunities contributed to cognition during lockdown, it is unclear how working influences thought patterns in a more normal context. Finally, it is important to note that there are other influences on people's ongoing thoughts during lockdown beyond those assessed in our study. For example, the current study did not account for economic changes, fear of illness, whether an individual (or close friend/family member) contracted COVID-19 during the study, or bereavements. Nonetheless, our study suggests that in addition to other changes in life circumstances, changes to socialization and opportunities for work are important contributors to how lockdowns influence the contents of people's thoughts in daily life.

Our examination of how broad, naturally occurring changes in society influence cognition also raises important questions for future investigations of ongoing thought. Emerging evidence highlights the lockdown's consequences on mental health (Banks & Xu, 2020; O'Connor et al., 2020; White & Van Der Boor, 2020), so future studies should examine relationships between risk factors such as anxiety and depression and ongoing thought in daily life and during lockdowns. Furthermore, our data indicate that both younger and older adults reported being alone more in the lockdown sample than prelockdown. However, we could not make an equivalent comparison of changes in specific daily activities (including work). Therefore, it remains unclear the extent to which different daily routines in younger and older adults may contribute to age differences in thought patterns. Finally, although studies conducted before the pandemic show that features of ongoing thoughts (e.g., a focus on the future) are prevalent across cultures (Song & Wang, 2012), our study used a UK sample, so it is important to understand how lockdowns change ongoing thought patterns across cultures.

We close by considering the implications of our study for understanding ongoing thought patterns in daily life. Prior studies investigating ongoing thought have focused on assessing thought within laboratory and neuroimaging contexts, revealing links between thought content and neural activity (e.g., Konu et al., 2020; Smallwood et al., 2016; Turnbull et al., 2020b; Wang et al., 2018b), cognitive ability (e.g., Kane et al., 2007; Rummel & Boywitt, 2014), affective style (e.g., Deng et al., 2014; Hoffmann et al., 2016; Konu et al., 2021), and task and social contexts (e.g., Konu et al., 2021; Mildner & Tamir, 2021). Our study complements these findings by highlighting the role that aspects of our daily routines—particularly social interactions and work—play in shaping our cognition. It is perhaps unsurprising that ongoing thought patterns are shaped by these activities since 1) we spend a large proportion of our lives interacting with others (Mildner & Tamir, 2021) and working and 2) that successful adaptation within both of these domains is critical for well-being. For example, loneliness increases the likelihood of death by 26% (Holt-Lunstad et al., 2015), while unemployment is associated with reduced psychological and physical well-being (McKee-Ryan et al., 2005). In this way, our study illustrates that features of a person's daily routine are important in scaffolding their ongoing thought patterns and highlights that experience sampling in naturalistic contexts is an important way to understand when and how what we do influences ongoing human cognition both during lockdowns and in more normal times.

2.5 Materials and Methods

2.5.1 Participants

The full study protocol was approved by the Psychology Department's ethics committee at the University of York. All participants gave informed consent (either written or online) before taking part and were debriefed upon completion. In the prelockdown sample, younger participants were recruited between October 2016 and March 2017 from undergraduate and postgraduate student bodies and were either paid or given course credits. A total of 78 younger participants completed experience-sampling surveys (female = 57, male = 21; age: M = 19.64; SD = 1.62; and range = 18 to 27). These data have been analyzed and reported previously by Ho et al. (2020). In the prelockdown sample, older participants were recruited between August 2016 and November 2016 and were paid for their time. A total of 35 older participants completed experience-sampling surveys (female = 20, male = 15; age: M = 66.80; SD = 6.88; and range = 55 to 87). In the lockdown sample, all participants were invited to participate in the daily-life experience sampling after completing an initial survey, as part of a larger project, on Prolific (https://www.prolific.co). All participants were paid for their time. A total of 91 participants completed experience-sampling surveys between April 29, 2020 and May 13, 2020. Two participants were removed from the study on day 1, as they were not currently residing in the United Kingdom, and their data were excluded. Two participants were excluded for having missing age data. Five participants were excluded because they did not fall into either the young (18 to 35 y) or older (55+ y) age groups. The final sample comprised 59 younger participants (female = 40, male = 17, self-described = 1, and prefer not to say = 1; age: M = 24.22; SD = 4.07; and range = 18 to 35) and 23 older participants (female = 13, male = 9, and self-described = 1; age: M = 63.91; SD = 7.06; and range = 55 to 78).

2.5.2 Procedure

Participants received a text message with a link to an online Qualtrics survey five times daily for 7 d at quasirandom intervals between 9:00 AM and 9:00 PM (8:45 PM in the lockdown sample) administered via SurveySignal (Hofmann & Patel, 2015). Each survey link expired after 2 h. In the prelockdown sample, seven older participants completed up to eight surveys a day for 10 d. However, this procedure was shortened after participant feedback that the procedure was too intensive. Rerunning our analyses after removing these additional observations did not substantially change the results. Additionally, in the prelockdown sample, 23 older participants and one younger participant opted to complete the study on paper. They were provided with a phone on which texts acted as signals (see *SI Appendix* for comparison of completion type). Participants in both samples also completed daily diary questionnaires, and participants in the lockdown sample completed an exit questionnaire at the end of the study. These questionnaires did not sample ongoing thought and are therefore not reported here.

2.5.3 Experience-Sampling Surveys

The experience-sampling survey first asked participants to consider the contents and form of their thoughts immediately before being signaled on various dimensions using a 1 to 5 Likert scale. We sought to compare thought patterns observed across both samples, so we focused on the 22 items present in both (*SI Appendix,* Table S1). The survey then asked participants to rate their emotions and feelings on various dimensions using a 1 to 5 Likert scale (see *SI Appendix*, Table S15 for the 12 affect items present in both samples that were included in supplementary analyses). Participants were also asked "Were you alone or with other people just before taking this survey?" (in the lockdown sample, the question specified "physically and not virtually"). Response options were: "Alone," "Around people but NOT interacting," or "Around people and interacting." In the lockdown sample, participants were also asked "Virtually, were you alone or with other people just before taking this survey?" Response options were the same as those for the physical interaction question. Additionally, in the lockdown sample, participants were asked to indicate their location (seven options; see Figure 2.1B) and primary activity (24 options; *SI Appendix*) immediately before answering the survey. The activity options were based on those used in the "day reconstruction method" (Kahneman et al., 2004) and modified to include activities that were likely to be prevalent during lockdown. In both samples, participants were also asked several other questions about their ongoing experience (e.g., whether they had recently accessed new information regarding COVID-19), which are not the focus of this paper. All experience-sampling survey questions and response options included in the current study are available in *SI Appendix*, Tables S1, S15, and S23.

2.6 Analysis

2.6.1 Data and Code Availability Statement

For details of the R packages used in analysis, see *SI Appendix*. All code used in the analysis and preparation of figures is available online at https://github.com/Bronte-Mckeown/pre_vs_during_lockdown_ESQ_analysis. All anonymized data used in the preparation of this manuscript is openly available via Mendeley data (http://dx.doi.org/10.17632/n3wz7y8mhs.1).

2.6.2 Assessing Changes to Daily Life during Lockdown

To assess whether the percentage of responses for which participants reported being alone was higher in the lockdown sample than the prelockdown sample, we first calculated the percentage of each participant's responses in which they said they were 1) alone, 2) around people but not interacting with them, or 3) around people and interacting with them. We then ran a two-way ANOVA with each participant's "alone" percentage as the outcome variable and sample (pre- versus during lockdown) and age group (young versus older) as the predictors. To examine where participants were located in the lockdown sample, we calculated the overall percentage of responses for each "location" option.

2.6.3 Preparing Data for PCA

Two experience-sampling questions ("positive" and "deliberate") in the prelockdown sample were measured on 7- rather than 5-point scales. All questions were therefore rescaled using the following computation: (observed score − 1)/(highest possible score on that scale − 1). The rescaled questions were then z-scored before applying PCA to the combined data.

2.6.4 PCA

To identify common patterns of thought across both samples, PCA with varimax rotation was applied to the combined thought data from both samples (22 items; *SI Appendix*, Table S1) using IBM SPSS Statistics (version 26). PCA was applied at the observation level in the same manner as in our previous studies (e.g., Konu et al., 2021; Ruby et al., 2013a; Wang et al., 2018b). The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.84, above the commonly recommended value of 0.6, and Bartlett's test of sphericity was significant [$\chi2(231) = 28737.22$, $P < 0.001$]. Five components, with an eigenvalue >1, were retained for inclusion as outcome variables in the LMMs. To ensure that the thought patterns identified across samples were present in both samples separately, we ran a PCA on each sample separately (specified five components for extraction) and correlated each participant's PCA score from this analysis with their PCA score from the combined analysis (see *SI Appendix*, Fig. S2 for scatterplots).

2.6.5 LMMs

LMMs were fitted by restricted maximum-likelihood estimation in R (4.0.2; R Core Team, 2020) using the lme4 package (1.1.26; Bates et al., 2015). We used the lmerTest package (3.1.3; Kuznetsova et al., 2017) to obtain P values for the F- and t tests returned by the lme4 package. For each set of models, the alpha level was set based on 0.05 divided by the number of models (i.e., Bonferroni-corrected alpha level). Degrees of freedom were calculated using the Satterthwaite approximation. For F-tests, type 3 sum of squares was chosen because imbalances in the data are assumed to occur randomly and not due to differences in the population (Singmann & Kellen, 2019). Contrasts were set to "contr.sum," meaning that the intercept of each model corresponds to the grand mean of all conditions and that when a factor has two levels, the parameter estimate is equal to half of the difference between the two levels (Singmann & Kellen, 2019). Estimated marginal means were calculated using the emmeans package (1.5.3; Lenth, 2020). Post hoc pairwise comparisons were also calculated using the emmeans package (Lenth, 2020) and corrected for multiple comparisons using the Bonferroni adjustment, which adjusts both the CIs and P values associated with each estimate and test. For contrasts of contrasts, custom contrasts were set manually and so could not be adjusted for multiple comparisons. Across all models, to account for multiple observations per participant, day number was nested within participant as a random intercept.

2.6.5.1 Comparing Thought Patterns between 1) Pre- and during Lockdown Samples, 2) Age Groups, and 3) Social Environments

We ran five LMMs—one with each thought component as the outcome variable modeling the following fixed factors and their interactions: 1) "sample" (two levels: pre- and during lockdown), 2) "age group" (two levels: younger and older), and 3) "social environment" (three levels: alone, around people but not interacting, and around people and interacting). Age group mean-centered age was included in all models as a nuisance covariate to control for age differences within age groups between the two samples. In total, 195 participants (4,870 observations) were included in these models.

Example model formula: lmer(Thought component × ∼ Sample * Age group * Social environment + Age group mean-centered age + (1|Participant/Day number))

In addition, to account for differences in age range in the younger groups between pre- and during lockdown samples, we reran these analyses while limiting the age range for the younger group to 18 to 27 y in both samples. Rerunning our analyses in this way did not change the overall interpretations of the paper (*SI Appendix*).

2.6.5.2 Comparing Thought Patterns between 1) Current Activities and 2) Age Groups in the Lockdown Sample

We ran five LMMs—one with each thought component as the outcome variable modeling the following fixed factors and their interactions: 1) "activity" (five levels) and 2) "age group" (two levels). The "activity" question had 24 options, which we condensed for analyses. Any observations containing the option "other" (n = 88) were removed, leaving 81 participants (1,777 observations) in the model. The remaining options were grouped into five categories: 1) working, 2) leisure activities, 3) social interactions, 4) media consumption, and 5) essential tasks (see *SI Appendix* for details).

Example model formula: lmer(Thought component × ∼ Activity * Age group + (1|Participant/Day number))

Chapter 3- What happens next? Ongoing thoughts about the future in the laboratory and daily life

This chapter is currently under review (at the time of thesis submission) at *PloS one*, as:

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Acknowledgements and authors' contributions:

Brontë Mckeown designed and implemented the affective laboratory paradigm for laboratory Sample 1, designed and implemented the laboratory paradigm for laboratory Sample 2, collected data for laboratory Sample 1, supervised data collection for laboratory Sample 2, designed the lockdown study, prepared the lockdown study materials, collected the lockdown data, performed the statistical analyses, interpreted the results, prepared visualisation of results, and wrote the manuscript for publication under the supervision of Dr Cade McCall, Prof. Elizabeth Jefferies, and Prof. Jonathan Smallwood. Delali Konu and Dr Adam Turnbull assisted in data collection for laboratory Sample 1, and Dr Adam Turnbull designed and implemented the documentary laboratory paradigm. Dr Theo Karapanagiotidis helped implement the TV-watching paradigms in PsychoPy. Dr Giulia Poerio and Will Strawson provided feedback on the design of the lockdown study and helped prepare lockdown study materials. Before the start of Brontë Mckeown's research degree, Prof. Jonathan Smallwood, Prof. Elizabeth Jefferies, Prof. Leigh Riby, and Dr Giulia Poerio designed the pre-lockdown study, and Dr Giulia Poerio and Dr Lea Martinon collected the pre-lockdown data. All co-authors contributed to reviewing and editing the manuscript for publication.

3.1 Abstract

How do people think under conditions of uncertainty? Our study used Multidimensional Experience Sampling to examine patterns of thought associated with uncertainty in the laboratory while watching videos and assessed the extent to which these laboratory findings generalised to uncertainty experienced in daily life during the COVID-19 pandemic. In the laboratory, participants watched videos in which either no threatening events unfolded ('control') or unfolded in either the first ('action') or last-minute ('suspense'). While watching 'action' and 'suspense' threat videos, laboratory participants reliably described thoughts with negative, social content related to future problem resolution. Critically, this

future-directed thought pattern was positively associated with subjective uncertainty in the laboratory and subjective uncertainty in daily life during the COVID-19 pandemic. Notably, in the laboratory, when subjective uncertainty was low, high-trait-anxiety individuals reported elevated levels of this pattern compared to low-trait-anxiety individuals. By examining the relationships between uncertainty and thought in laboratory and real-world contexts, our study establishes a generalisable pattern of thought that emerges under conditions of uncertainty that may reflect a process through which future situations are simulated to select appropriate actions, an important question for future research to address.

3.2 Introduction

Cognition supports behavioural flexibility. In some situations, we have a reasonable idea of what to do next, while in others, the best course of action is uncertain. When the outside world lacks compelling demands, we often engage in 'self-generated' thoughts that are largely unrelated to the external environment and deal with topics of greater personal relevance, including future events and other people (e.g., Mar et al., 2012; O'Callaghan et al., 2015; Song & Wang, 2012; Taatgen et al., 2021). Self-generated future-directed and social thoughts can be associated with benefits, including refining personal goals (Medea et al., 2018), creative problem-solving (Baird et al., 2012), and greater social wellbeing (Poerio & Smallwood, 2016). These data can be parsimoniously explained by assuming that perceptually-decoupled social-episodic thinking allows consideration of long-term priorities for behaviour (Cole & Kvavilashvili, 2019; D'Argembeau et al., 2011; Poerio & Smallwood, 2016; Ruby et al., 2013b; Smallwood & Andrews-Hanna, 2013). However, ongoing thought may shape actions more directly by adjusting goals in a manner sensitive to events in the immediate environment (Huijser et al., 2021). Our study explored the hypothesis that specific patterns of thought emerge when we feel uncertain about the world around us.

Uncertainty is also associated with anxiety and stress (Hirsh et al., 2012). In general, anxiety disorders are characterized by pervasive negative thinking about possible future events (American Psychiatric Association, 1980; Watkins et al., 2005), and anxious individuals generate negative future events more easily than controls (MacLeod & Byrne, 1996; Miloyan et al., 2014). But trait anxiety is also linked to sensitivity to, and intolerance of, uncertainty (Carleton et al., 2012) and a common feature of anxiety disorders is exaggerated responding to threat and uncertainty (Grupe & Nitschke, 2013). Therefore, if trait anxiety is linked to patterns of thought associated with uncertainty, anxious individuals may either show 1) a heightened response to uncertainty or 2) more inflexible thinking, changing the situations in which thought patterns emerge. Our study also explored how trait anxiety moderated the relationships between uncertainty and patterns of thought, facilitating contextualization of the psychological meaning of thought patterns related to uncertainty.

A key goal of our study was to explore how states of uncertainty predict patterns of thought under controlled laboratory conditions—where uncertainty can be induced experimentally—and in naturally-occurring and personally-meaningful circumstances as people go about their daily lives (Smallwood et al., 2021). Since prior studies document both similarities and differences between thinking in the laboratory and the real world (e.g., Ho et al., 2020; Kane et al., 2017; McVay et al., 2009), our study explicitly examined links between uncertainty and ongoing thought patterns across both contexts to assess the generalizability of our findings. To facilitate this goal, we used laboratory-based naturalistic viewing paradigms, which mimic the rich multimodal sensory and contextual features of real-world experiences (Sonkusare et al., 2019), a choice that should maximize the generalization of thinking between laboratory and daily life contexts. To experimentally induce states of uncertainty and arousal, we selected clips from television shows in which either no threatening events unfolded ('control') or unfolded in either the first ('action') or last-minute ('suspense'). Implementing this paradigm in two independent samples allowed us to assess the replicability of our manipulation.

To examine thoughts under naturally-occurring states of uncertainty and threat, we capitalized on data collected in daily life before and during the COVID-19 pandemic in the United Kingdom (Mckeown et al., 2021). We expected that individuals would find the COVID-19 situation threatening and uncertain since the virus was poorly understood, potentially fatal, and it was unclear how the situation would unfold. Accordingly, our projection of thought patterns from the laboratory directly onto the daily life data allowed us to test whether patterns experienced while watching threatening and uncertain videos in the laboratory are correlated with uncertainty as it occurs in a real-world situation.

To measure thought patterns across situations, we used Multidimensional Experience Sampling (MDES; Smallwood et al., 2016). MDES asks participants to describe the contents of their thoughts by rating momentary experiences along several dimensions (e.g., temporal focus, relationship to self or other). Dimension reduction techniques can then be applied to use covariation in the responses to different items to identify 'patterns of thought' (Smallwood et al., 2021). Previous MDES studies have identified common patterns of thought across both laboratory and daily life contexts (Ho et al., 2020; Konu et al., 2021; Turnbull et al., 2021; Wang et al., 2018b).

In the current study, we first identified patterns of thought in the laboratory data (n = 119) using Principal Components Analysis (PCA). We then projected these thought patterns onto MDES data recorded in daily life before and during the COVID-19 pandemic (n = 137). This projection step allowed us to examine data from different datasets in the same multidimensional space, thereby allowing us to investigate how the correlates of thought patterns induced by a manipulation within the laboratory relate to the thinking that happens in daily life. In both the laboratory and daily life, we were interested in links with subjective uncertainty and trait anxiety (Figure 3.1 shows a schematic of the current study's workflow).

In summary, the main aims of the current study were to 1) understand how people think under conditions of uncertainty and 2) directly assess the generalisability of laboratory findings in a real-world situation. Our analyses identified a generalisable pattern of emotional, social, and future-directed problem-solving that consistently emerges when people feel uncertain, in both the laboratory while watching videos and in daily life during the COVID-19 pandemic.

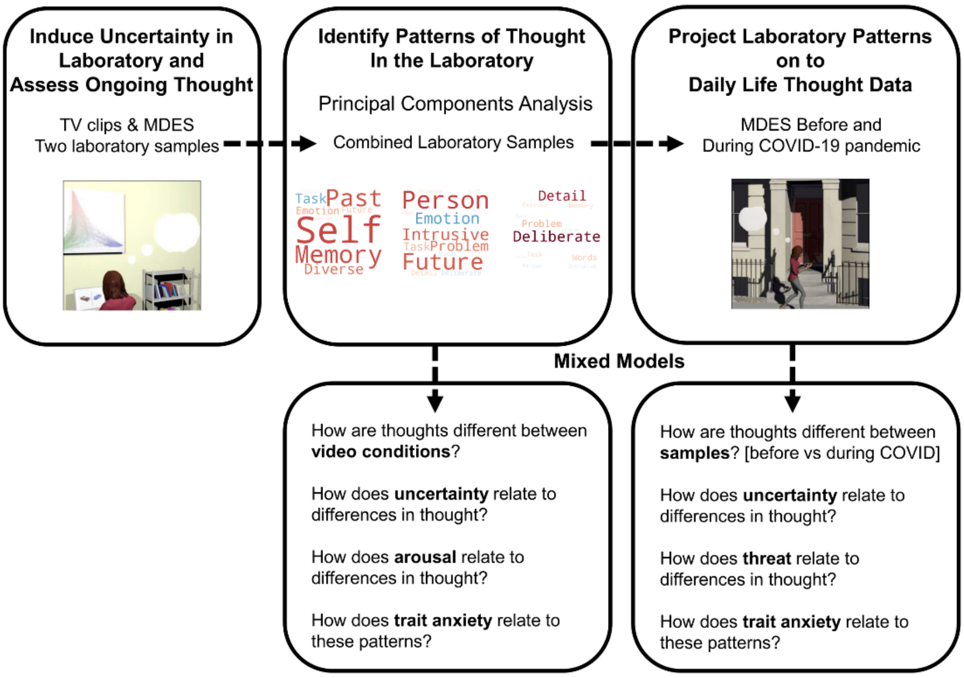

Figure 3.1.Schematic of the workflow of the current study. In two independent samples in the laboratory (n = 70 & n = 49), participants watched TV clips depicting varying levels of threat and uncertainty (3 conditions: 'control', 'action', and 'suspense'). Participants completed MDES probes at the end of each clip to assess ongoing thoughts and emotional states. Dimension reduction was applied to the combined thought data (n = 119) to identify common 'patterns of thought'. We then projected these patterns onto the daily life data collected before- (n = 78) and during (n = 59) the COVID-19 pandemic in the UK. Linear Mixed Models determined 1) how the prevalence of thought patterns differed between external contexts (laboratory: video conditions, daily life: before vs during the COVID-19 pandemic), 2) how thought patterns varied with uncertainty, and arousal or threat, and 3) how trait anxiety relates to these patterns.

3.3 Methods

3.3.1 Participants

The Department of Psychology's ethics committee at the University of York approved the laboratory and daily life experience-sampling studies. All participants provided informed written consent (either in person or online) and were debriefed at the end of the study. All participants received either course credit or monetary compensation for their participation, except for participants in laboratory Sample 2, in which they participated voluntarily as part of a final year undergraduate project.

3.3.1.1 Laboratory Samples

Both laboratory samples were recruited from undergraduate and postgraduate student bodies at the University of York. Sample 1 comprised 70 participants (female = 60, male = 10, Age: *M* = 20.60, *SD* = 2.10, range = 18-34) and Sample 2 comprised 50 participants (age and gender not recorded; although, likely to be similar to Sample 1 as participants were drawn from the same student population). In Sample 2, one participant's data were excluded since they had taken part in the first study, leaving 49 participants in Sample 2. The thought data from Sample 1 has been analysed and reported previously by Konu et al. (2021).

3.3.1.2 Daily Life Samples

In the 'pre-COVID' daily life sample, participants were recruited between October 2016 and March 2017 from undergraduate and postgraduate student bodies at the University of York. Seventy-eight participants completed experience-sampling surveys (female = 57, male = 21, Age: M = 19.64, SD = 1.62, range = 18-27) and 70 of these participants completed the trait anxiety questionnaire (female = 52, male = 18, Age: M = 19.56, SD = 1.39, range = 18-25). This thought data has been analysed and reported previously by Ho et al. (2020), Mckeown et al. (2021), and Turnbull et al. (2021). In the 'COVID' daily life sample, all participants were invited to participate in the daily-life experience sampling after completing an initial survey, as part of a larger project, on Prolific (www.prolific.co). This initial survey included the trait anxiety questionnaire. Fifty-nine participants residing in the United Kingdom completed experience-sampling surveys between April 29th, 2020, and May 13th, 2020 (female = 40, male = 17, self-describe = 1, prefer not to say = 1, Age: M = 24.22, SD = 4.07, range = 18-35). This thought data has been analysed and reported previously by Mckeown et al. (2021). The key details for each of the four samples examined in the current study are summarized in Table 3.1.

Table 3.1. A summary of the four samples examined in the current study.

Context	Sample	MDES N	Anxiety N	Exc. N	PCA N	LMM N	LMM N obs	Gender	Age
Lab	Sample 1	70	70	0	70	70	763	F = 60 M = 10	*M* = 20.60 *SD* = 2.10 Range = 18-34
Lab	Sample 2	50	0	1	49	49	575	Not Recorded	Not Recorded
Daily Life	Pre-COVID	78	70	0	78	70	1843	PCA: F = 57 M = 21 LMM: F = 52 M = 18	PCA: *M* = 19.64 *SD* = 1.62 Range = 18-27 LMM: *M* = 19.56 *SD* = 1.39 Range = 18-25
Daily Life	COVID	59	59	0	59	59	1256	F = 40 M = 17 Self-describe = 1 Prefer not to say = 1	*M* = 24.22 *SD* = 4.07 Range = 18-35

Note: 'Lab' = laboratory. 'MDES N' = number of participants that completed Multidimensional Experience Sampling. 'Anxiety N' = number of participants that completed the trait anxiety questionnaire. 'Exc. N' = number of participants excluded from all analyses. 'PCA N' = number of participants included in Principal Components Analyses. 'LMM N' = number of participants included in Linear Mixed Models. 'LMM N obs' = minimum number of complete observations included in Linear Mixed Models. 'F' = female, 'M' = male.

3.3.2 Multidimensional Experience Sampling (MDES)

3.3.2.1 Laboratory

In both laboratory samples, ongoing thought and emotional states were assessed using Multidimensional Experience Sampling (MDES). In total, 16 MDES items were presented to participants at the end of each video clip (each set of 16 items = 1 MDES probe). Thirteen of these items assessed the focus, form, and content of ongoing thoughts, while three items assessed emotional states. Participants were first asked how much their thoughts were focused on the task (i.e., the video) and to report on their levels of arousal (‘The level of my arousal was:’), tension (‘I felt tense:’) and uncertainty (‘I felt uncertain:’), followed by 12 items assessing the content and form of thoughts presented in a random order (see Table A in *S1 Text* for all 13 thought items). The ‘tension’ item was included as part of a larger project but was not examined in the current study. All items were rated on a continuous scale from 1 to 10 using a slider. Once participants were satisfied with their response, they clicked a key to move on to the next item.

3.3.2.2 Daily Life

In both daily life samples, the MDES survey first asked participants to describe the focus, form, and content of their ongoing thoughts immediately before being signalled by rating multiple items on a 1-5 Likert scale (see Table A in *S1 Text* for items included in the current study’s analyses that have the best correspondence with items used in the laboratory). As in the laboratory, the first item always assessed the focus of their thoughts, and the remaining thought items were randomized. In both daily life samples, the survey then asked participants to describe their emotions and feelings immediately before being signalled by rating multiple items on a 1-5 Likert Scale. In the COVID sample, this section of the survey included an ‘uncertainty’ item (‘I felt uncertain’) that was examined in the current study. The remaining affect items were not examined in the current study (see Mckeown et al. (2021) for more details). In addition, to assess in-the-moment levels of threat caused by the COVID-19 pandemic, participants were asked, ‘Right now, how threatening is the COVID-19 situation to you?’ (1-100 scale, anchored from ‘not at all’ to ‘extremely’). Finally, to assess in-the-moment levels of uncertainty caused by the COVID-19 pandemic, participants were asked, ‘Right now, how much uncertainty is the COVID-19 situation causing you?’ (1-100 scale, anchored from ‘none at all’ to ‘a great deal’). The presentation of these two questions was randomized. In both samples, participants were also asked several other questions about their ongoing experience (e.g., location, activities, and social interactions; see Mckeown et al. (2021)), which are not the focus of this paper.

3.3.3 Trait Anxiety

To assess participants’ trait-level anxiety in laboratory Sample 1 and in the daily life samples, we administered the State and Trait Anxiety Inventory (STAI) (Spielberger, 1983). This inventory includes 20 items for assessing trait-level anxiety, and participants rate themselves on each item using a 1-4 Likert scale. In the laboratory, this questionnaire was completed during the ‘task’ session (alongside several other questionnaires collected as part of a larger project that are not the focus of the current study; see Konu et al. (2021) for details) and was administered using Qualtrics software (Copyright © 2019 & 2020 Qualtrics, Qualtrics and all other Qualtrics product or service names are registered trademarks or trademarks of Qualtrics, Provo, UT, USA, https://www.qualtrics.com). Due to a technical error, responses to one question for three participants on the Trait Anxiety Inventory of the STAI were not recorded. In both daily life samples, the questionnaire was administered via Qualtrics alongside several other questionnaires prior to completing the MDES surveys (pre-COVID sample: ~three months before; COVID sample: one day before). In the pre-COVID sample, eight participants did not have trait anxiety data, so they were excluded from the Linear Mixed Model analyses. Across all samples, the mean score of the 20 trait-anxiety items (19 items for three participants with missing responses in the laboratory) was calculated to provide each participant’s trait anxiety score (higher scores indicate higher levels of trait anxiety). Violin plots showing the distribution of trait anxiety scores across all samples examined are presented in Fig A in *S1 Text*.

3.3.4 Laboratory Procedure

3.3.4.1 Sample 1

In laboratory Sample 1, participants took part in a two-day study (~2 hours of testing per day) in which they completed a range of tasks (total = 9) and reported their ongoing thoughts and emotional states using MDES at the end of each task block (for full details of the two-day study, see Konu et al., 2021). The order of session and task was counterbalanced across participants using a pseudo-random fixed order. In one session—that the current study focuses on—participants completed two TV-based paradigms (‘documentary’ and ‘affective’) and MDES probes. They also completed a state-anxiety questionnaire (STAI; Spielberger (1983)) before and after the ‘affective’ TV paradigm, a comprehension questionnaire after the ‘documentary’ paradigm, and a debrief questionnaire at the end of the session asking whether they had seen the ‘action’ and ‘suspense’ clips before. These additional questionnaires were collected (via Qualtrics) as part of a larger project and are not considered in the current study. Congruent audio-visual clips from the ‘documentary’ paradigm were selected as the ‘control’ videos in the current study as they were low in threat and uncertainty. In both paradigms, no clips were shown twice to the same participant.

In the affective TV-based paradigm, participants were instructed to attend to the screen as they watched and listened to 3–4-minute clips from a range of BBC TV crime dramas and thrillers: *Happy Valley* (BBC One, 2014), *Line of Duty* (BBC One/Two, 2012), *Luther* (BBC One, 2010) and *Bodyguard* (BBC One, 2018). These clips were selected to include a threatening event. There were two conditions that varied in the timing of the threatening event: 1) 'action' clips depicting direct threat in the first minute with the remainder of the clip following the protagonist(s)' response to the threat and 2) 'suspense' clips depicting a potential threat, high in uncertainty, early on in the clip with the direct threat only occurring in the last minute. Three independent raters identified when the direct threat occurred in each clip. An example of an 'action' clip is a scene from Bodyguard (Season 1, Episode 2). Within the first minute, gunshots from a roof are fired (threatening event) at the protagonists, and the remainder of the clip follows the protagonists' reaction to continuing shots. An example of a 'suspense' clip is a scene from Luther (Season 3, Episode 2) in which two characters, believing to be at home alone, hear a noise and go upstairs to investigate; in the last minute of the clip, the characters are attacked (threatening event after a period of uncertainty and suspense).

The order of the affective TV conditions was pseudo-randomized such that the first clip was either from the 'action' or 'suspense' condition (counterbalanced across participants). The remaining clips were pseudo-randomized such that each condition would not be shown more than twice consecutively. Each session had eight clips, with four in each condition. Participants were informed that the clips involved dangerous behaviour, strong language, and violence on several occasions prior to starting, and they were reminded repeatedly that they had the right to withdraw at any time, without giving reason and without prejudice. After each clip and answering the MDES questions, participants were invited to 1) take a break for as long as they needed and 2) withdraw from the task if they were feeling distressed.

In the documentary TV-based paradigm, participants were instructed to attend to the screen as they watched and listened to 3–4-minute clips from Season 1 of a BBC documentary series called 'Connections' (BBC One, 1978) that reviews the history of science and innovation. Nine clips were presented under three audio-visual conditions with three clips per condition: 1) congruent visual and auditory presentation in which participants watched and listened to the documentary TV clips, 2) audio condition in which participants had audio input of the documentary clip accompanied by a white fixation cross, and 3) Inscapes in which participants had audio input of the documentary clip with visuals from

Inscapes (a nonverbal, non-social TV paradigm that features slowly moving abstract shapes; Vanderwal et al., 2017; Vanderwal et al., 2015).

The order of audio-visual conditions was pseudo-randomized, such that three consecutive clips always included one from each condition. Participants were informed that they would watch documentary TV clips with varying visual input but were unaware of which condition they were in before starting the block. At the end of the paradigm, participants were asked questions about the content of the TV clips in a comprehension questionnaire (this data was part of a larger project and has not been examined in the current study). Seven participants were informed that they would be required to answer comprehension questions about the clips before the protocol was changed; the remaining participants were unaware that this was required. The current study only included the MDES probes following the congruent audio-visual documentary clips (three per participant) in analyses, which served as a 'control' condition (low in threat and uncertainty).

In total, four 'suspense', four 'action', and three 'control' MDES probes for each participant in laboratory Sample 1 were included in analyses. It is worth noting that, while the eight affective video clips shown were the same across all participants, the three 'control' videos varied across participants (i.e., nine clips in total, but each participant only saw three). In addition, seven participants completed seven MDES probes rather than eight in the affective TV-based task due to a technical error, and two participants completed the sessions in a different order compared to the rest of the cohort.

3.3.4.2 Sample 2

In Sample 2, participants took part in a one-session study (~one hour of testing) during which they watched both 'affective' and 'control' video clips and reported ongoing thought and emotional states via MDES probes at the end of each video clip. Participants watched 12 clips: four 'action', four 'suspense', and four 'control'. The 'action' and 'suspense' clips were the same as Sample 1 (described above). The 'control' clips for Sample 2 were 3–4-minute TV clips from Episode 9 of a BBC documentary series called 'Life' (BBC One, 2009) that reviews various types of plants in different climates across the planet. The order of the video conditions in this paradigm was pseudo-randomized such that the first TV clip presented was either from the 'action', 'suspense', or 'control' condition (counterbalanced across participants). The remaining clips were pseudo-randomized so that each condition would not be shown more than twice consecutively. Participants were provided with the same warnings about the affective video clips as in laboratory Sample 1. They were also invited to take breaks between video clips and withdraw from the task if they felt distressed. Due to technical errors, one participant had a missing response for a ‘focus’ item, one participant had missing responses for six ‘focus’ items, and one participant had six full MDES probes missing out of 12. The seven observations with missing values for the ‘focus’ item were excluded from analyses.

3.3.5 Daily Life Procedure

In daily life, to complete MDES probes, participants received a text message with a link to an online Qualtrics survey five times daily for seven days at quasi-random intervals between 09:00 and 21:00 (20:45 in the COVID sample) administered via SurveySignal (Hofmann & Patel, 2015). Each survey link expired after two hours. In the pre-COVID sample, one participant opted to complete the study on paper and was provided with a phone where texts acted as signals. Participants in both samples also completed daily diary questionnaires, and participants in the COVID sample completed an exit questionnaire at the end of the study. These questionnaires did not sample ongoing thought and are therefore not reported here. In both samples, trait anxiety was assessed using the STAI via Qualtrics in a separate questionnaire prior to completing MDES surveys.

3.4 Analysis

3.4.1 Principal Components Analysis (PCA) to Identify ‘Patterns of Thought’ in the Laboratory

To identify common ‘patterns of thought’ across both laboratory samples (n = 119), PCA with varimax rotation was applied to the combined thought data from both samples (13 items; see Table A in *S1 Text*) using python (3.8.10). In the same manner as our previous studies (e.g., Ho et al., 2020; Konu et al., 2021; Konu et al., 2020; Mckeown et al., 2021; Smallwood et al., 2016), PCA was applied at the observation level, and items were z-scored prior to applying PCA. In total, 1338 observations were included in the PCA. The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.73, above the commonly recommended value of 0.6, and Bartlett’s test of sphericity was significant ($\chi 2[78] = 2992.36$, $p < .001$). Based on the elbow of the scree plot (see Fig B in *S1 Text*), three components were retained for further analysis (see Results and see Table B in *S1 Text* for exact component loadings). Violin plots showing the distribution of each component are shown in Fig C in *S1 Text*. While applying varimax rotation to the PCA solutions is consistent with our previous studies (e.g., Ho et al., 2020; Konu et al., 2021; Konu et al., 2020; Mckeown et al., 2021; Smallwood et al., 2016), in the current study, we also conducted supplementary analyses to demonstrate that the PCA solutions are highly similar when using other forms of rotation (see Fig D in *S1 Text* for scatterplots).

To ensure that the thought patterns identified across both laboratory samples were present in both samples separately, we ran a PCA on each sample separately (z-scored each sample separately and specified three components for extraction; see Figs E and F in *S1 Text* for scree plots and Tables C and D in *S1 Text* for component loadings) and correlated each participant's PCA score from this analysis with their PCA score from the combined analysis. This analysis revealed a high correspondence between the two-sample and one-sample solutions (see *S1 Text* for more details and Fig G in *S1 Text* for scatterplots). In addition, we ran a PCA on each sample and video condition separately (z-scored each sample and condition separately and specified three components for extraction; see Fig H in *S1 Text* for scree plots) and correlated each participant's PCA score from this analysis with their PCA score from the combined analysis (see Figs I-K in *S1 Text* for scatterplots).

Finally, we also projected the three thought patterns identified in each sample separately onto the other respective sample's data. In this context, projection means computing the dot product between the component loadings from one laboratory sample and the z-scored experience-sampling items from the other laboratory sample (see Fig L in *S1 Text* for correspondence between one-sample projected and one-sample normal solutions). We used these projected solutions, as well as solutions derived from applying PCA to each sample directly, in supplementary analyses to assess the reliability of findings across laboratory samples and to establish that the various solutions are largely interchangeable (see Results).

3.4.2 Projecting Laboratory Thought Patterns onto Daily Life Data

To examine the same patterns of thought in the laboratory and in daily life, we projected the three components identified from the laboratory data onto the daily life data using the same method described above (calculated dot product between laboratory component loadings and z-scored items from daily life data). Since two items ('emotion' and 'deliberate') in the pre-COVID daily life sample were measured on 7- rather than 5-point scales, all daily life thought items were rescaled using the following computation before z-scoring: (observed score − 1)/(highest possible score on that scale − 1) (as in Mckeown et al., 2021).

Out of the 13 items used in the laboratory PCA, eight of these items had like-for-like equivalents in the daily life data, and three items had approximate equivalents in the daily life data: 1) 'modality' = 'words', 2) 'person' = average of 'close-other' and 'not-close others', and 3) 'intrusive' = reverse of 'wanted'. In the laboratory, the 'modality' item had 'images' at the negative end of the scale and 'words' at the positive end. In daily life, there were two separate questions to assess the modality of thought ('images' and 'words'), so we included the 'words' item in the projection. In the laboratory data, the 'person' item did not differentiate between 'close' and 'not-close' others, while in the daily life data, there were two separate items to assess thoughts about both 'close' and 'non-close' others. Accordingly, we computed the average of the two 'person' items in the daily life data and used this averaged item in the projection. In addition, while there was no 'intrusive' item in the daily life data, there was a question assessing how 'wanted' participants' thoughts were, and so we reverse-scored this question for inclusion in the projection. Finally, two items ('diverse' and 'source') included in the laboratory PCA did not have any equivalents in the daily life data, leaving a total of 11 items that were used in the projection between the laboratory components and the daily life data (see Table A in *S1 Text* for a summary of items used in analyses).

To support the validity of the projection using only 11 items, we ran a PCA on these 11 items in the combined laboratory data (specified three components for extraction; see left-hand-side of Fig M in *S1 Text* for scree plot and Table E in *S1 Text* for component loadings) and correlated each participant's PCA score from this analysis with their 13-item PCA score. This analysis revealed a high correspondence between the 11-item and 13-item patterns (see *S1 Text* for more details and Fig N in *S1 Text* for scatterplots). In addition, we ran a PCA on the eight items in the combined laboratory data that had like-for-like equivalents in the laboratory and daily life data (specified three components for extraction; see right-hand-side of Fig M in *S1 Text* for scree plot and Table F in *S1 Text* for component loadings) and correlated each participant's PCA score from this analysis with their 13-item PCA score. This analysis revealed a high correspondence between the eight-item and 13-item patterns (see *S1 Text* for more details and Fig N in *S1 Text* for scatterplots).

Finally, to understand how the projected laboratory patterns related to patterns present in the daily life data, we ran a PCA on the combined daily life data (11 items; specifying three components for extraction, see Fig O in *S1 Text* for scree plot and Table G in *S1 Text* for component loadings) and correlated each participant's PCA score from this analysis with their projected PCA score. This analysis revealed a moderate correspondence between the direct and projected patterns (see *S1 Text* for more details and Fig P in *S1 Text* for scatterplots). In addition, we ran a PCA on each sample separately (z-scored items in each sample separately) in the daily life data (before- and during-COVID; specified three components for extraction, see Figs Q and R in *S1 Text* for scree plots and Tables H and I in *S1 Text* for component loadings) and correlated each participant's PCA score from this analysis with their projected PCA score (see *S1 Text* for more details and Figs S and T in *S1 Text* for scatterplots).

3.4.3 Preliminary Correlation Analyses

3.4.3.1 Mean Ongoing Thought Patterns and Trait Anxiety

Owing to the complexity of Linear Mixed Models, we first examined the relationship between thought patterns and trait anxiety using a series of Pearson correlations between mean thought patterns and trait anxiety scores in 1) each video condition separately in the laboratory (n = 70) and 2) each sample separately in daily life (n = 129).

3.4.3.2 Mean Emotional States and Trait Anxiety

To aid the interpretation of any thought-anxiety relationships identified in our analyses, we examined the relationships between emotional states and trait anxiety in the laboratory using a series of Pearson correlations between trait anxiety scores, and mean subjective arousal and mean subjective uncertainty, for each video condition separately (n = 70). To examine the relationships between emotional states and trait anxiety in the daily life COVID sample, we ran also ran a series of Pearson correlations between trait anxiety scores, and mean COVID threat, mean COVID uncertainty, and mean subjective uncertainty (n = 59).

3.4.4 Linear Mixed Models (LMMs)

LMMs were fitted by restricted maximum-likelihood estimation in R (4.1.1; R Core Team, 2021) using the lme4 package (1.1.27.1; Bates et al., 2015). We used the lmerTest package (3.1.3; Kuznetsova et al., 2017) to obtain p values for the F-tests and t-tests returned by the lme4 package. For each set of models, the alpha level was set based on 0.05 divided by the number of models (i.e., Bonferroni-corrected alpha level). The reported alpha levels for main effects and interactions in our paper are unadjusted and are only reported as significant if they passed the Bonferroni-corrected alpha level (0.05/3 = .017). Degrees of freedom were calculated using the Satterthwaite approximation. For F-tests, type 3 sum of squares was chosen because imbalances in the data are assumed to occur randomly and not due to differences in the population (Singmann & Kellen, 2019). Contrasts were set to 'contr.sum,' indicating that the intercept of each model corresponds to the grand mean of all conditions. Estimated marginal means (i.e., predicted means) and simple slopes were calculated using the emmeans package (1.7.0; Lenth, 2021). Post hoc pairwise comparisons of estimated marginal means and simple slopes were also calculated using the emmeans package (Lenth, 2021) and were corrected for multiple comparisons using the Bonferroni adjustment, which adjusts both the CIs and *p* values associated with each estimate and test. In these cases, the adjusted alpha levels are reported in parentheses.

Across all laboratory LMMs, to account for multiple observations per participant, participant was included as a random intercept and to account for variation between specific videos, video name was also included as a random intercept. Across all daily life LMMs, to account for multiple observations per participant, day number was nested within participant as a random intercept. Across all LMMs, continuous independent and dependent variables were z-scored prior to analysis to provide standardized parameter estimates.

3.4.4.1 Manipulation Check of Video Condition

Before considering the thought patterns evoked by each video condition, we first established that the video conditions changed arousal and uncertainty ratings in the expected manner. We ran two LMMs— one with 'arousal' as the outcome variable and one with 'uncertainty' as the outcome variable— with 'video condition' as a fixed effect in both cases (three levels: 'control', 'action', and 'suspense'). In total, 119 participants (1338 observations) were included in these models. Since the residual plots from these models indicated non-randomness of the residuals (see Fig A in *S2 Text*), we also performed a series of one-way repeated measures ANOVAs (as well as non-parametric Friedman tests with and without outliers) using mean ratings for 'arousal' and 'uncertainty' for each video condition as outcome variables and 'video condition' as a predictor variable (see *S2 Text* for more details, Figs B-D in *S2 Text* for box plots showing results and Fig E in *S2 Text* for QQ plots).

3.4.4.2 Laboratory: Ongoing Thought Patterns by 1) Video Condition and 2) Emotional States (n = 119)

To examine how ongoing thought patterns varied by video condition and emotional states in the laboratory, we ran three LMMs— one with each thought component as the outcome variable—modelling the following fixed effects and their two-way interactions: 1) ‘video condition’ (three levels: ‘control’, ‘action’, and ‘suspense’), 2) ‘subjective uncertainty’, and 3) ‘subjective arousal’. In total, 119 participants (1338 observations) were included in these models.

Example model formula: lmer(z-scored thought component x ~ z-scored arousal + z-scored uncertainty + condition + z-scored arousal : z-scored uncertainty + condition : z-scored arousal + condition : z-scored uncertainty + (1|participant) + (1|video))

To understand whether the thought components used in this omnibus analysis generalised across both laboratory samples, we repeated this analysis in each sample separately using 1) one-sample thought components and 2) projected one-sample thought components. These supplementary analyses demonstrated that the decompositions are largely interchangeable and do not substantially influence the interpretation of the results. These analyses also demonstrate the reliability of our findings since they indicate a high degree of consistency in the patterns derived from both samples and in how these patterns relate to video condition and emotional states (see Table A in *S2 Text* for a summary of the consistency of the main effects and interactions using the different decompositions).

3.4.4.3 Laboratory: Ongoing Thought Patterns by 1) Video Condition, 2) Emotional States, and 3) Trait Anxiety (n = 70)

To examine how ongoing thought patterns varied by video condition, emotional states, and how this interacted with trait anxiety in the laboratory, we ran three LMMs— one with each thought component as the outcome variable—modelling the following fixed effects and their two-way interactions: 1) ‘video condition’ (three levels: ‘control’, ‘action’ and ‘suspense’), 2) ‘subjective uncertainty’, 3) ‘subjective arousal’, and 4) ‘trait anxiety’ (mean score). In total, 70 participants (763 observations) from laboratory Sample 1 were included in these models since trait anxiety was not assessed in laboratory Sample 2.

Example model formula: lmer(z-scored thought component x ~ z-scored arousal + z-scored uncertainty + z-scored trait anxiety + condition + z-scored arousal : z-scored uncertainty + z-scored arousal : z-scored trait anxiety + z-scored uncertainty : z-scored trait anxiety + condition : z-scored arousal + condition : z-scored uncertainty + condition : z-scored trait anxiety + (1|participant) + (1|video))

3.4.4.4 Daily Life: Ongoing Thought Patterns by 1) Sample (pre- vs during-COVID) and 2) Trait Anxiety (n = 129)

To examine how the prevalence of the projected thought patterns differed before and during COVID and how this interacted with trait anxiety in daily life, we ran three LMMs—one with each projected thought component as the outcome variable—modelling the following fixed effects and their interaction: 1) 'sample' (two levels: 'pre-COVID' and 'during-COVID') and 2) 'trait anxiety' (mean score). In total, 129 participants (3100 observations) were included in these models. In all models, age was included as a nuisance covariate to account for differences in age between the two daily life samples.

Example model formula: lmer(z-scored thought component x ~ sample : z-scored trait anxiety + z-scored age + (1|participant/day))

3.4.4.5 Daily Life during COVID-19 Pandemic: Ongoing Thought Patterns by 1) Subjective Uncertainty and 2) Trait Anxiety (n = 59)

To examine how the projected thought patterns related to subjective uncertainty (same item as examined in the laboratory) and how this interacted with trait anxiety in the COVID daily life sample, we ran three LMMs—one with each projected thought component as the outcome variable—modelling the following fixed effects and their interaction: 1) 'subjective uncertainty' (item: 'I felt uncertain') and 2) 'trait anxiety' (mean score). In total, 59 participants (1257 observations) were included in these models. To maintain consistency with the previous daily life models, age was also included as a nuisance covariate.

Example model formula: lmer(z-scored thought component x ~ z-scored uncertainty : z-scored trait anxiety + z-scored age + (1|participant/day))

3.4.4.6 Daily Life during COVID-19 Pandemic: Ongoing Thought Patterns by 1) COVID Uncertainty, 2) COVID Threat, and 3) Trait Anxiety (n = 59)

Finally, to examine how the projected thought patterns related to the uncertainty and threat caused by the COVID-19 pandemic specifically and how this interacted with trait anxiety in the COVID daily life sample, we ran three LMMs—one with each projected thought component as the outcome variable—modelling the following fixed effects and their two-way interactions: 1) 'COVID uncertainty' (item: 'Right now, how much uncertainty is the COVID-19 situation causing you?'), 2) 'COVID threat' (item: 'Right now, how threatening is the COVID-19 situation to you?'), and 3) 'trait anxiety' (mean score). In total, 59 participants (1256 observations) were included in these models. To maintain consistency with the previous daily life models, age was also included as a nuisance covariate.

Example model formula: lmer(z-scored thought component x ~ z-scored COVID uncertainty + z-scored COVID threat + z-scored trait anxiety + z-scored COVID uncertainty : z-scored COVID threat + z-scored COVID uncertainty : z-scored trait anxiety + z-scored trait anxiety : z-scored COVID threat + z-scored age + (1|participant/day))

3.5 Results

3.5.1 Patterns of Thought

To identify common ‘patterns of thought’ in the laboratory, we combined the thought data from the two laboratory samples (n = 119) and decomposed these in a single PCA (see Methods). Based on the elbow of the scree plot, three components—accounting for 48% of the total variance—were retained for further analysis: 1) ‘self-relevant and past-focused off-task thought’—describing patterns of thought with the highest loadings on ‘Self’, ‘Memory’, ‘Past’, ‘Diverse’, and ‘Off-task’; 2) ‘emotional, social and future-directed problem-solving’—with the highest loadings on ‘Person’, ‘Future’, ‘Intrusive’, ‘Negative’, and ‘Problem’; and 3) ‘detailed deliberate thought’—with the highest loadings on ‘Deliberate’, ‘Detail’, ‘Problem’, and ‘Words’. These thought patterns are represented as word clouds in panel B of Figure 3.2 and see Table B in *S1 Text* for exact component loadings.

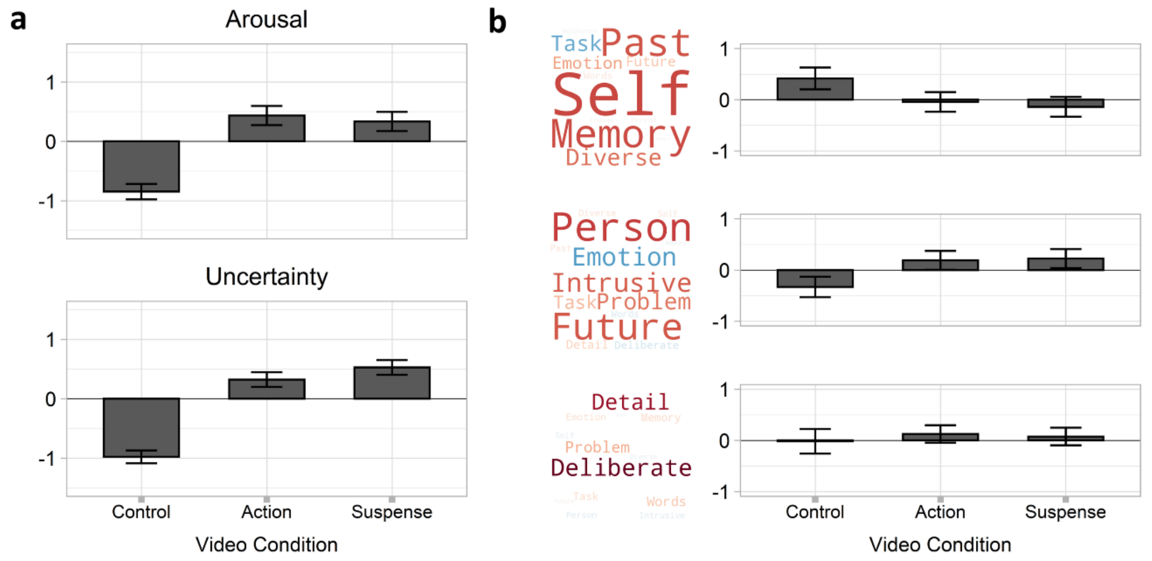

Figure 3.2. Summary of the LMMs' results comparing (a) arousal and uncertainty ratings between video conditions and (b) ongoing thought patterns between video conditions in the combined laboratory samples. Panel (a) shows the predicted means (y-axis) of arousal (top) and uncertainty (bottom) ratings for each video condition (x-axis). Left-hand side of panel (b) shows word clouds representing the three thought patterns identified by applying PCA to the combined laboratory thought data. Each word represents an experience-sampling item (13 items; see Table A in *S1 Text*). Font size represents the magnitude of the loading, and colour describes the direction (warm = positive, cool = negative). Right-hand side of panel (b) shows the predicted means (y-axis) of each thought pattern (represented as word clouds) for each video condition (x-axis). Error bars represent the 95% CIs for each predicted mean. In total, 119 participants (1338 observations) were included in these analyses. All continuous variables were z-scored before analysis.

3.5.2 Laboratory: Manipulation Check of Video Condition

The LMMs comparing subjective arousal and subjective uncertainty between video conditions confirmed that relative to control conditions, the 'action' and 'suspense' conditions had higher arousal (Bonferroni adjusted for 3 tests; 'action' – 'control': b = 1.28, 95% CI (1.07, 1.49), $t(13)$ = 16.56, p < .001; 'suspense' – 'control': b = 1.18, 95% CI (0.97, 1.39), $t(13)$ = 15.25, p < .001) and higher uncertainty (Bonferroni adjusted for 3 tests; 'action' – 'control': b = 1.30, 95% CI (1.14, 1.46), $t(16)$ = 21.90, p < .001; 'suspense' – 'control': b = 1.51, 95% CI (1.35, 1.66), $t(16)$ = 25.29, p < .001). These results are summarised in panel A of Figure 3.2 and see Tables B-D in *S2 Text* for ANOVA tables, parameter estimates, and variance explained by random effects.

The supplementary ANOVAs comparing mean arousal and mean uncertainty ratings between video conditions revealed a similar pattern of results (see *S2 Text*), with the addition that arousal was significantly higher in the 'action' video condition compared to the 'suspense' condition (Bonferroni adjusted for 3 tests; 'action' – 'suspense': *b* = 0.28, 95% CI (0.08, 0.49), $t(118) = 2.70$, $p < .001$) and uncertainty was significantly higher in the 'suspense' video condition compared to the 'action' condition (Bonferroni adjusted for 3 tests; 'suspense' – 'action': *b* = 0.61, 95% CI (0.37, 0.86), $t(118) = 5.00$, $p < .001$). In addition, the non-parametric Friedman tests (with and without outliers) revealed a similar pattern of results (see *S2 Text*). Therefore, these results suggest that the video conditions evoked emotional states in the expected manner. However, it is worth noting that the difference in uncertainty ratings between the 'action' and 'suspense' conditions was smaller than anticipated, potentially undermining the ability of the experimental manipulation to detect differences in thought between the 'action' and 'suspense' videos.

3.5.3 Laboratory: Thought Patterns by Video Condition, Subjective Uncertainty, and Subjective Arousal

3.5.3.1 Video Condition

Having established that the video conditions evoked emotional states in the expected manner, we assessed whether they also elicited robust differences in patterns of thought. The LMMs examining how each thought pattern varied by video condition and emotional states in the combined laboratory samples (n = 119) revealed a significant main effect of video condition for self-relevant and past-focused off-task thought ($F(2, 16) = 10.10$, $p = .001$). This off-task pattern was significantly higher in the 'control' condition compared to the 'action' and 'suspense' conditions (Bonferroni adjusted for 3 tests; 'control' – 'action': *b* = 0.46, 95% *CI* (0.14, 0.78), $t(37) = 3.60$, $p < .001$; 'control' – 'suspense': *b* = 0.55, 95% *CI* (0.23, 0.88), $t(37) = 4.34$, $p < .001$). There was also a significant main effect of video condition for emotional, social future-directed problem-solving ($F(2, 17) = 12.14$, $p < .001$). This future-directed pattern was significantly higher in the 'action' and 'suspense' conditions compared to the 'control' condition (Bonferroni adjusted for 3 tests; 'action' – 'control': *b* = 0.52, 95% *CI* (0.21, 0.83), $t(38) = 4.26$, $p < .001$; 'suspense' – 'control': *b* = 0.55, 95% *CI* (0.25, 0.86), $t(38) = 4.56$, $p < .001$). However, there was no significant difference between the 'action' and 'suspense' conditions (Bonferroni adjusted for 3 tests; 'action' – 'suspense': *b* = -0.04, 95% *CI* (-0.34, 0.27), $t(10) = -0.33$, $p = 1.000$). Finally, there was no significant main effect of video condition for detailed deliberate thought ($F(2, 19) = 0.60$, $p = .561$). Therefore, while watching 'action' and 'suspense' video clips in the laboratory, emotional, social future-directed problem-solving was more prevalent and self-relevant and past-focused off-task thought was less prevalent (see Figure 3.2, panel B and Tables E-G in *S2 Text* for ANOVA tables, parameter estimates, and variance explained by random effects).

3.5.3.2 Uncertainty and Arousal

We also sought to map how the patterns of thought linked to each video condition related to measures of emotional state (uncertainty and arousal). The LMMs examining how each thought pattern varied by video condition and emotional states revealed that there was a significant main effect of arousal ($F(1, 1308) = 83.58$, $p < .001$) and uncertainty ($F(1, 1323) = 14.79$, $p < .001$) on levels of self-relevant and past-focused off-task thought. Higher arousal ($b = -0.29$, 95% *CI* (-0.36, -0.23), $t(1308) = -9.14$, $p < .001$) and higher uncertainty ($b = -0.13$, 95% *CI* (-0.20, -0.07), $t(1323) = -3.85$, $p < .001$) were both associated with reduced self-relevant and past-focused off-task thought. However, a significant two-way interaction between uncertainty and video condition ($F(2, 1252) = 5.82$, $p = .003$) indicated that the negative relationship between uncertainty and this off-task thought pattern was only present in the 'action' ($b = -0.27$, 95% *CI* (-0.36, -0.18), $t(1305) = -5.93$, $p < .001$) and 'suspense' ($b = -0.12$, 95% *CI* (-0.21, -0.03), $t(1303) = -2.53$, $p = .012$) conditions, and not the 'control' condition ($b = -0.01$, 95% *CI* (-0.16, 0.15), $t(1280) = -0.08$, $p = .936$). Therefore, higher arousal was consistently related to reduced off-task thought in the laboratory independent of video condition, whereas higher uncertainty was only related to reduced off-task thought in the 'action' and 'suspense' conditions.

There was also a significant main effect of arousal ($F(1, 1310) = 20.13$, $p < .001$) and uncertainty ($F(1, 1322) = 74.52$, $p < .001$) on levels of emotional, social future-directed problem-solving. Higher arousal ($b = 0.14$, 95% *CI* (0.08, 0.20), $t(1310) = 4.49$, $p < .001$) and higher uncertainty ($b = 0.28$, 95% *CI* (0.22, 0.35), $t(1322) = 8.63$, $p < .001$) were both associated with greater emotional, social future-directed problem-solving. Therefore, subjective uncertainty and subjective arousal were consistently related to increased future-directed problem-solving in the laboratory independent of video condition. Finally, there was no significant main effect of arousal ($F(1, 1284) = 1.13$, $p = .288$) or uncertainty ($F(1, 1326) = 0.38$, $p = .536$) on levels of detailed deliberate thought. The results from these LMMs are summarised in the left-hand panel of Figure 3.3 under the 'Laboratory' heading and see Tables E-G in *S2 Text* for ANOVA tables, parameter estimates, and variance explained by random effects.

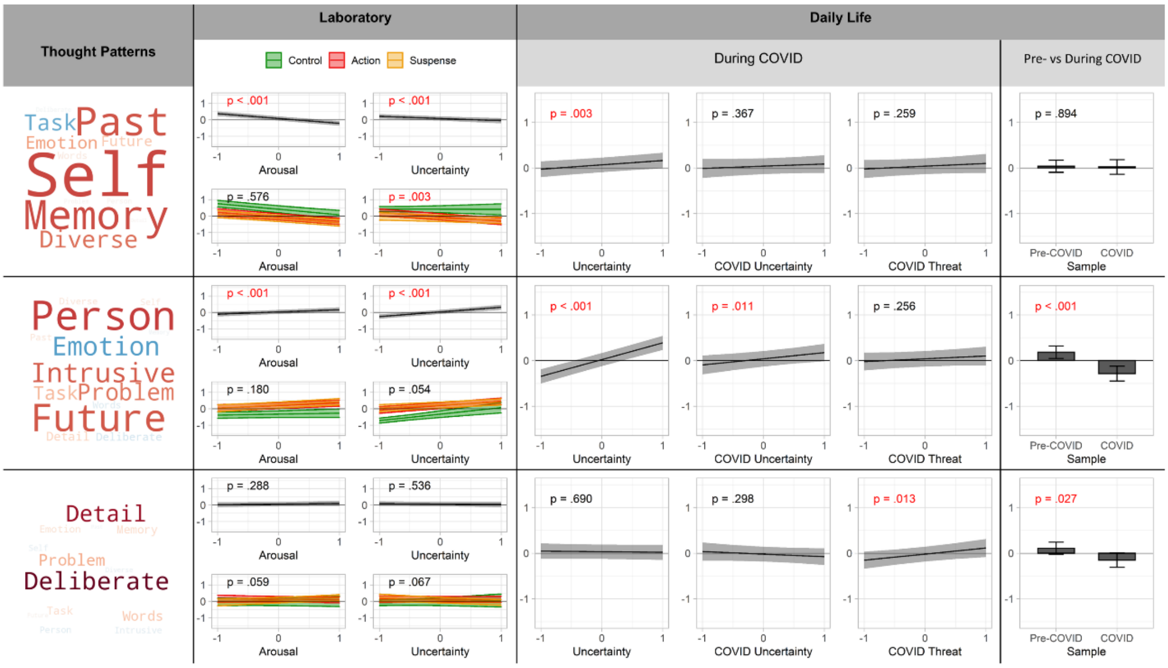

Figure 3.3. Ongoing thought patterns by emotional states in the laboratory and daily life. Left-hand side shows word clouds representing the three thought patterns identified by applying PCA to the combined laboratory thought data (n = 119). Each word represents an experience-sampling item (13 items; see Table A in *S1 Text*). Font size represents the magnitude of the loading, and colour describes the direction (warm = positive, cool = negative). Plots under the 'Laboratory' heading (n = 119) show predicted values for each thought pattern (y-axis) by 1) arousal, 2) uncertainty, 3) arousal : condition, and 4) uncertainty : condition. The predictor variable is shown on the x-axis of each plot. Legend shows the three video conditions. Plots under the 'Daily life, During COVID' heading (n = 59) show the predicted values for each projected thought pattern (y-axis) by 1) uncertainty, 2) COVID-specific uncertainty, and 3) COVID-specific threat. The predictor variable is shown on the x-axis of each plot. Plots under the 'Daily life, Pre vs During COVID' heading (n = 129) show the predicted values for each projected thought pattern (y-axis) by 1) sample (pre-COVID vs during-COVID) (x-axis). P-values for the F-test for each main effect or interaction are shown in the top right of each plot. P-values < .05 are shown in red and p-values > .05 are shown in black. Error bars represent the 95% CIs for each predicted slope or mean. All continuous variables were z-scored before analysis.

3.5.4 Laboratory: Thought Patterns and Trait Anxiety

Next, we examined how patterns of ongoing thought related to levels of trait anxiety in laboratory Sample 1 (n = 70). The preliminary correlational analyses examining how mean thought patterns varied by trait anxiety—split by video condition—revealed that self-relevant and past-focused off-task thought was significantly positively correlated with trait anxiety in the 'control' condition only (r = 0.36, p = .002) but not in the 'action' (r = 0.14, p = .241) or 'suspense' (r = 0.20, p = .094) conditions. In addition, emotional, social future-directed problem-solving was significantly positively correlated with trait anxiety in the 'control' condition only (r = 0.30, p = .012) but not in 'action' (r = 0.12, p = .328) or 'suspense' (r =

0.10, *p* = .394) conditions. These results indicate that these thought patterns may be linked to trait anxiety only in low threat and low uncertainty conditions in the laboratory (i.e., ‘control’ condition). The results from these correlational analyses are summarised in Fig F in *S2 Text*.

The LMMs examining how each thought pattern varied by video condition, emotional states, and trait anxiety in the laboratory revealed that the positive relationship between self-relevant and past-focused off-task thought and trait anxiety did not reach significance (*b* = 0.12, 95% *CI* (-0.01, 0.26), *t*(72) = 1.86, *p* = .068), nor did the positive relationship between emotional, social future-directed problem-solving and trait anxiety (*b* = 0.13, 95% *CI* (-0.01, 0.28), *t*(71) = 1.85, *p* = .069). However, a significant two-way interaction between trait anxiety and uncertainty (*F*(1, 725) = 7.38, *p* = .007) indicated that while there was a significant positive relationship between uncertainty and emotional, social future-directed problem-solving for low- or moderate-trait-anxiety individuals (when trait anxiety = -2: *b* = 0.44, 95% *CI* (0.27, 0.61), *t*(728) = 5.10, *p* < .001; when trait anxiety = 0: *b* = 0.24, 95% *CI* (0.16, 0.32), *t*(728) = 5.64, *p* < .001), there was no significant relationship between this thought pattern and uncertainty for high-trait-anxiety individuals (when trait anxiety = 2: *b* = 0.04, 95% *CI* (-0.12, 0.20), *t*(725) = 0.49, *p* = .626). In addition, high-trait-anxiety individuals reported higher levels of this thought pattern when uncertainty was low compared to low-trait-anxiety individuals (when trait anxiety = 2 and uncertainty = -1 – when trait anxiety = -2 and uncertainty = -1: *b* = 0.93, 95% *CI* (0.30,1.56), *t*(106) = 2.92, *p* = .004). This interaction indicates that high-trait-anxiety individuals show a weaker association between the future-directed thought pattern and subjective uncertainty and tend to report higher levels of this thought pattern when uncertainty is low compared to low-trait-anxiety individuals.

Finally, although it did not pass the Bonferroni-adjusted alpha level, a two-way interaction between trait anxiety and arousal (*F*(1, 705) = 5.15, *p* = .024) indicated that while there was a positive relationship between arousal and detailed deliberate thought for low-trait-anxiety individuals (when trait anxiety = -2: *b* = 0.27, 95% *CI* (0.06, 0.49), *t*(736) = 2.50, *p* = .013), there was no significant relationship between this thought pattern and arousal for moderate- or high-trait-anxiety individuals (when trait anxiety = 0: *b* = 0.07, 95% *CI* (-0.05, 0.18), *t*(722) = 1.16, *p* = .245; when trait anxiety = 2: *b* = -0.14, 95% *CI* (-0.35, 0.07), *t*(713) = -1.34, *p* = .180). The results from these LMMs are summarized in the left panel of Figure 3.4 and see Tables H-J in *S2 Text* for ANOVA tables, parameter estimates, and variance explained by random effects.

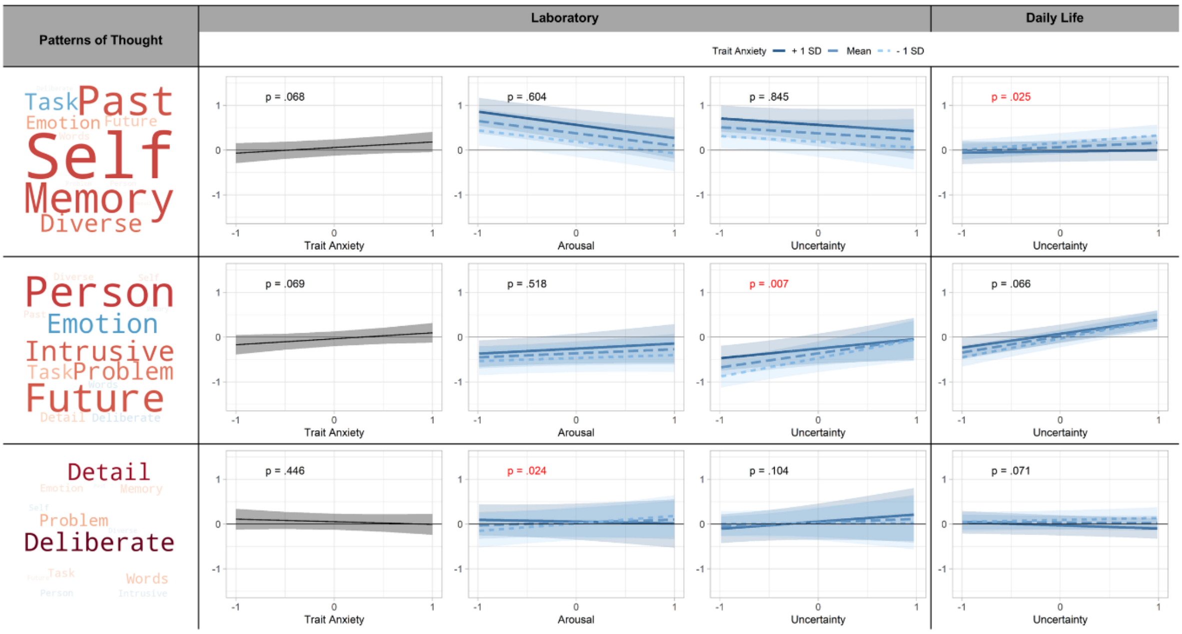

Figure 3.4. Ongoing thought patterns and trait anxiety in the laboratory and daily life. Left-hand side shows word clouds representing the three ongoing thought patterns identified by applying PCA to the combined laboratory thought data (n = 119). Each word represents an experience-sampling item (13 items; see Table A in *S1 Text*). Font size represents the magnitude of the loading, and colour describes the direction (warm = positive, cool = negative). Plots under the 'Laboratory' heading (n = 70) show the predicted slopes for each thought pattern (y-axis) by 1) trait anxiety, 2) trait anxiety : arousal, and 3) trait anxiety : uncertainty. The predictor variable is shown on the x-axis of each plot. Legend shows different levels of trait anxiety. Plots under the 'Daily Life' heading (n = 59) show the predicted slopes for each projected thought pattern (y-axis) by 1) trait anxiety : uncertainty in the during-COVID daily life sample. P-values for the F-test for each main effect or interaction are shown in the top right of each plot. P-values < .05 are shown in red and p-values > .05 are shown in black. In all plots, error bars represent the 95% CIs for each predicted slope. All continuous variables were z-scored before analysis.

3.5.5 Laboratory: Emotional States and Trait Anxiety

The correlational analyses examining how emotional states related to trait anxiety—split by video condition—in the laboratory revealed that trait anxiety was negatively correlated with mean arousal in the 'control' (*r* = -0.25, *p* = .033) and 'action' (*r* = -0.29, *p* = .014) conditions, but not the 'suspense' condition (*r* = -0.16, *p* = .174) (see left-hand-side of Fig G in *S2 Text*). In addition, there was no relationship between mean uncertainty and trait anxiety across all video conditions (*p* > .5) (see right-hand-side of Fig G in *S2 Text*). Therefore, in the laboratory, high-trait-anxiety individuals generally reported lower levels of arousal and comparative levels of uncertainty compared to low-trait-anxiety individuals.

3.5.6 Laboratory Results Summary

In summary, we successfully induced states of uncertainty and arousal in participants via video watching (Figure 3.2). A pattern of social and future-directed problem-solving with emotional features was significantly higher in both the ‘action’ and ‘suspense’ threat video conditions compared to the ‘control’ conditions (Figure 3.2). While there was no significant difference in this future-directed pattern between ‘action’ and ‘suspense’ videos, this pattern was positively associated with the continuous measure of subjective uncertainty across all video conditions (Figure 3.3). Notably, high-trait-anxiety individuals reported more of this future-directed pattern than low-trait-anxiety individuals when subjective uncertainty was low, but not high. Overall, therefore, they showed a weaker relationship between this future-directed pattern of thought and uncertainty (Figure 3.4).

3.5.7 Daily Life: Thought Patterns between Pre- and during COVID Samples

Having identified patterns of thoughts associated with uncertainty in the laboratory, we next examined how the prevalence of these patterns varied between the daily life pre- and during-COVID samples. The LMMs examining how each thought pattern varied by sample (pre- vs during-COVID) and trait anxiety (n = 129) revealed a significant main effect of sample for emotional, social future-directed problem-solving ($F(1, 125) = 15.39$, $p < .001$). This pattern was significantly lower in the COVID sample compared to the pre-COVID sample ($b = -0.23$, 95% *CI* (-0.35, -0.12), $t(125) = -3.92$, $p < .001$). In addition, although it did not pass the Bonferroni-adjusted alpha level, there was a main effect of sample for detailed deliberate thought ($F(1, 126) = 5.02$, $p = .027$). This pattern was lower in the COVID sample compared to the pre-COVID sample ($b = -0.13$, 95% *CI* (-0.24, -0.02), $t(126) = -2.24$, $p = .027$). Therefore, levels of emotional, social future-directed problem-solving and detailed deliberate thought were lower in the COVID sample compared to the pre-COVID sample. These results are summarised in Figure 3.3 and see Tables K-M in *S2 Text* for ANOVA tables, parameter estimates, and variance explained by random effects.

3.5.8 Daily Life during COVID-19 Pandemic: Thought Patterns and Subjective Uncertainty

We next examined how the laboratory results relating to thought patterns and uncertainty generalised to data collected in daily life. Although there was a general tendency for emotional, social future-directed problem-solving to be lower during COVID compared to pre-COVID, subsequent LMM analyses examining the effect of subjective uncertainty and trait anxiety on thought patterns revealed that, during COVID, higher levels of uncertainty were associated with *increased* emotional, social future-directed problem-solving (b = 0.37, 95% CI (0.31, 0.43), t(1208) = 11.89, p < .001). In addition, these models revealed that higher uncertainty was also associated with increased self-relevant and past-focused off-task thought (b = 0.10, 95% CI (0.03, 0.16), t(1231) = 2.99, p = .003). Therefore, during the COVID-19 pandemic, feeling uncertain was associated with an increase in daily life thoughts that reflected 1) self-relevant and past-focused off-task thought and 2) emotional, social future-directed problem-solving. These results are summarised in Figure 3.3 and see Tables N-P in *S2 Text* for ANOVA tables, parameter estimates, and variance explained by random effects.

3.5.9 Daily Life during COVID-19 Pandemic: Thought Patterns, COVID Uncertainty, and COVID Threat

Having identified patterns of thought associated with subjective uncertainty in daily life, we next examined the relationship between these thought patterns and uncertainty caused specifically by the COVID-19 situation, as well as its perceived threat. The LMMs examining how each thought pattern varied by COVID uncertainty, COVID threat, and trait anxiety in the COVID daily life sample revealed that higher COVID uncertainty was associated with increased emotional, social future-directed problem-solving (b = 0.14, 95% CI (0.03, 0.24), t(991) = 2.55, p = .011). However, COVID uncertainty showed no significant association with self-relevant and past-focused off-task thought (b = 0.05, 95% CI (-0.06, 0.15), t(1017) = 0.90, p = .367) or detailed deliberate thought (b = -0.06, 95% CI (-0.16, 0.05), t(945) = -1.04, p = .298). Finally, higher COVID threat was associated with increased detailed deliberate thought (b = 0.13, 95% CI (0.03, 0.24), t(786) = 2.48, p = .013) but showed no significant relation to either emotional, social future-directed problem-solving (b = 0.06, 95% CI (-0.04, 0.17), t(832) = 1.14, p = .256) or self-relevant and past-focused off-task thought (b = 0.06, 95% CI (-0.05, 0.17), t(867) = 1.13, p = .259). Therefore, in daily life during the COVID-19 pandemic, COVID-related uncertainty was associated with an increase in emotional, social future-directed problem-solving whereas COVID-related threat was associated with an increase in detailed deliberate thought. These results are summarized in Figure 3.3 and see Tables Q-S in *S2 Text* for ANOVA tables, parameter estimates, and variance explained by random effects.

3.5.10 Daily Life: Thought Patterns and Trait Anxiety

3.5.10.1 Sample and Trait Anxiety

Next, we examined whether the relationships between trait anxiety and ongoing thoughts differed between pre- and during-COVID daily life samples. The preliminary correlational analyses examining how mean thought patterns varied by trait anxiety—split by sample—in daily life indicated that emotional, social future-directed problem-solving was significantly positively correlated with trait anxiety in the COVID sample (r = 0.34, p = .009) but not in the pre-COVID sample (r = 0.03, p = .787). The results from these correlational analyses are summarised in Fig H in *S2 Text*.

The LMMs examining how each thought pattern varied by sample (pre- vs during-COVID) and trait anxiety in the daily life samples (n = 129) revealed that the positive relationship between trait anxiety and emotional, social future-directed problem-solving did not reach significance (b = 0.09, 95% *CI* (-0.00, 0.18), t(121) = 1.92, p = .057). In addition, there was no significant relationship between trait anxiety and self-relevant and past-focused off-task thought (b = -0.02, 95% *CI* (-0.11, 0.07), t(124) = -0.52, p = .603) or detailed deliberate thought (b = -0.05, 95% *CI* (-0.14, 0.04), t(123) = -1.11, p = .269). Finally, there were no significant interactions between sample and trait anxiety for any of the three thought patterns (see Tables K-M in *S2 Text* for ANOVA tables, parameter estimates, and variance explained by random effects).

3.5.10.2 Subjective Uncertainty and Trait Anxiety

We next examined whether the relationship between trait anxiety, social and future-directed problem-solving, and uncertainty observed in the laboratory extended to daily life. The LMMs examining how each thought pattern varied by subjective uncertainty and trait anxiety in the COVID daily life sample revealed that the two-way interaction between trait anxiety and uncertainty for emotional, social future-directed problem-solving did not reach significance (F(1, 1078) = 3.37, p = .066). However, for completeness, it is worth noting that the underlying pattern of results was consistent with those found in the laboratory since high-trait-anxiety individuals (when trait anxiety = 2: b = 0.26, 95% *CI* (0.13, 0.38), t(1098) = 4.04, p < .001) showed a weaker positive relationship between uncertainty and this thought pattern than low-trait-anxiety individuals (when trait anxiety = -2: b = 0.48, 95% *CI* (0.34, 0.61), t(1125) = 6.89, p < .001).

While it did not pass the Bonferroni-adjusted alpha level, there was also a two-way interaction between trait anxiety and uncertainty for self-relevant and past-focused off-task thought ($F(1, 1132) = 5.07$, $p = .025$). This interaction indicated that while there was a significant positive relationship between uncertainty and this thought pattern for low- or moderate-trait-anxiety individuals (when trait anxiety = -2: $b = 0.23$, 95% *CI* (0.09, 0.37), $t(1167) = 3.26$, $p = .001$; when trait anxiety = 0: $b = 0.10$, 95% *CI* (0.03, 0.16), $t(1231) = 2.99$, $p = .003$), there was no significant relationship between uncertainty and this thought pattern for high-trait-anxiety individuals (when trait anxiety = 2: $b = -0.04$, 95% *CI* (-0.17, 0.09), $t(1151) = -0.64$, $p = .524$). These results are summarized in Figure 3.4 and see Tables N-P in *S2 Text* for ANOVA tables, parameter estimates, and variance explained by random effects.

3.5.10.3 COVID Uncertainty, COVID Threat, and Trait Anxiety

The LMMs examining how each thought pattern varied by COVID uncertainty, COVID threat, and trait anxiety in the COVID daily life sample revealed that there was no significant main effect of trait anxiety for self-relevant and past-focused off-task thought ($F(1, 58) = 2.00$, $p = .163$), emotional, social future-directed problem-solving ($F(1, 59) = 1.83$, $p = .182$), or detailed deliberate thought ($F(1, 60) = 1.82$, $p = .182$) (see Tables Q-S in *S2 Text* for ANOVA tables, parameter estimates, and variance explained by random effects).

3.5.11 Daily Life during COVID-19 Pandemic: Emotional States and Trait Anxiety

In daily life during the COVID-19 pandemic, trait anxiety was positively correlated with both the threat ($r = 0.43$, $p < .001$) and uncertainty ($r = 0.41$, $p = .001$) caused by the COVID-19 situation, and subjective uncertainty generally ($r = 0.39$, $p = .002$) (see Fig I in *S2 Text* for scatterplots).

3.5.12 Daily Life Results Summary

In summary, projection of the laboratory thought patterns directly onto the daily life data demonstrated that the pattern of social and future-directed problem-solving that was positively related to subjective uncertainty in the laboratory was also positively related to subjective uncertainty in daily life during the COVID-19 pandemic as well as COVID-specific uncertainty (Figure 3.3). In addition, although it did not reach significance, there was weak evidence to suggest that the two-way interaction between trait anxiety and uncertainty for this future-directed pattern identified in the laboratory was also present in the COVID daily life sample, indicating that high-trait-anxiety individuals show a weaker relationship between uncertainty and this future-directed pattern (Figure 3.4).

3.6 Discussion

Our study established a pattern of social and future-directed problem-solving with emotional features that is commonly engaged during periods of uncertainty across situations: both under experimentally induced conditions of uncertainty (Figures 3.2 and 3.3) and in daily life under conditions of naturally-occurring uncertainty elicited by the COVID-19 pandemic (Figure 3.3). Our findings are consistent with a broad view of the function of ongoing thought in supporting a ‘predictive mode’ aimed at resolving or reducing uncertainty, allowing individuals to imagine and select appropriate future actions. This interpretation aligns with prior work highlighting that future-directed thinking can help resolve uncertainty through forming and refining concrete personal goals (Medea et al., 2018), planning actions, and making decisions (D'Argembeau et al., 2011). Furthermore, similar to our current findings, future thinking is often social (e.g., Konu et al., 2021), and prior studies indicate that social cognition can help individuals prepare for and adapt to anticipated, or actual, threats to socio-emotional wellbeing (Poerio & Smallwood, 2016; Poerio et al., 2016). Notably, while previous research highlights that potentially-adaptive future thinking occurs when thoughts are unrelated to events taking place in the here-and-now, our study shows a similar externally-focused predictive mode (positive loading on ‘task’ item; Figure 3.2) emerges when the environment leads us to feel uncertain. Importantly, although our study identified a predictive mode of social problem-solving related to uncertainty across situations, it remains to be determined whether this contributes to future actions, an important limitation of our current study.

Our results also highlight that uncertainty may contribute to both perceptually coupled and decoupled modes of thinking. As previously highlighted, a pattern of externally-focused future-directed thought was *positively* related to uncertainty across contexts (Figure 3.3). At the same time, we found that the relationship between uncertainty and internally-focused, self-relevant and past-focused thought varied between contexts (Figure 3.3). In the laboratory, uncertainty was *negatively* related to this form of decoupled thought, while in daily life, it showed a positive relationship. Together, our results suggest that context might determine when uncertainty is associated with perceptually coupled versus decoupled modes of thinking. Regardless, there may be similarities in the processes underlying both coupled and decoupled thought patterns when they emerge during states of uncertainty. For example, resolving uncertainty may rely on cognitive control processes required to plan and evaluate different possible actions. Indeed, emerging evidence suggests that neural processes in the dorsolateral prefrontal cortex organize both on- and off-task modes of thought (Turnbull et al., 2019b). Similarly, information from memory helps shape actions in the moment (Behrens et al., 2007; Jefferies et al., 2020) and is also an important feature in states of decoupled thinking (Wang et al., 2020).

As well as examining links between thinking and uncertainty, our study explored how these patterns relate to trait anxiety, with the aim of 1) understanding how anxious individuals' thought patterns differ from non-anxious individuals and 2) further contextualising the patterns of thought identified in the current study. While there was weak evidence that high-trait-anxiety individuals reported more emotional, social and future-directed problem-solving than low-trait-anxiety individuals (see Figure 3.4 and Figs F and H in *S2 Text*), our findings are not consistent with the idea that the link between this thought pattern and uncertainty are synonymous with the repetitive pattern of worry that characterises anxious thoughts. For example, in the laboratory, while this future-directed pattern was generally positively related to subjective uncertainty, anxious individuals reported this pattern in an uncertainty-independent manner, consistent with prior work highlighting that anxiety and related phenomena such as trait rumination are linked to cognitive, autonomic, and neural inflexibility (Ottaviani et al., 2015; Ottaviani et al., 2013; Ottaviani et al., 2016; Raffaelli et al., 2021). However, our participants were not clinically anxious, so firm conclusions concerning anxiety must wait until we replicate these findings in patients.

We also found evidence of general links between ongoing thought and affective processing. In daily life, COVID-related threat positively correlated with detailed deliberate thought. This same thought pattern was associated with high arousal states in the laboratory (specifically among low-trait-anxiety individuals). These findings align with our prior work, demonstrating that detailed deliberate cognition is higher during demanding tasks (e.g., Konu et al., 2021; Mckeown et al., 2021; Sormaz et al., 2018). Together, they also suggest that this pattern may emerge when individuals are motivated to engage with the outside world. More generally, these findings and prior work (Engert et al., 2014; Poerio et al., 2013; Smallwood & O'Connor, 2011; Stawarczyk et al., 2013b) highlight the importance of an integrated multidimensional view of affective experience (Barrett et al., 2007) when investigating patterns of ongoing thought.

A methodological goal of our study was to examine how thought patterns identified in the laboratory, under controlled conditions, relate to uncertainty experienced in daily life. Although prior work has examined ongoing thought in laboratory and daily life contexts (e.g., Ho et al., 2020; Kane et al., 2017; McVay et al., 2009), our study extends this by directly projecting patterns identified in the laboratory onto daily life data. Importantly, this projection technique demonstrates an empirical link between social and future-directed cognition and uncertainty in both settings, offering support for the generalisability of this relationship across contexts. Furthermore, this approach also allows for identifying inconsistent relationships across situations (e.g., the differing relationship between off-task thinking and uncertainty in the laboratory versus daily life), confirming prior work that laboratory-based experience sampling reveals different cognitive features than daily life (Kane et al., 2017). Together, this study highlights MDES as a useful tool for bridging the gap between controlled laboratory paradigms and real-world experiences that may help develop more ecologically valid paradigms and theories in the future (Kingstone et al., 2008; Kingstone et al., 2003).

Although our study established a pattern of cognition linked to uncertainty in the laboratory and daily life, it leaves several questions open. First, although ‘action’ and ‘suspense’ videos both elicited high levels of arousal, the difference in uncertainty ratings between these conditions was lower than anticipated, perhaps because a direct threat event occurred by the end of each clip. This may have impacted our ability to detect differences in thought between these conditions. Future work, therefore, should sample thoughts intermittently while watching events unfold over time to assess changes in thought that occur before and after threatening events. Second, although examining two laboratory samples allowed replication of findings relating to video condition and emotional states (see Table A in *S2 Text*), we could not replicate findings related to trait anxiety because anxiety was only measured in one laboratory sample. Moreover, although we found a significant interaction between subjective uncertainty and anxiety for levels of future-directed problem-solving in the laboratory, this interaction did not reach significance in daily life (p = .066). Therefore, although we found broadly similar patterns in both cases, firm conclusions on associations with anxiety require future work to establish their reliability. Third, while our analyses identified links between arousal and detailed thought in the laboratory and between threat and detailed thought in daily life, we were unable to assess the consistency of these effects across contexts as we did not collect the same measures in both contexts. Finally, since prior work highlights age-related differences in ongoing thought and how factors, including activity context, differ between younger and older individuals (e.g., Maillet & Rajah, 2013; Mckeown et al., 2021; Turnbull et al., 2021), it will be important to examine whether the relationships we find in younger individuals generalise to older people.

In closing, it is worth noting that our prior work highlights important links between ongoing thought patterns and the activities individuals engage in when these thoughts emerge (Mckeown et al., 2021; Turnbull et al., 2021). It will be important for future studies to map how thought patterns identified in laboratory settings correspond to the many and varied activities that individuals engage in as they go about their daily lives. Such an endeavour will improve our understanding of how internal states and daily activities relate to how we think and what we think about, insights that will be helpful for understanding how these factors interact to predict mental health and wellbeing outcomes. Our current findings highlight that there is not always a one-to-one mapping between ongoing thought patterns and affective factors across all contexts: future work should focus on understanding *how, when, and for whom* thought patterns emerge since there appear to be multiple ‘routes’ to the same types of thinking (Cole & Kvavilashvili, 2021).

Chapter 4- The relationship between individual variation in macroscale functional gradients and distinct aspects of ongoing thought

This chapter is adapted from:

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Acknowledgements and authors' contributions:

Brontë Mckeown developed the research question, implemented the BrainSpace pipeline, performed the inferential analyses, interpreted the results, prepared visualisation of results, and wrote the manuscript for publication under the supervision of Dr Cade McCall, Prof. Elizabeth Jefferies, and Prof. Jonathan Smallwood. Will Strawson, Dr Hao-Ting Wang, and Dr Daniel Margulies contributed to study conceptualization. Prior to the start of Brontë Mckeown's research degree, Dr Hao-Ting Wang collected the resting-state fMRI dataset and Dr Theo Karapanagiotidis performed pre-processing on this resting-state fMRI dataset. Dr Theo Karapanagiotidis also helped implement the BrainSpace pipeline. Dr Hao-Ting Wang, Dr Reinder Vos de Wael, Dr Oualid Benkarim, Dr Daniel Margulies, and Dr Boris Bernhardt provided guidance on the methodology and software implementation. Will Strawson, Dr Hao-Ting Wang, Dr Reinder Vos de Wael, Dr Oualid Benkarim, Dr Adam Turnbull, and Dr Boris Bernhardt contributed to reviewing and editing the manuscript for publication.

4.1 Abstract

Contemporary accounts of ongoing thought recognise it as a heterogeneous and multidimensional construct, varying in both form and content. An emerging body of evidence demonstrates that distinct types of thought are associated with unique neurocognitive profiles, that can be described at the whole-brain level as interactions between multiple large-scale networks. The current study explored the possibility that whole-brain functional connectivity patterns at rest may be related to distinct aspects of ongoing thought reported over this period. Participants underwent resting-state functional magnetic resonance imaging (rs-fMRI) followed by a questionnaire retrospectively assessing the content and form of their ongoing

thoughts during the scan. A non-linear dimension reduction algorithm was applied to the rs-fMRI data to identify components explaining the greatest variance in whole-brain connectivity patterns. Using these data, we examined whether specific types of thought measured at the end of the scan were predictive of individual variation along the first three low-dimensional components of functional connectivity at rest. Multivariate analyses revealed that individuals for whom the connectivity of the sensorimotor system was maximally distinct from the visual system were most likely to report thoughts related to finding solutions to problems or goals and least likely to report thoughts related to the past. These results add to an emerging literature that suggests that unique features of experience are associated with distinct distributed neurocognitive profiles and highlight that unimodal systems may play an important role in this process.

4.2 Introduction

When unoccupied by events in the immediate environment, such as during the so-called resting-state, humans often spend substantial amounts of time focused on information that is relevant to themselves but absent from the here and now. These self-generated experiences can be a source of unhappiness and distress (Killingsworth & Gilbert, 2010; Poerio et al., 2013). However, they can also allow individuals to mentally reframe their goals in a more concrete way (Medea et al., 2018), and reduce loneliness (Poerio et al., 2015), perhaps because of links between self-generated thought with creativity (Baird et al., 2012; Gable et al., 2019; Smeekens & Kane, 2016; Wang et al., 2018b), social problem solving (Ruby et al., 2013b), or generation of information based on semantic knowledge (Wang et al., 2020). Understanding the neural basis of these experiences is, therefore, an important goal for cognitive neuroscience because it may help describe the underlying neural architecture which supports aspects of human cognition that are both beneficial and detrimental to health and well-being. In this study, we examined whether an individual's ongoing thoughts could predict individual variation in their functional organization at rest.

Contemporary views on how the structure of the cortex constrains its functions have identified the important roles that macroscale patterns of cortical organization play in determining cognition (Margulies et al., 2016; Mesulam, 1998). These patterns, or motifs, can be well captured by dimension reduction techniques that identify low-dimensional manifold spaces, often referred to as 'cortical gradients'. This approach has been important in characterizing the axis upon which cortical structure is organized (Paquola et al., 2019; Vázquez-Rodríguez et al., 2019) and how the specific topological features of the cortex give rise to different functional hierarchies (Margulies et al., 2016). This approach has also been used to describe changes in brain function in developmental disorders (Hong et al., 2019) and across primate species (Xu et al., 2020) and to capture dynamic changes between states of external task focus and self-generated social episodic thought (Turnbull et al., 2020b). One advantage of gradient approaches to neural function is that they describe multivariate whole-brain patterns of organization (i.e., the relationship between different neural systems), and so allow the investigation of whether macroscale features of cortical organization relate to features of cognition. This approach is particularly useful for understanding features of higher-order cognition hypothesised to depend upon the interaction between multiple neural systems (e.g., Jefferies et al., 2020; Smallwood et al., 2011; Smallwood & Schooler, 2015).

Our current study, therefore, explores the possibility that macroscale properties of the cortex captured by low-dimensional descriptors of functional organization at rest are related to individual variation in ongoing experience that emerges during this period. Resting-state fMRI was used to record patterns of intrinsic neural activity in a large cohort (N = 277). We employed the BrainSpace toolbox (Vos de Wael et al., 2020) to calculate the dimensions that characterize the functional connectivity of the brain at rest. At the end of the scan, participants completed a questionnaire that retrospectively assessed their experiences during the scan. The questions were based on those used in previous studies exploring population variation in functional connectivity and aimed at capturing the heterogeneity of ongoing thought (Karapanagiotidis et al., 2017; Smallwood et al., 2016). While retrospective experience-sampling sacrifices temporal specificity, it is particularly beneficial for understanding the neural basis of ongoing experience because the absence of interruptions ensures that neural dynamics unfold in a relatively natural way (Smallwood & Schooler, 2015). Using these data, we examined whether specific types of thought measured at the end of the scan were predictive of individual variation along low-dimensional gradients of macroscale functional connectivity at rest. These data have previously been examined by Karapanagiotidis et al. (2019), who applied Hidden Markov modelling to identify neural states occurring at rest. They found states linked to autobiographical planning and intrusive rumination that were related to differences in the relative dominance of frontoparietal and motor systems, and default mode and visual systems.

Prior studies have highlighted three cortical gradients which each relate to meaningful features of cognition. The first gradient describes the difference between regions of unimodal and transmodal cortex (Margulies et al., 2016). Studies have shown that this neural motif is observed when participants must use information from memory to guide behaviour, such as when visuospatial decisions must be made with previously encountered information rather than immediate perceptual information (Murphy et al., 2018; Murphy et al., 2019). The second gradient is related to the dissociation between unimodal systems concerned with vision and sensorimotor functions (Margulies et al., 2016). Finally, the third gradient describes a distinction between the so-called default mode and task-positive systems (Margulies et al., 2016). This pattern is often observed when researchers compare easy and demanding cognitive tasks (Cole et al., 2013; Duncan, 2010). Prior studies have shown that this pattern is linked to the difference between on- and off-task states and that this distinction also helps describe neurocognitive changes related to the passage of time (Turnbull et al., 2020b). Our study aimed to explore whether any of these macroscale neural motifs were related to the participants' reports at the end of the experimental session.

4.3 Methods

4.3.1 Participants

Two hundred and seventy-seven healthy participants were recruited from the University of York. Written informed consent was obtained for all participants and the study was approved by the York Neuroimaging Centre Ethics Committee. Twenty-three participants were excluded from analyses; two due to technical issues during the neuroimaging data acquisition and twenty-one for excessive movement during the fMRI scan (mean framewise displacement (Power et al., 2014) > 0.3 mm and/or more than 15% of their data affected by motion), resulting in a final cohort of n = 254 (169 females, mean ± SD age = 20.7 ± 2.4 years). The questionnaire and functional MRI data in this study are the same as those reported in Karapanagiotidis et al. (2019).

4.3.2 Data and Code Availability Statement

Gradient maps one to ten from the group-averaged dimension reduction analysis described in section 4.3.5.3 below are publicly available on NeuroVault in a collection with the title of this article (https://neurovault.org/collections/6746/). Raw fMRI and questionnaire data are restricted in accordance with ERC and EU regulations. All code used in the production of this manuscript is publicly available online in the following repository: https://github.com/Bronte-Mckeown/GradientAnalysis.

4.3.3 Retrospective Experience-Sampling

Participants' experience during the resting-state fMRI scan was sampled by asking them to retrospectively report their thoughts during the resting-state period at the end of the scan. Experience was measured using a 4-point Likert scale with the question order randomised (all 25 questions are shown in Table 4.1).

Table 4.1. 25-item experience-sampling questionnaire completed at the end of the resting-state fMRI scan. Answers were given on a 4-point Likert scale ranging from "Not at all" to "Completely".

Dimension	**Question (My thoughts…)**
Vivid	… were vivid as if I was there
Normal	… were similar to thoughts I often have
Future	… involved future events
Negative	… were about something negative
Detail	… were detailed and specific
Words	… were in the form of words
Evolving	… tended to evolve in a series of steps
Spontaneous	… were spontaneous
Positive	… were about something positive
Images	… were in the form of images
People	… involved other people
Past	… involved past events
Deliberate	… were deliberate
Self	… involved myself
Stop	… were hard for me to stop
Distant time	… were related to a more distant time
Abstract	… were about ideas rather than events or objects
Decoupled	… dragged my attention away from the external world
Important	… were on topics that I care about
Intrusive	… were intrusive
Problem Solving	… were about solutions to problems (or goals)
Here and Now	… were related to the here and now
Creative	… gave me a new insight into something I have thought about before
Realistic	… were about an event that has happened or could take place
Same Theme	… at different points in time were all on the same theme

4.3.4 Procedure

All participants underwent a 9-minute resting-state fMRI scan. During the scan, they were instructed to passively view a fixation cross and not to think of anything in particular. Immediately following the scan, they completed the 25-item experience-sampling questionnaire while still in the scanner.

4.3.5 Resting-state fMRI

4.3.5.1 MRI Data Acquisition

MRI data were acquired on a GE 3 T Signa Excite HDxMRI scanner, equipped with an eight-channel phased array head coil at York Neuroimaging Centre, University of York. For each participant, we acquired a sagittal isotropic 3D fast spoiled gradient-recalled echo T1-weighted structural scan (TR = 7.8 ms, TE = minimum full, flip angle = 20°, matrix = 256x256, voxel size = 1.13x1.13 × 1 mm3, FOV = 289 × 289 mm2). Resting-state fMRI data based on blood oxygen level-dependent contrast images with fat saturation were acquired using a gradient single-shot echo-planar imaging sequence (TE = minimum full (≈19 ms), flip angle = 90°, matrix = 64x64, FOV = 192 × 192 mm2, voxel size = 3x3x3 mm3, TR = 3000 ms, 60 axial slices with no gap and slice thickness of 3 mm). Scan duration was 9 minutes which allowed us to collect 180 whole-brain volumes. These acquisition details are identical to the ones described in Karapanagiotidis et al. (2019).

4.3.5.2 MRI Data Pre-Processing

fMRI data pre-processing was performed using SPM12 (http://www.fil.ion.ucl.ac.uk/spm) and the CONN toolbox (v.18b) (https://www.nitrc.org/projects/conn) (Whitfield-Gabrieli & Nieto-Castanon, 2012) implemented in Matlab (R2018a) (https://uk.mathworks.com/products/matlab). Pre-processing steps followed CONN's default pipeline and included motion estimation and correction by volume realignment using a six-parameter rigid body transformation, slice-time correction, and simultaneous grey matter (GM), white matter (WM) and cerebrospinal fluid (CSF) segmentation and normalisation to MNI152 stereotactic space (2 mm isotropic) of both functional and structural data. Following pre-processing, the following potential confounders were statistically controlled for: 6 motion parameters calculated at the previous step and their 1st and 2nd order derivatives, volumes with excessive movement (motion greater than 0.5 mm and global signal changes larger than z = 3), linear drifts, and five principal components of the signal from WM and CSF (CompCor approach) (Behzadi et al., 2007). Finally, data were band-pass filtered between 0.01 and 0.1 Hz. No global signal regression was performed. The pre-processing steps reported here are identical to the ones described in Karapanagiotidis et al. (2019).

4.3.5.3 Whole-brain Functional Connectivity: Dimension Reduction

Following pre-processing, the functional time-series from 400 ROIs based on the 400 Schaefer parcellation (Schaefer et al., 2018) were extracted for each individual. A connectivity matrix for each individual was then calculated using Pearson correlation resulting in a 400x400 connectivity matrix for each participant. These individual connectivity matrices were then averaged to calculate a group-averaged connectivity matrix. The BrainSpace Toolbox (Vos de Wael et al., 2020) was then used to extract ten group-level gradients from the group-averaged connectivity matrix (dimension reduction technique = diffusion embedding, kernel = normalized angle, sparsity = 0.9). Although we were only interested in the first three gradients, as they all have reasonably well described functional associations, we extracted ten gradients to maximize the degree of fit between the group-averaged gradients and the individual-level gradients (see Table S1 for the average degree of fit for gradients one to three when extracting ten gradients compared to three). These group-averaged gradients act as a template to which individual gradients can be compared, to allow an investigation of individual differences along each gradient in the current sample. The variance explained by each group-averaged gradient one to ten is shown in Figure S1.

The group-level gradient solutions were aligned using Procrustes rotation to a subsample of the HCP dataset ([n = 217, 122 women, mean ± sd age = 28.5 ± 3.7 y]; for full details of subject selection see Vos de Wael et al. (2018)) openly available within the BrainSpace toolbox (Vos de Wael et al., 2020)). This alignment step improves the stability of the group-level gradient templates by maximising the comparability of the solutions to those from the existing literature (i.e., Margulies et al., 2016). The first three group-averaged gradients, with and without alignment to the HCP data are shown in Figure S2. To demonstrate the benefits of this alignment step, we calculated the similarity using Spearman Rank correlation between the first five aligned and unaligned group-level gradients with the first five gradients reported in Margulies et al. (2016) which were calculated using 820 participants over an hour resting-state scan. Aligning our gradients with a subsample of the HCP data increased the similarity between our gradients and Margulies' et al. (2016) gradients (see Table S2).

Using identical parameters, individual-level gradients were then calculated for each individual using their 400x400 connectivity matrix. These individual-level gradient maps were aligned to the group-level gradient maps using Procrustes rotation to improve the comparison between the group-level gradients and individual-level gradients (N iterations = 10). This analysis resulted in ten group-level gradients and ten individual-level gradients for each participant explaining maximal whole-brain connectivity variance in descending order. All ten group-level gradients are shown in Figure 4.1, however, only the first three gradients were retained for further analysis. To demonstrate the variability of individual-level gradients, Figure S3 shows the highest, lowest, and median similarity gradient maps for gradients one to three.

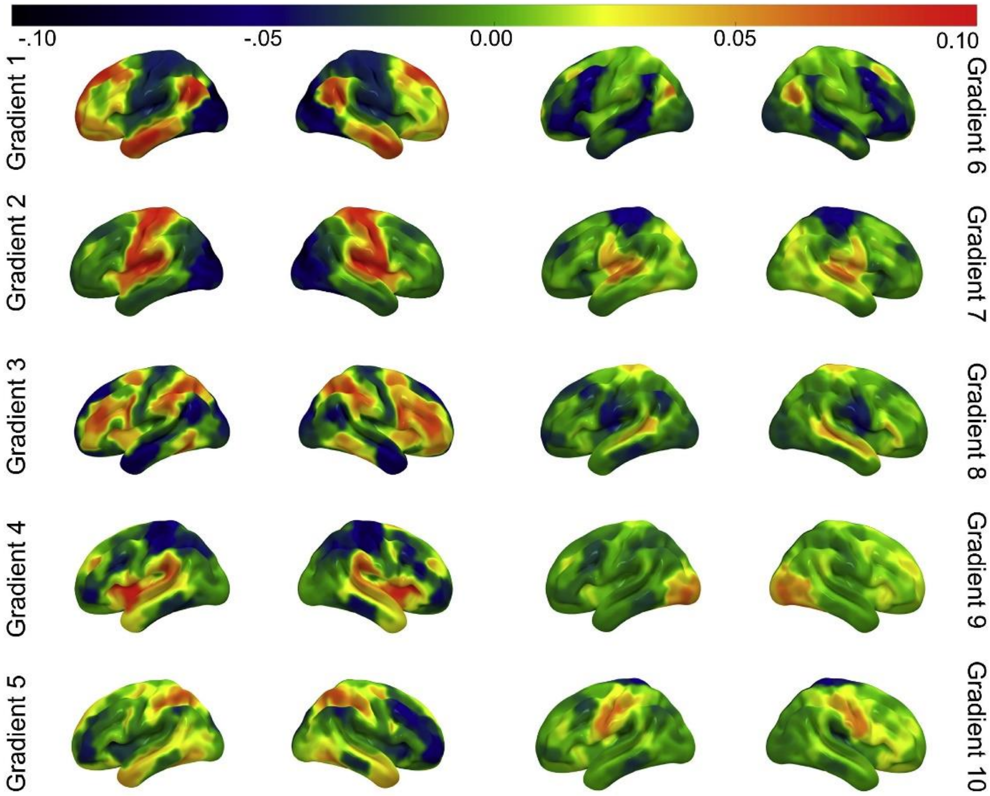

Figure 4.1. Group-averaged gradients one to ten (left and right lateral views) explaining maximal variance in whole-brain functional connectivity patterns. Regions that share similar connectivity profiles fall close together along each gradient (similar colours), and regions that have more distinct connectivity profiles fall further apart (different colours). The positive and negative loading is arbitrary. Regions which fall at the extreme end of each gradient have the greatest dissimilarity in their connectivity profiles. Only gradients one to three were included in the multivariate analysis. These ten group-averaged gradient maps are publicly available on NeuroVault (https://neurovault.org/collections/6746/).

4.3.5.4 Individual-Level Similarity Analysis: Spearman's Rank Correlation

In order to investigate individual differences for each of the three connectivity gradients, a Spearman's rank correlation was used to calculate the extent to which each individual-level gradient was related to each group-level gradient. In this way, the correlation coefficient calculated for each participant for gradients one to three is used as a second-order statistic indicating the similarity between the group-level and individual-level gradients. Fishers R-to-Z transformation was applied to these correlation coefficient scores. These z-transformed correlation coefficients will be referred to as 'gradient similarity scores' from this point onwards. These similarity scores were then entered as dependent variables in subsequent multivariate regression analyses to investigate whether individual variation in ongoing thought could predict individual variation along the first three whole-brain connectivity gradients. A schematic for the analysis pipeline is shown in Figure 4.2.

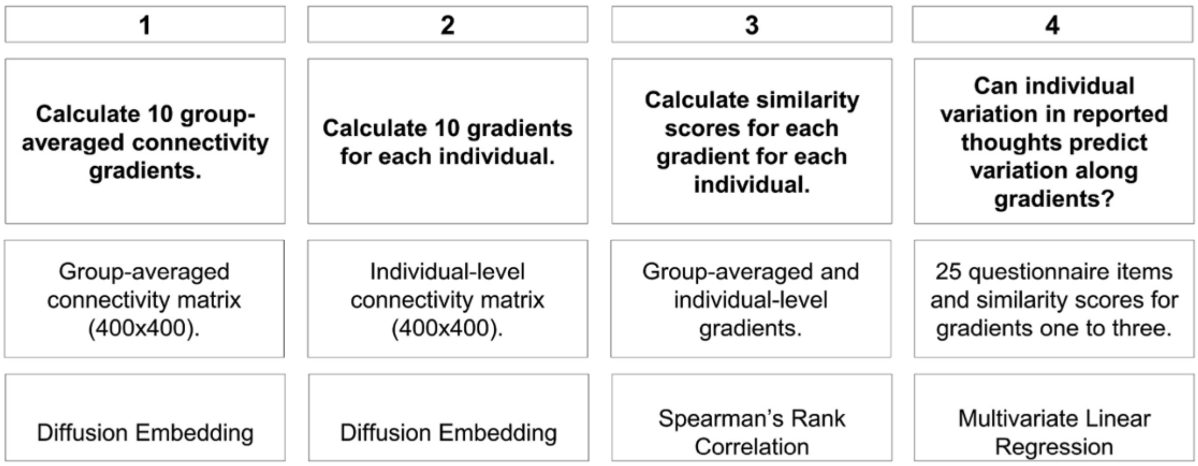

Figure 4.2. Summary of the analysis pipeline. Numbers represent the order of the analysis step. The top panel in bold describes the overarching goal of each step. The middle panel specifies the data used. The bottom panel indicates which analysis or statistical test was used to achieve the step.

4.4 Results

4.4.1 Experience-Sampling Responses

The experience-sampling data are summarised in Figure 4.3, revealing the distribution of responses for each item as well as the covariance between each item. While some questionnaire items are significantly correlated, the variance inflation factor for each questionnaire item was <2, indicating that multicollinearity is not a concern in the multivariate regression analysis described below.

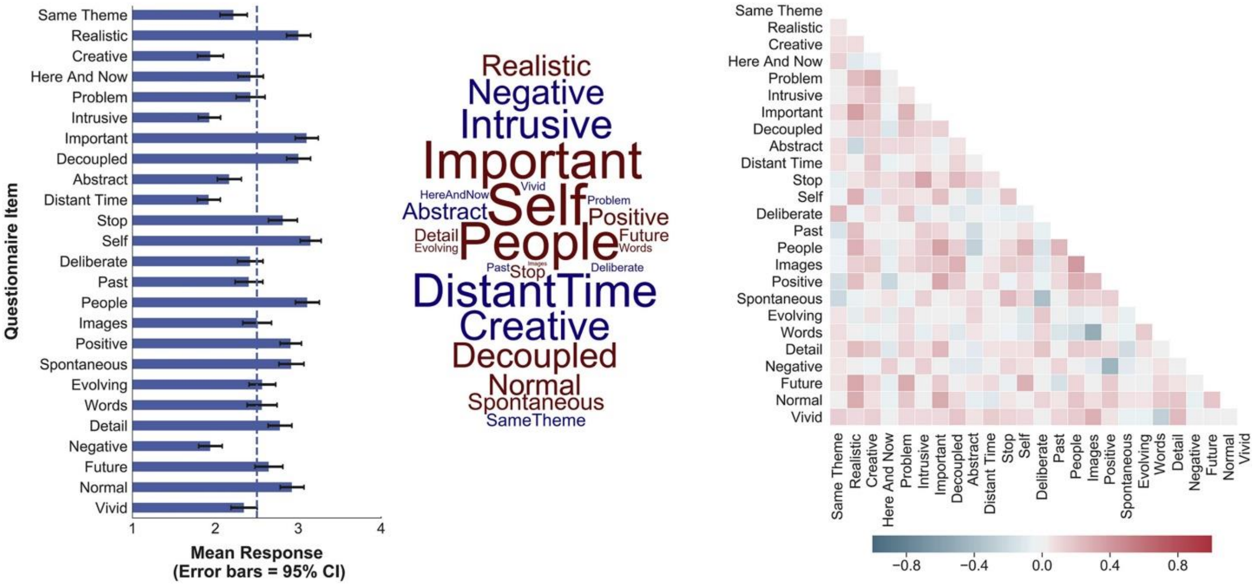

Figure 4.3. Summary information describing the distribution of the retrospective measures of ongoing experience recorded in our study. In the left-hand panel, the bar graph shows the average loading on each question relative to the mid-point of the scale (indicated by the dashed line). The error bars reflect 95% confidence intervals, adjusted to account for family-wise error (i.e., the 25 items). The word cloud shows this information in a different form in which the size of the word describes its distance from the mid-point and its colour (cold/warm) reflects its direction (negative/positive). The right-hand panel illustrates the patterns of covariation between these items (Pairwise Pearson correlation).

4.4.2 Multivariate Analysis

We examined whether there was any relationship between the low-dimensional representations of the macroscale organization of neural function and the experience of participants during the scanning. We used a multivariate linear regression (SPSS; version 26) in which individual items from the experience-sampling questionnaire were included as explanatory variables and the similarity scores for gradients one to three were entered as dependent variables. Age, gender, and mean movement during the scan were entered as nuisance covariates. This analysis revealed that there was a multivariate effect for the ‘problem-solving’ item [Pillai’s trace = 0.046, $F(3, 223) = 3.54$, $p = .015$] and the ‘past’ item [Pillai’s trace = 0.051, $F(3, 223) = 3.97$, $p = .009$]. These results establish that these two aspects of the questionnaire varied significantly with the similarity scores for the functional motifs apparent at rest.

We calculated the parameter estimates for these multivariate effects for ‘past’ (Gradient one ($b = -0.018$, 95% CI = [-0.042, 0.006], $p = .137$), Gradient two ($b = -0.032$, 95% CI = [-0.056, −0.008], $p = .009$) and Gradient three ($b = 0.006$, 95% CI = [-0.011, 0.024], $p = .490$) and for ‘problem-solving’ (Gradient one ($b = 0.020$, 95% CI = [-0.005, 0.044], $p = .112$), Gradient two (b = 0.036, 95% CI = [0.011, 0.061], p = .004) and Gradient three (b = −0.001, 95% CI = [-0.019, 0.018], p = .951)). In both cases, therefore, the only association in which the confidence intervals did not overlap with zero was with Gradient two.

Together, these analyses revealed that the multivariate effect for the ‘problem-solving’ item is most clearly positively associated with gradient two while the multivariate effect for the ‘past’ item shows the reverse pattern. To understand these associations, we visualised the average map of gradient two for individuals in the top and bottom third of similarity with the group-level description, and also calculated the difference. This data is presented in the left-hand panel of Figure 4.4, where it can be seen that individuals with higher similarity to group-averaged gradient two showed decreased shared connectivity between the visual and sensorimotor systems.

To visualise the associations between the ‘problem-solving’ and ‘past’ questionnaire items with gradient two, we calculated the unique variance associated with gradient two and both questionnaire items separately. To do this, we calculated the residual variance linked to both types of thoughts using linear regressions in which the dependent variable was gradient two similarity scores and the explanatory variables were all of the questionnaire items (as well as age, gender, and mean movement) except for the relevant item (either ‘problem-solving’ or ‘past’). We performed a comparable analysis to identify the residual variance in gradient two. Together this data is presented in the right-hand panel of Figure 4.4, where it can be seen that individuals with high similarity scores for gradient two reported more problem-solving thoughts and fewer past-related thoughts.

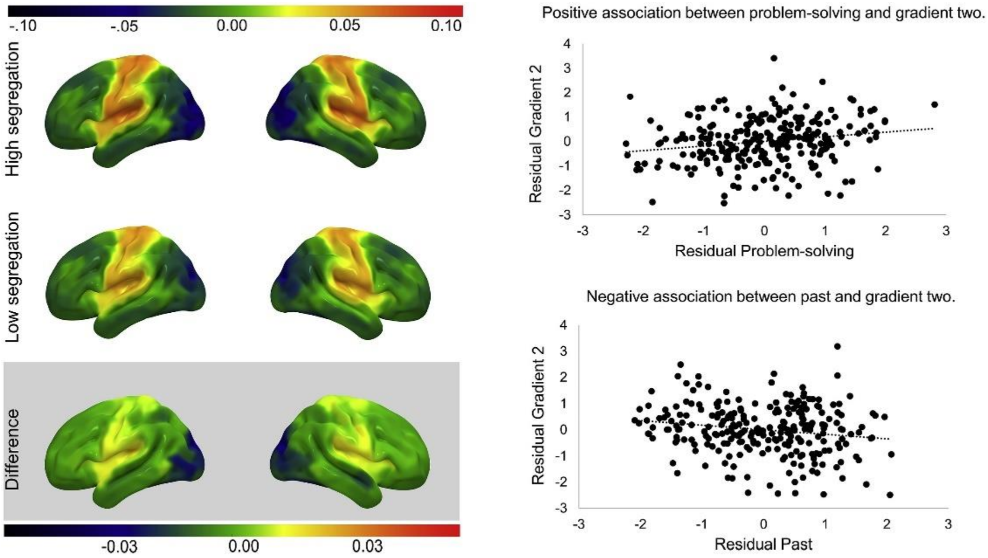

Figure 4.4. Greater functional segregation between visual and sensorimotor cortices was positively associated with reports of problem-solving thoughts during rest and negatively associated with reports of thoughts about past events. Left panel: group-averaged maps for high (top) and low (middle) similarity scores for gradient two as well as the difference between these groups (bottom). The top colour bar reflects the scale of the high and low similarity group-averaged maps while the bottom colour bar reflects the scale of the difference map. Individuals with high similarity scores showed more functional segregation between visual (blue) and sensorimotor cortices (orange). The proximity of colours reflects greater similarity in connectivity patterns between regions. Right panel (upper): Scatterplot of residuals describing the positive relationship between gradient two similarity and the 'problem-solving' questionnaire item. Each point is a participant. Right panel (lower): Scatterplot of residuals describing the negative relationship between gradient two similarity and the 'past' questionnaire item. Using raw scores, a Pearson correlation confirmed the positive association with problem solving thoughts ($r(252) = 0.16$, $p = .013$) and the negative relationship with past related thoughts ($r(252) = -0.13$, $p = .040$).

4.5 Discussion

The current study employed a data-driven approach to identify whole-brain connectivity patterns associated with distinct aspects of ongoing thought at rest. Specifically, we were interested in identifying whether three reasonably well-described macroscale patterns of neural function ('cortical gradients') were related to the experiences an individual had at rest. Participants completed a rs-fMRI scan followed by an experience-sampling questionnaire retrospectively assessing the content and form of their ongoing thoughts during the scan. To reduce the dimensional structure of the rs-fMRI data, we used a non-linear dimension reduction algorithm to embed the functional connectivity in a low-dimensional space. We found that individuals with less similarity between the pattern of functional connectivity in visual and sensorimotor cortices were more likely to report thoughts related to finding solutions to problems or goals and less likely to report thoughts related to past events (as demonstrated in Figure 4.4).

It is worth considering the relationship between the current results and previous findings reported by Karapanagiotidis et al. (2019). They used the same dataset as the current study and applied Hidden Markov modelling to identify neural states. This analysis found two states which were associated with measures of experience. One state was linked to patterns of autobiographical planning (future-oriented problem-solving) and was associated with the dominance of the motor system relative to the visual system. In contrast, a second state was linked to intrusive rumination about the past and exhibited reasonably similar levels of activity in both the visual and motor systems. There is, therefore, an encouraging correspondence between the results of the current analysis, which entails a decomposition of the resting-state data into low dimensional manifolds, and the prior analyses identifying neural states that reoccur at rest.

Together, these results add to a growing body of evidence that suggests neural processing in either the primary motor or visual cortex may play an important role in aspects of higher-order cognition, especially those that involve imagining events other than those in the immediate environment. For example, Medea and colleagues asked participants to complete two writing sessions in which they either wrote about three personal goals or three TV programmes (Medea et al., 2018). Before and after each writing session, participants completed an experience-sampling session. They found that if participants reported future-directed thought between writing session one and two, the concreteness of their personal goals increased between sessions. Importantly, this pattern was most pronounced for individuals who showed stronger connectivity between the hippocampus and a region of the motor cortex at rest. Consistent with the possibility that motor cortex activity can be important during periods of self-generated thought, Sormaz and colleagues used online experience-sampling and found that neural patterns in regions of the motor cortex were able to differentiate between thoughts related to a working memory task and those related to personal concerns about the future (Sormaz et al., 2018). Matheson and Kenett (2020) propose that the motor system is likely to be important in creative problem solving because of the capacity for this system to model the simulation of possible actions. Future work will be needed to understand the precise role that motor cortex activity plays in different features of ongoing thought.

There is also converging evidence from fMRI studies that suggests that the primary visual cortex is recruited during internal processing independent from external stimuli (Muckli, 2010). For example, activity in the visual cortex has been observed during the retention period of a working memory task in which no external stimulus was presented (Harrison & Tong, 2009), while Japardi et al. (2018) found that visual system connectivity was important during periods of creativity for visual artists. Furthermore, Villena-Gonzalez et al. (2018) found that the degree of connectivity between the visual cortex and retrosplenial cortex was associated with a tendency to employ social information when engaged in task-based prospection. Together with these prior studies, the current work provides converging evidence linking processes in unimodal cortex to aspects of imaginative thought, an important question for future work to explore.

More generally our data suggest that different aspects of ongoing thought may vary in the degree to which unimodal systems are integrated. Mesulam (1998) argued that if a cortical system only contained unimodal regions, it would have difficulties in performing cognitive acts that depended on regularities that spanned multiple modalities. The connectivity pattern identified in gradient two recapitulates this theoretical functional organization proposed by Mesulam; the relative segregation of the unimodal systems coupled with common connectivity with transmodal and integrative systems such as the default mode network (see Figure 4.5 for a schematic of this architecture). It is possible that the degree of integration between these unimodal systems may help encode and retrieve visual and auditory features of an experience, a process for which regions in the medial temporal lobe such as the hippocampus (Moscovitch et al., 2016) or the anterior temporal lobe (Ralph et al., 2017) may be particularly important. Based on our data, we hypothesize that different types of experience may vary with the degree of overlap between these primary systems. Plausibly, a focus on thoughts relating to the past can rely on co-recruitment in both visual and motor regions because these experiences can capitalize on pre-existing memory traces, which may have been particularly strongly encoded if they spontaneously come to mind in a fluent fashion. In contrast, when attempting to generate a novel solution to a problem, it is less easy to capitalize directly on whole-brain associations from the past. Problem solving, therefore, may depend to a greater extent on processes that simulate the specific sequence of actions that should be performed, or the arrangement of specific features of the environment, which may be relatively achievable without interactions across different forms of unimodal cortex.

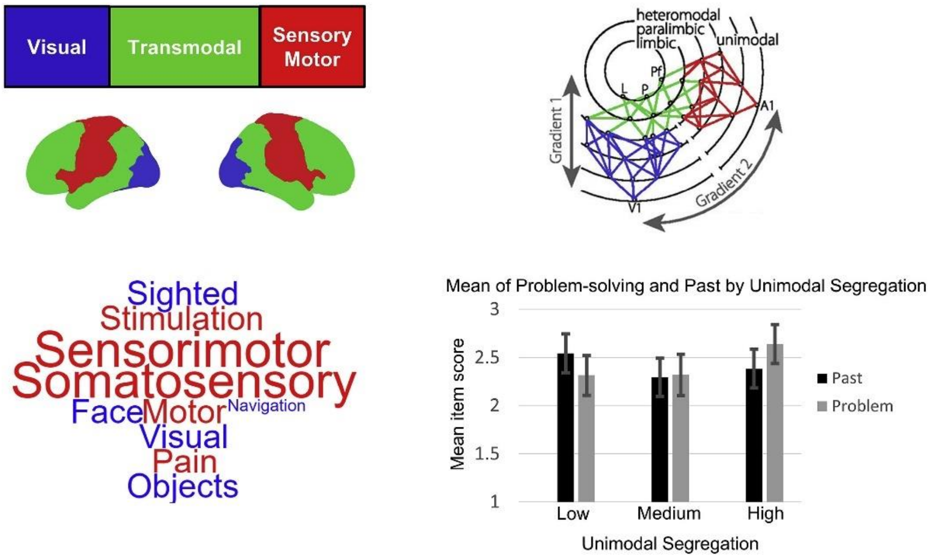

Figure 4.5. Schematic of a hypothesized relationship between macroscale functional organization and distinct features of ongoing thought. Left panel (top): Simplified schematic of gradient two representing the segregation of unimodal systems with intermediary transmodal regions in between. Left panel (bottom): Word cloud representing the Neurosynth terms associated with the positive (red) and negative (blue) end of gradient two, demonstrating the differences in function in the different unimodal systems. Font size represents the magnitude of the relationship, while the colour illustrates the associated system (blue = visual and red = sensorimotor). Right panel (top): Modified illustration of Mesulam's (1998) proposal of how the cortex is organized according to a functional hierarchy of processing from distinct unimodal systems to integrative transmodal regions. Gradient 1 and 2 labels correspond to the results reported in Margulies et al. (2016). Right panel (bottom): Schematic illustration of how unimodal segregation and integration may be differentially associated with distinct aspects of experience. We divided individuals into low, medium, and high groups based on the similarity between visual and sensorimotor systems and plotted the mean scores for problem-solving and past-related thoughts. It can be seen that based on our data individuals showing less segregation between unimodal systems reported more thoughts about past events and fewer problem-solving thoughts (and vice versa). Error bars indicate the 95% confidence intervals.

Finally, the current results lend further support to the view that it is necessary for researchers to distinguish between distinct types of ongoing thought (Seli et al., 2018). Our study shows that different types of ongoing thought are differentially associated with macroscale connectivity patterns, suggesting that different types of ongoing thought are supported by related but distinct mechanisms. Previously, many researchers have conflated various types of ongoing thought under one unitary measure (e.g., Mason et al., 2007; Smallwood et al., 2008a). The current results suggest that in doing so, researchers may have made erroneous conclusions regarding the neural correlates of states that may often be discussed together under broad umbrella concepts such as 'mind-wandering'. Accordingly, our results demonstrate the value of the family-resemblances view of mental states which stresses the importance of operationalizing and describing the specific type of experience under investigation (Seli et al., 2018).

Although our study highlights a relationship between the macroscale organization of neural function at rest and concurrent features of ongoing experience, it nonetheless leaves several important questions unanswered. First, the present study focused on assessing static rather than dynamic functional connectivity and so cannot address important questions regarding the relationship between neural dynamics and ongoing experience (Kucyi, 2018; Lurie et al., 2018). The choice of static functional connectivity coupled with retrospective sampling at the end of the scan means that the current study is unable to identify neuro-experiential associations that are highly transient and dynamic. One way to extend the current findings could be to incorporate sliding window analysis which consists of calculating a given functional connectivity measure (e.g., correlation) over consecutive windowed sections of data and to measure experience on multiple occasions. This method results in a time series of functional connectivity values which can then be used to assess the temporal fluctuations in functional connectivity within a scanning session (Hutchison et al., 2013). Future work combining gradient analyses with dynamic functional connectivity techniques such as Hidden Markov modelling (Vidaurre et al., 2018) or time-varying multi-network approaches (Betzel & Bassett, 2017) with multiple online experience-sampling measures, could help understand how macroscale connectivity patterns and ongoing thoughts fluctuate together over time.

While retrospective sampling was chosen in the current study to allow neural dynamics to unfold in a relatively natural way over the scan period (Smallwood & Schooler, 2015), this method is not without its limitations which are important to consider when interpreting the current results. For example, retrospective sampling, compared to online sampling, relies more heavily on the participant’s ability to remember their own thoughts. This introduces a number of potential confounds such as participants only reporting their most salient thoughts over the scanning period or some participants being more able than others to accurately recall their own thoughts. However, it is important to note that with more frequent sampling of ongoing experience the time series upon which cortical gradients are calculated would be shortened and this could temper the reliability of these metrics as indicators of neural function (Hong et al., 2020). Another limitation of the current study is that there was no experimental manipulation, making the causal link between macroscale patterns of neural activity and ongoing thoughts unclear. This issue could be fruitfully explored by priming participants to think about finding solutions to problems or goals and observe the changes in ongoing neural connectivity, or through the use of techniques such as trans-magnetic stimulation to disrupt either the visual or motor cortex and observe the subsequent changes in ongoing thought.

Finally, it is important to note that it is not necessarily the case that the absence of associations with the majority of the items in this battery indicates that these aspects of experience are unimportant at rest. It is possible that other types of neural metric that focus on local patterns are important (such as fractional amplitude of low-frequency fluctuations [fALFF] or regional homogeneity [ReHo]; for example, see Gorgolewski et al. (2014)) and that these types of relationship would be missed by our current analytic approach which focused on macroscale patterns of neural organization. It is also possible that other features of experience are more state-like and detecting these types of patterns would require the capacity to measure both ongoing experience and neural experience across several time points (see Vatansever et al. (2020) for an exploration of this question). Finally, although resting-state is a common method for acquiring brain data and one in which patterns of ongoing experience are important, it is also possible that other contexts provoke different types of experience (for example see Ho et al. (2020)). Thus, while our study shows that problem-solving and past related thoughts are likely to be important aspects of a participants experiences at rest, in the future, it will be important to carefully determine the most appropriate items for efficiently describing different features of experience in different situations and examining their relationships to a range of different metrics of static and dynamic neural function.

4.6 Conclusions

The current study investigated whether individual variation in ongoing thought is associated with low-dimensional representations of macroscale functional connectivity at rest. Results revealed that reports of thoughts about finding solutions to problems or goals were linked to greater segregation between the visual and sensorimotor systems, while thoughts about past events were linked to less segregation. These associations suggest that the degree of segregation of unimodal systems determines important features of ongoing experience. Future work could investigate the extent to which priming individuals to think about particular topics changes patterns of ongoing neural activity, or use neurostimulation techniques to alter neural activity and examine how this changes ongoing experience. Such studies would provide important causal evidence on the relationship between macroscale patterns of neural activity and features of ongoing thought. Moving forward, it is likely to be increasingly important for scientists studying patterns of functional connectivity in states such as rest, or even tasks, to acquire measures of ongoing experience in order to fully appreciate the significance of neural motifs that are revealed through the application of advanced analysis methods. Likewise, it will be important for researchers studying ongoing thought to recognize that these states are sometimes encoded in complex distributed whole-brain patterns of neural activity, and are not always localizable to a specific modular region of cortex.

Chapter 5- General Discussion

In laboratory, neuroimaging, and daily life contexts, the current thesis used Multidimensional Experience Sampling (MDES) in three studies to explore how differences in ongoing thought relate to: (a) changes in external contexts (Studies 1 and 2), (b) changes in internal contexts (Study 2), and (c) individual differences in age (Study 1), trait anxiety (Study 2), and neural architecture (Study 3). In doing so, these investigations have improved our theoretical understanding of:

- How common 'patterns of thought' emerge across a wider range of situations,
- How individual differences in age and anxiety moderate these thought-situation relationships, and
- The neural basis of distinct features of ongoing thought at rest.

This general discussion will first summarise each empirical study's primary aims and findings (section 5.1). Then, the key theoretical and methodological contributions will be considered (section 5.2), including the role that social and future-directed thoughts play in everyday life and the value of MDES for building a comprehensive account of cognition. Finally, the limitations of the thesis will be discussed (section 5.3), and future directions outlined (section 5.4), focusing on how the techniques developed in the current thesis can be leveraged in the future for mental health applications.

5.1 Summary of Empirical Studies

Study 1 examined MDES data collected in daily life before and during the UK's first COVID-19 lockdown to understand how changes in daily activities related to changes in ongoing thought patterns. This study had two key findings. First, under conditions of social isolation during lockdown, episodic social thinking was reduced compared to pre-lockdown. However, on the rare occasions in which social interactions were possible, episodic social thinking increased to a greater extent than was observed pre-lockdown. Second, the lockdown was associated with an overall reduction in future-directed problem-solving, but this thought pattern was reinstated when individuals were actively engaged in work. Together, these findings suggest that the lockdown was associated with significant changes in ongoing thought patterns in daily life and that these changes were linked to disruptions to daily routines imposed by lockdown restrictions. More generally, these results highlight the important role of external contexts in shaping patterns of ongoing thought in everyday life because changes in behaviour and daily life activities during lockdown were associated with changes in the prevalence of different patterns of thought.

Study 2 examined MDES data collected in the laboratory and in daily life to understand how people think under conditions of uncertainty and whether individual differences in trait anxiety moderate the relationship between affective states and ongoing thought patterns. Study 2 identified a pattern of social and future-directed problem-solving with emotional features that consistently emerged during periods of uncertainty across situations: both under experimentally induced conditions of uncertainty and in daily life under conditions of naturally-occurring uncertainty elicited by the COVID-19 pandemic. Notably, in the laboratory, high-trait-anxiety individuals reported elevated levels of this future-directed pattern when subjective uncertainty was low compared to less anxious individuals. Overall, therefore, Study 2 established a generalisable pattern of socio-emotional and future-directed problem-solving, perhaps reflecting a process through which possible actions are considered to adjust future behaviour. More generally, these results highlight important links between internal contexts—going beyond positive and negative affect—and differences in ongoing thought patterns since thought patterns varied significantly according to states of uncertainty, arousal, and threat.

Study 3 examined the neural basis of distinct features of ongoing thought by exploring whether individual differences along three reasonably well-explained 'cortical gradients'—describing patterns of whole-brain connectivity—were related to individual differences in ongoing thought at rest. Analyses indicated that individuals with higher functional segregation between visual and sensorimotor cortices were *more* likely to report thoughts related to finding solutions to problems or goals and *less* likely to report past-related thoughts. These results suggest that neural activity in unimodal regions may contribute to aspects of imaginative thought since past-related thought and problem-solving differentially predicted these systems' relative integration and segregation. More generally, this study established a role for macroscale features of functional neural organisation in individual differences in ongoing thought.

5.2 Theoretical and Methodological Contributions

The following section will first discuss how this thesis has advanced our understanding of situations in which social thinking is especially prevalent and its potential functional benefits (section 5.2.1). Then, it will discuss how this thesis contributes to our understanding of situations in which future-directed problem-solving is prevalent—and potentially helpful—in everyday life and the neural mechanisms underlying problem-solving at rest (section 5.2.2). Next, it will discuss how the findings highlight the need to consider the context in which experience unfolds to provide a more comprehensive understanding of differences in ongoing thought (section 5.2.3). It will then discuss the implications of findings highlighting a one-to-many mapping between different patterns of thought and the situations in which they emerge (section 5.2.4). Finally, it will discuss how the current thesis demonstrates the value of MDES for building a complete account of cognition (section 5.2.5), the value of cortical gradients for understanding the neural basis of a broad range of cognitive features (section 5.2.6), and the value of naturalistic viewing paradigms for understanding context-dependent cognition in controlled laboratory conditions (section 5.2.7).

5.2.1 Social Thoughts in a Social World

This thesis has advanced our understanding of situations in which social thinking is especially prevalent in everyday life and, consequently, the potential functional benefits that this form of cognition may serve. It has been established that individuals spend a lot of time thinking about other people in their daily lives (Mar et al., 2012; Song & Wang, 2012). More recently, Mildner and Tamir (2021) implemented a series of laboratory-based experiments to arbitrate between two hypotheses explaining the predominance of social thought. The 'social needs hypothesis' predicts that when an individual's environment is insufficiently social, their thoughts should become increasingly social since this account argues that the role of social thinking is to help individuals fulfil their innate social needs (Mildner & Tamir, 2021). In support of this account, evidence suggests that social thinking helps individuals regulate their social needs (Mar et al., 2012; Poerio & Smallwood, 2016; Poerio et al., 2016). For example, prior work indicates that during the transition to university, social thoughts are associated with feeling more socially connected and less lonely over time (Poerio et al., 2016). However, according to the 'social processing hypothesis', social thoughts are so prevalent *because* we live in a social world (Mildner & Tamir, 2021), and they help process incoming social information and prepare individuals for social interactions (Meyer, 2019). This hypothesis predicts that if social interactions are reduced, individuals should think less about other people and that if social interactions increase, individuals should think more about other people.

In support of the social processing hypothesis, Mildner and Tamir (2021) found that spontaneous social thoughts declined following periods of solitude and increased following periods of social interaction in the laboratory. However, a limitation of this study is that the periods of solitude were artificially enforced by researchers and may, therefore, not reflect how cognition emerges under these circumstances in everyday life. Critically, this thesis (Study 1) provides real-world support for the social processing hypothesis, demonstrating that social thinking fluctuates with levels of social interaction. Across both daily life samples, episodic social cognition was lower when individuals were alone and higher when individuals were socially interacting. In the lockdown sample—when social interactions were less common— these associations were even more apparent: episodic social thinking was further reduced under solitude and further increased during social interaction. Therefore, this thesis offers ecologically valid support for the view that the prevalence of social thinking is linked to the availability of social interactions. To provide additional support for the social processing hypothesis, it will be important for future work to examine the extent to which this form of thinking in daily life facilitates the consolidation of incoming social information and whether it helps individuals prepare for future social interactions.

It is important to note that the two hypotheses proposed by Mildner and Tamir (2021) are not mutually exclusive, and the findings of the current thesis are not necessarily incompatible with prior work demonstrating that social thinking is linked to the regulation of socio-emotional needs (Poerio et al., 2015, 2016). Based on prior work and findings from the current thesis, it is likely that social thoughts can serve multiple functional benefits, depending on the specific content and quality of these thoughts, the situations in which they emerge, and individual differences in cognitive and affective style. For example, prior work highlights that the functional outcomes associated with mind-wandering depend on the contents of these experiences (e.g., Ruby et al., 2013a), the context in which they occur (Smallwood & Andrews-Hanna, 2013), and that individual differences in factors such as intelligence and depression determine when and how individuals mind-wander (Hoffmann et al., 2016; Turnbull et al., 2019a). Furthermore, prior work indicates that the contents of social thoughts, such as whether they are about close- or not-close others, determine how they relate to outcomes such as loneliness (Mar et al., 2012).

The current thesis also highlights a complex interplay between changes in context, individual differences such as age or trait anxiety, and ongoing thought patterns. For example, in Study 1, older (but not younger) adults, reported higher levels of a pattern of pleasant engagement while working in daily life, highlighting age as one reason why thought content can be heterogeneous. Accordingly, building a comprehensive account of the functional roles that episodic social cognition plays in daily life requires that future work explores *how*, *when*, and *for whom* social thinking confers adaptive benefits. For example, it may be that individuals higher in extraversion are more likely to engage in social thinking when alone to address their innate social needs compared to those higher in introversion. Since prior work indicates that extraversion was associated with higher levels of depression and loneliness during COVID-19 restrictions (Alt et al., 2021), future work could also examine whether patterns of episodic social cognition act as a protective mechanism against the negative effects associated with prolonged social isolation in extraverted individuals.

More generally, Study 2 indicates that episodic social thinking in everyday life may help individuals resolve uncertainties arising from the complex social environment in which we live. A pattern of social and future-directed problem-solving was reliably described under conditions of threat and uncertainty in the laboratory and was positively related to subjective uncertainty in the laboratory and in daily life during the COVID-19 pandemic. These findings provide empirical, ecologically valid support for the view that individuals are motivated to reduce social uncertainty and may do so through various social cognitive processes, including making predictions about other people's intentions and actions (FeldmanHall & Shenhav, 2019). However, future work is needed to determine the extent to which this form of thought is associated with functional advantages, perhaps through the formulation of appropriate goals to reduce levels of uncertainty (Medea et al., 2018). For example, it will be important to establish whether engaging in this form of thought when uncertainty is high in daily life is associated with subsequently reduced uncertainty at a later point in time.

5.2.2 Problem-solving: Contextual Influences and Neural Mechanisms

This thesis also advances our understanding of situations in which future-directed problem-solving is prevalent—and potentially helpful—in everyday life and the neural mechanisms underlying problem-solving at 'rest'. In daily life, Studies 1 and 2 indicate that the prevalence of future-directed problem-solving is linked to the relative demands of the future. Both studies found that during the UK's first national lockdown—when socialising, travel, and work were restricted—future-directed problem-solving was significantly reduced overall. However, future-directed problem-solving was prevalent during lockdown when people were actively engaged in work (Study 1) or when they felt uncertain during the pandemic (Study 2). These results suggest that future-directed problem-solving is especially prevalent when demands from the future are higher (e.g., when working or when feeling uncertain). These findings are consistent with the view that our ongoing thought content reflects our current concerns (Gold & Reilly III, 1985; Klinger, 2013; Klinger et al., 2018) since the prevalence of future-directed problem-solving was related to whether an individual was working (Study 1) and how much uncertainty an individual was experiencing (Study 2). Moreover, these findings are consistent with the 'pragmatic' theory of prospection (Baumeister et al., 2016), which argues that we predominantly think about the future in order to guide our actions to reach desirable outcomes, since patterns of future-directed problem-solving were more prevalent when individuals were working (Study 1) or experiencing high levels of uncertainty (Study 2). Accordingly, these results suggest that patterns of future-directed problem-solving in daily life may help individuals meet the demands of their anticipated futures (Baird et al., 2011; Cole & Berntsen, 2016; D'Argembeau et al., 2011; Klinger et al., 2018; Kvavilashvili & Rummel, 2020; Medea et al., 2018). It will be important for future work to test this hypothesis empirically. For example, while Study 1 highlights that future-directed problem-solving commonly emerges when individuals are actively engaged in work, future research is needed to assess the extent to which this thought pattern confers adaptive benefits such as improved productivity or attainment of long-term work-related goals over time (Eubanks et al., 2022).

Study 3 indicated that problem-solving at rest is associated with higher functional segregation between visual and sensorimotor cortices. This finding adds to an emerging body of work suggesting that neural processing in unimodal systems may contribute to aspects of higher-order imaginative thought (Danker & Anderson, 2010; Medea et al., 2018; Sormaz et al., 2018; Villena-Gonzalez et al., 2018). For example, Medea et al. (2018) found that individuals whose personal goals became more concrete following a period of future-directed thinking showed stronger functional connectivity between the hippocampus and a region of the motor cortex at rest. Furthermore, Villena-Gonzalez et al. (2018) found that the tendency to employ social information when engaged in task-based prospection was associated with increased functional connectivity between the visual cortex and retrosplenial cortex, a region linked to spatial navigation, scene construction, episodic memory, and future thinking (Vann et al., 2009). Therefore, the current thesis, along with prior work, suggests that functional connections between unimodal systems and other regions of the cortex may differentially support specific features of higher-order thought. For example, these results are consistent with the view that the motor system plays a functional role in creative problem-solving because it enables the mental simulation of possible actions (Albus, 1979; Matheson & Kenett, 2020). Moving forward, however, it will be important to provide causal evidence regarding the relationship between macroscale patterns of neural activity and distinct features of thought. For example, future work could examine the extent to which priming individuals to think about particular topics (e.g., by using naturalistic viewing paradigms) induces changes along each cortical gradient describing patterns of whole-brain connectivity.

Across all three studies, this thesis highlights two different types of thought, one focused on the past and related to information from memory, and another focused on the future and related to attempts at problem-solving. For example, Study 1 identified a pattern of future-directed problem-solving that was reduced during lockdown but reinstated when individuals engaged in work and a pattern of past-focused visual imagery positively associated with consuming media during lockdown. Study 2 identified a pattern of future-directed problem-solving that was most common when watching emotional videos in the laboratory and a pattern of past-focused off-task thought that was most common when watching documentary videos. Finally, Study 3 suggests that these two types of thought may depend on the relative functional segregation and integration between unimodal regions in the cortex. At rest, problem-solving was associated with greater segregation between unimodal systems, while past-related thought was associated with greater integration between these systems. Contemporary views on how the cortex constrains its functions highlight that some brain regions serve more segregated functions while others can serve more integrated functions; critically, however, the balance between these two processes can vary over time (Sporns, 2013). Accordingly, it is possible that these two broad modes of thinking identified in the current thesis may depend on time-varying integration and segregation between unimodal regions of the cortex. It will, therefore, be important for future work to examine how the integration and segregation of regions of the cortex differentially relate to these two modes of operation over time. For example, it may be that the off-task pattern observed while watching documentary videos in Study 2 is associated with increased integration, while the future-directed pattern observed while watching emotional videos in Study 2 is associated with increased segregation. More generally, the studies in this thesis suggest that different situations in daily life may vary on their need for brain activity to exhibit high degrees of segregation or integration, with conditions that promote uncertainty relying to a greater extent on the former.

Although the results from Study 3 describe patterns of whole-brain connectivity associated with problem-solving and past-related thought at rest, highlighting that unimodal regions may play a role in aspects of imaginative thought, it is worth noting that, mechanistically, it is possible that regions in the medial temporal lobe (MTL) and prefrontal cortex (PFC) may be important for organising these processes. For example, the MTL (a) is thought to play a role in organising multiple features of cognition including memory (Horner et al., 2015; Moscovitch et al., 2016) and future thinking (Addis et al., 2007; Buckner, 2010; Schacter & Addis, 2007), (b) has been shown to contain gradients that map on to the whole-brain gradients examined in Study 3 (Paquola et al., 2020), and (c) is theorised to support the partial reactivation of brain regions involved during the encoding of an episode when remembering that episode (Buckner & Wheeler, 2001). At the same time, the PFC is thought to be important for various features of cognition including episodic memory and simulation, planning, and problem-solving (Benoit & Schacter, 2015; Fuster, 2014; Mushiake et al., 2009; Tanji & Hoshi, 2001). It will, therefore, be valuable for future work to investigate how regions of the MTL and PFC interact with unimodal regions (e.g., visual or motor) when individuals think about the past or think about solutions to problems or goals (Danker & Anderson, 2010).

5.2.3 Importance of Context

The current thesis also lends further support to the view that considering the context in which experience unfolds has important explanatory power for understanding differences in ongoing thought (Konu et al., 2021; Smallwood & Andrews-Hanna, 2013; Smallwood et al., 2021; Turnbull et al., 2020b; Turnbull et al., 2021). For example, in daily life during lockdown, patterns of pleasant engagement were prevalent when individuals engaged in leisure activities, while patterns of detailed task focus and future-directed problem-solving were prevalent when individuals were working. The variation of ongoing thought patterns according to activity highlights the importance of our external environment and daily routine in shaping our internal experiences. These findings emphasise the value of MDES in real-world contexts for understanding how our behaviour influences our ongoing cognition since it facilitates an efficient mapping between ongoing thought patterns and naturally-occurring contexts in daily life. Accordingly, future work examining differences in ongoing thought and how they relate to other outcomes should consider the context in which experience is sampled. For example, recent work suggests that associations between thought and variables such as mood vary across different situations in daily life (Nyklíček et al., 2021).

The current thesis further highlights important links between ongoing thought patterns and internal contexts, going beyond patterns of off-task thinking during states of positive versus negative affect (e.g., Smallwood et al., 2009) towards an understanding of affective states with specific meanings and relevance for individuals. For example, Study 2 found that states of uncertainty were significantly related to differences in self-relevant and past-focused off-task thought and socio-emotional and future-directed problem-solving in the laboratory. In addition, in daily life, COVID-related uncertainty was associated with higher levels of socio-emotional and future-directed problem-solving, while COVID-related threat was associated with higher levels of detailed and deliberate thought. Moreover, Study 2 highlights that internal and external contexts can interact to differentially predict differences in ongoing thought. For example, the association between uncertainty and off-task thinking in the laboratory depended on the video condition; the negative association was stronger in the 'suspense' and 'action' threat videos compared to the 'control' videos. These findings suggest that simultaneously assessing changes in internal and external contexts is valuable for building a more comprehensive account of cognition since the relationship between uncertainty and off-task thought varies depending on the external context in which uncertainty emerges.

5.2.4 Thoughts and Situations: One-to-Many Mapping

More generally, findings from the current thesis demonstrate that there is more than one 'route' to thoughts that share similar features (Cole & Kvavilashvili, 2021). For example, off-task thinking was higher in the laboratory when participants watched 'control' videos associated with low levels of arousal and uncertainty, but this thought pattern was also higher in daily life during the COVID-19 pandemic when individuals felt uncertain. In addition, future-directed thought tended to be higher in the laboratory when concurrent uncertainty was high. However, high-trait-anxiety individuals reported this thought pattern in an uncertainty-independent manner, suggesting that reasons other than in-the-moment uncertainty may be contributing to the emergence of this thought for highly anxious individuals, an important avenue for future work to explore. Finally, detailed, deliberate thought was linked to both high levels of perceived COVID-related threat and being actively engaged in work in daily life. Other studies have found a similar thought pattern is engaged during working memory (Sormaz et al., 2018) and in other executively demanding tasks (Konu et al., 2021).

Therefore, based on the work in this thesis, it is important for future work to understand the many and varied situations in which specific thought patterns emerge, and to understand how these situations differ between individuals. In turn, this will improve our theoretical understanding of why these patterns emerge and their consequences for wellbeing and productivity. There has been a historical tendency to categorise specific types of thought as either ‘good’ or ‘bad’ (e.g., Killingsworth & Gilbert, 2010). However, this thesis highlights such a perspective may be too narrow and instead suggests that a one-to-many mapping between different patterns of thought and the situations in which they emerge is more likely. Accordingly, future work could focus on understanding *how, when* and *for whom* different thought patterns are helpful or detrimental in daily life rather than assuming that specific thought patterns are necessarily better or worse.

5.2.5 The Value of MDES for Building a Comprehensive Account of Cognition

The current thesis highlights that we can use MDES to understand both internally- and externally-focused cognition across a wide range of situations. Traditionally, internally- and externally-focused experiences have been examined using different approaches; internally-focused cognition via experience sampling and external via performance on tasks. However, the current thesis demonstrates that MDES can be successfully implemented to understand both states simultaneously across a wide range of situations within the same framework. For example, Study 2 indicates that while watching videos in the laboratory, a pattern of internally-focused cognition was negatively correlated with uncertainty, and a pattern of externally-focused cognition was positively correlated with uncertainty. In daily life during the COVID-19 pandemic, however, both internally- and externally-focused patterns were positively correlated with uncertainty. These results indicate that both internally- and externally-focused cognitive states may emerge during periods of uncertainty, depending on the context in which uncertainty is experienced. Moreover, these findings highlight the value of MDES for building a more comprehensive account of cognition since it can simultaneously and parsimoniously examine how a broad range of cognitive features—including internally- and externally-focused cognition—emerge across a wide range of situations in both laboratory and daily life contexts.

These findings also demonstrate the utility of directly projecting thought patterns between MDES datasets to examine multidimensional cognition across contexts. Although prior work has compared ongoing thought in both the laboratory and daily life (e.g., Ho et al., 2020; Kane et al., 2007; Kane et al., 2017; Linz et al., 2019), projecting patterns directly from one context to another allows for the empirical examination of how laboratory MDES findings generalise to real-world situations. Since this thesis has established that this novel method can be used to assess the generalisability of laboratory-based findings, it will be helpful for developing more ecologically valid paradigms in laboratory and neuroimaging contexts in the future (Kingstone et al., 2003). In addition, this projection technique could be leveraged to examine the neural basis of different types of naturally-occurring thoughts in daily life. For example, it would be possible to first identify patterns of thought in daily life contexts using MDES and then project these patterns onto MDES data collected following resting-state fMRI. This approach would improve the ecological validity of thought-brain relationships since the thought patterns identified would be grounded in real-world experiences.

Importantly, the current thesis demonstrates that dimension reduction techniques applied to MDES data can robustly identify ‘patterns of thought’ across a wide range of situations. For example, using this approach, Study 1 demonstrated highly consistent patterns of thought between the before- and during-lockdown samples (see Appendix 1, Fig. S2). In addition, Study 2 identified highly consistent patterns of thought between the two laboratory samples (see Appendix 2, S1 text, Fig G) and confirmed the reliability of thought-situation associations between the laboratory samples (see Appendix 2, S2 text, Table A). Accordingly, the current thesis demonstrates that MDES is a robust method for characterising ongoing thought patterns in laboratory and daily life contexts and shows that these patterns are reliably and meaningfully related to other aspects of experience.

5.2.6 Cortical Gradients

Another methodological contribution of this thesis is demonstrating that cortical gradients provide a compact method for examining how interactions between large-scale networks relate to differences in the types of thought people have at rest (Study 3). As previously discussed, it will be important for future work to provide causal evidence regarding the relationships between macroscale patterns of activity and distinct forms of thought (e.g., using naturalistic viewing paradigms). In addition, since Study 3 was based on retrospective reports of problem-solving over a 9-minute resting-state scan, it will be important for future work to incorporate dynamic measures of neural activity and online measures of ongoing thought to pinpoint state, over more trait-like, influences. For example, Study 3 may have identified a trait-level tendency to engage in problem-solving at rest with a trait-level pattern of whole-brain organisation that may be partially constrained by underlying differences in structural architecture. Nonetheless, Study 3 highlights the utility of the gradient approach for understanding the mechanisms underlying features of higher-order cognition that are hypothesised to depend upon the interaction between multiple neural systems (e.g., Smallwood et al., 2011; Smallwood and Schooler, 2015; Jefferies et al., 2020). For instance, using this approach, subsequent research has identified how individual differences along cortical gradients relate to distinct aspects of semantic cognition (Gonzalez Alam et al., 2022; Shao et al., 2022). Shao et al. (2022) found that within the semantic network, individuals whose intrinsic connectivity showed higher similarity to the gradient describing segregation between unimodal and transmodal cortices were faster at identifying weak semantic associations, while those who showed higher similarity to the gradient describing segregation between visual and sensorimotor cortices were faster on picture semantic judgements. Accordingly, cortical gradients provide a common space within which to understand the broad similarities and differences in whole-brain patterns of connectivity underlying multiple features of cognition.

5.2.7 Naturalistic Viewing Paradigms

A final methodological contribution of this thesis is the demonstrated utility of naturalistic viewing paradigms to robustly induce emotional states and accompanying changes in ongoing thought in the laboratory. For example, in Study 2, ‘action’ and ‘suspense’ threat videos increased levels of subjective arousal, subjective uncertainty, and social and future-directed problem-solving. Importantly, laboratory findings generalised to the real world: social and future-directed problem-solving was positively associated with subjective uncertainty in both the laboratory and in daily life during the COVID-19 pandemic. This study, therefore, adds to a growing body of research demonstrating that naturalistic viewing paradigms can be leveraged to simulate the richness of real-world experiences to examine cognition and emotion in controlled laboratory and neuroimaging contexts (Sonkusare et al., 2019).

Given the success of this approach for manipulating emotion and ongoing thought, future work could use naturalistic viewing paradigms to examine the effect of external and internal contexts on changes in ongoing thought in neuroimaging contexts. Such an approach would help identify the neural mechanisms underlying different thought patterns across different situations. For example, one could sample ongoing thoughts and record neural activity via fMRI while participants watched the video clips used in Study 2 to understand how the changes in thought induced by the videos relate to changes in macroscale connectivity patterns using gradient analyses. This approach would allow us to go beyond simply describing experiences to identify how the brain’s functional architecture supports these experiences. In addition, this would allow for the examination of whether differences in thought-uncertainty relationships reported by high-trait-anxiety individuals are associated with differences in underlying neural substrates (Kirk et al., 2022). In doing so, this would provide important validation of these self-reported findings.

5.3 Key Limitations

Although the current thesis has made significant theoretical, conceptual, and methodological contributions to understanding ongoing thought, several key limitations should be noted. First, while Studies 1 and 2 identified situations in which social and future-directed cognition are especially prevalent (e.g., during social interactions or when uncertainty is high), they did not directly assess the extent to which these thought patterns actually help individuals successfully navigate their social environments, resolve uncertainty, or prepare for the future. To understand the (mal)adaptive nature of these patterns in daily life, future work should capitalise on the methods developed in the current thesis to assess the extent to which thought-situation associations predict subsequent functional outcomes using time-lagged analyses. For instance, it would be useful to use MDES in daily life to understand whether engaging in episodic social cognition following or preceding social interactions is associated with more successful social interactions. For example, one could assess whether engaging in episodic social cognition prior to different types of interactions (e.g., work meetings) predicts better mood following those interactions (e.g., Quoidbach et al., 2019). It will also be important to determine situations where the relationship between contexts and thought might be maladaptive. For example, excessively or inflexibly engaging in episodic social cognition preceding or following social interactions may be associated with poorer social well-being (Katz et al., 2019). Likewise, engaging in future-directed problem-solving while working may be associated with improved productivity over time (Baer et al., 2021). However, indiscriminately engaging in this form of thought may also be associated with emotional and cognitive costs, such as an inability to disengage from work-related stressors or focus on ongoing tasks.

While Study 2 examined how trait anxiety moderated the relationships between thought patterns and uncertainty, the reliability of these associations remains to be established, and the reasons underlying these associations remain a matter of debate. For example, in the laboratory, compared to less anxious individuals, high-trait-anxiety individuals reported elevated levels of social and future-directed thinking under conditions of low subjective uncertainty and overall showed a weaker relationship between this pattern and concurrent uncertainty. However, since trait anxiety was not examined in both laboratory samples, the reliability of this interaction could not be established. Nonetheless, in daily life during the

COVID-19 pandemic, although the interaction did not reach significance (p = .066), the underlying pattern was similar since anxious individuals showed a weaker relationship between future thinking and concurrent uncertainty. Taken together, these results provide some evidence that anxious individuals show differences in how state uncertainty relates to levels of future thinking and are generally consistent with the view that trait anxiety is characterised by cognitive inflexibility (Ottaviani et al., 2016). However, the nature of the study design precludes firm conclusions regarding the origin of this interaction and its clinical relevance. Future work could, therefore, focus on tracking these relationships longitudinally in daily life using MDES (Bosquet & Egeland, 2006; Fortea et al., 2021; Pawluk et al., 2021; Sun et al., 2019)—from early development to later life—to examine how these thought-uncertainty relationships emerge over time to understand the causal nature and clinical relevance of these differences.

5.4 Future Directions: Mental Health

The theoretical and methodological advancements made in the current thesis are important for future work investigating how thought-situation relationships relate to aspects of mental health and well-being. Prior work indicates that behaviour and cognition are both important predictors of mental health. For example, depression can be maintained by an absence of reinforcing activities (Hopko et al., 2003; Lewinsohn & Graf, 1973) and anxiety disorders can be maintained by behavioural avoidance of situations that cause worry or concern (Whiteside et al., 2013). At the same time, depression and anxiety are both associated with perseverative thinking styles, including worry and rumination (Drost et al., 2014; MacLeod & Byrne, 1996; Miloyan et al., 2014; Ottaviani et al., 2013; Ottaviani et al., 2016; Seli et al., 2019). Finally, interventions targeting behavioural avoidance in these types of disorders can reduce cognitive symptoms (Dimidjian et al., 2006). Therefore, a large body of work highlights important links between behaviour, cognition, and features of mental health.

However, to date, there has been little research examining how multiple patterns of thought (going beyond rumination and worry) differentially emerge in the many and varied situations we encounter in daily life and how these thought-situation relationships predict aspects of mental health. Using MDES, this thesis has demonstrated that: (a) internal and external contexts play a key role in shaping patterns of ongoing thought, (b) MDES is sensitive to thought-situation relationships in the laboratory and daily life, and (c) MDES is sensitive to individual variation in thought-situation relationships. Future work should capitalise on these methodological advances to understand which thought-situation relationships are associated with positive and negative mental health outcomes in daily life. For example, MDES in daily life could be used to identify mappings between ongoing thought and activities associated with worsened symptomology over time in non-clinical samples that may contribute to the development of psychiatric conditions. In addition, MDES in daily life could be used to identify thought-situation relationships that differ in a range of clinical samples and how changes in the mapping between thought and activities relate to longitudinal changes in the prognosis of various clinical disorders like depression and anxiety. Such investigations would simultaneously improve our theoretical understanding of the psychological nature of different thought patterns and affective disorders associated with disrupted cognitive styles.

Ultimately, if future work establishes that MDES can map reliable relationships between thoughts, contexts, and mental health outcomes, it is a method that could be used in clinical settings as both a diagnostic tool and to inform and assess clinical interventions. From a diagnostic standpoint, many mental health disorders have high levels of comorbidity and share multiple cognitive and emotional features. For example, prior work suggests that the high comorbidity between generalised anxiety disorder (GAD) and major depressive disorder (MDD) is, in part, influenced by the diagnostic overlap between these two conditions (Zbozinek et al., 2012). Accordingly, MDES-based research could be used to identify key differences in thought-situation relationships between these disorders that could ultimately be used to differentiate between these disorders during diagnosis. For example, individuals presenting with symptoms common to both disorders upon initial evaluation could be asked to track their thoughts, activities, and internal states using MDES via smartphones in their daily lives. Clinicians could use this data to inform their diagnosis if MDES-based research has successfully identified important thought-situation relationships that differ between anxious and depressed individuals.

MDES could also be used to inform and assess clinical interventions. For example, MDES could be used to identify activities in daily life that lead to changes in thought patterns associated with improved well-being, and these activities could be promoted to individuals reporting relevant mental health issues. Moreover, recent work has begun to use various forms of experience sampling in daily life to aid individualised diagnosis and treatment of disorders, often referred to as ‘precision psychiatry’ (Fortea et al., 2021; Pawluk et al., 2021; Robinaugh et al., 2020). For example, Robinaugh et al. (2020) had two patients diagnosed with panic disorder complete five experience-sampling measures daily for two weeks before and after a cognitive-behavioural therapy intervention. Each probe asked them to rate their in-the-moment experience according to 20 different panic symptoms. In contrast to traditional psychiatric assessments—which ask participants to self-report their symptoms over prolonged periods (e.g., over the past week) to provide an overall score of symptom severity—this approach provides key information about symptom dynamics and information on the relationships between symptoms as they unfold over time within patients (Robinaugh et al., 2020). For example, both patients reported comparable mean levels of feelings of anxiety and panic. However, one patient's variance was almost twice as big as the other, suggesting that these patients have heterogeneous experiences with feelings of anxiety and panic, and consequently suggests that their optimal treatment plans may differ. Although this study demonstrates the utility of daily life experience sampling for individualised psychiatric diagnosis and treatment, this study only assessed panic-related symptoms and did not assess patterns of ongoing thought or the contexts in which experiences occurred. Moving forward, it will be useful if studies like these incorporated MDES in their experience-sampling procedures. This approach would improve our understanding of the similarities and differences in common patterns of thought across a wide range of psychiatric disorders, thereby improving our understanding of the shared and unique cognitive and behavioural profiles associated with different disorders.

5.5 Concluding Remarks

This thesis has integrated multiple methods across three studies to shed light on the factors contributing to differences in ongoing thought in the laboratory and in daily life. These investigations have improved our theoretical understanding of situations in which social and future-directed thoughts are especially prevalent in everyday life, how macroscale connectivity patterns relate to distinct types of imaginative thought at rest, and highlight the importance of context in understanding differences in ongoing thought. Moreover, it highlights the value of MDES for building a comprehensive account of cognition since it has demonstrated that it can be used to understand between- and within-person differences in both internally- and externally-focused cognition across a wide range of situations in both the laboratory and daily life. Moving forward, it will be important for future work to build on the methods and findings described here to assess the functional outcomes associated with thought-situation relationships, understanding which might ultimately be leveraged for practical applications in mental health settings. In summary, therefore, this thesis emphasises the power of MDES to reliably capture ongoing thought patterns across contexts, a tool that will ultimately help answer important questions regarding how our brains and the world around us shape our thoughts and how our thoughts shape our lives.

Appendices

A.1 Supplementary Materials: Chapter 2

This section contains the supplementary materials for Chapter 2 including:

- SI Appendix
    - Supplementary Text
    - Figures S1 to S7
    - Tables S1 to S26

Supplementary Text

Paper vs Online Completion of Experience-Sampling Surveys

In the prelockdown sample, twenty-three older participants and one younger participant opted to complete the study on paper. They were provided with a phone where SMS messages acted as signals prompting the participant to complete a paper version of the survey. To ensure that the different completion methods did not significantly alter participant responses, we conducted a series of ANCOVAs using IBM SPSS Statistics (Version 26), in which mean factor scores (1-5) were the outcome variables, the completion method (online vs paper) was the predictor variable, and age was included as a nuisance covariate. All older participants from the prelockdown sample were included in this analysis (N = 35). The results showed no significant main effects of the completion method on any of the five thought patterns ($P > .234$), allaying concerns that the paper vs online completion may have affected our key measurement.

R Packages and Code used in Analysis

To conduct the two-way ANOVA assessing whether the ‘alone’ percentage differed significantly between samples (pre- vs during lockdown) or age groups (young vs older), we used the car package (3.0.10; Fox & Weisberg, 2019). In addition, partial eta squared for this ANOVA was calculated using the effectsize package (0.4.1; Ben-Shachar et al., 2020). All graphs included in the main text and supplementary materials were created and collated using the ggplot2 (3.3.2; Wickham, 2016), ggthemes (4.2.0; Arnold, 2019), and patchwork (1.1.0; Pedersen, 2020) packages, and supplementary tables were made using the sjPlot package (2.8.7; Lüdecke, 2021b). All code used in the analysis and preparation of figures is available online at https://github.com/Bronte-Mckeown/pre_vs_during_lockdown_ESQ_analysis.

Grouping of ‘Activity’ Options for Analysis

In the lockdown sample, participants reported their primary activity immediately before being signalled from a list of twenty-four options. To condense the activity options for analysis, we first excluded the ‘other’ option (N observations = 88). We then grouped the remaining twenty-three options: 1) thematically while 2) maintaining an approximate balance of the number of observations for each higher-order category. Two authors (BM & CM) independently assigned the activities to higher-order categories in line with these two aims, leading to highly similar allocations. Any differences in category coding were identified and were resolved through discussion between the two independent coders. The five activity categories were: 1) Working (N observations = 212) comprising ‘Working,’ 2) Social interactions (N observations = 152) comprising ‘Talking/conversation’ both virtually and in person, 3) Media consumption (N observations = 549) comprising ‘Social media,’ ‘Watching TV/film,’ ‘Listening to music,’ ‘Listening to radio/podcast,’ ‘Reading/listening to/watching the news,’ ‘Reading for pleasure,’ 4) Leisure activities (N observations = 375) comprising ‘Other leisure activity,’ ‘Arts and crafts,’ ‘Gardening,’ ‘Playing a game,’ ‘Exercising,’ and 5) Essential tasks (N observations = 489) comprising ‘Caring for an adult,’ ‘Childcare,’ ‘Cooking,’ ‘Eating and/or drinking,’ ‘Getting ready for bed,’ ‘Getting ready for the day,’ ‘Household chores,’ ‘Shopping,’ and ‘Sleeping’. Analyses using these activity categories as predictors are based on 1777 observations from a total of 81 participants. Counts for each activity category split by age group are displayed in Table S6.

Comparing Thought Patterns between 1) Virtual and Physical Social Interactions and 2) Age Groups during Lockdown

To examine the effects of virtual social interaction on thoughts in the lockdown sample, we conducted a series of linear mixed models (LMMs) in which each thought pattern was the outcome measure, and 1) ‘interaction type’ and 2) ‘age group’ were the explanatory variables. Interaction type had four levels: 1) no interaction at all, 2) virtual interaction only, 3) physical interaction only, and 4) both virtual and physical interaction (see Table S10 for how this variable was coded). The alpha level was set to < .01 (two-tailed) to account for family-wise error emerging from conducting five models (i.e., .05/5). The reported alpha levels below are unadjusted; main effects and interactions are considered significant only at the $p < .01$ level. When probing these significant main effects and interactions using pairwise comparisons, the alpha level was Bonferroni adjusted to account for the number of tests being conducted; here, the adjusted alpha levels are reported in parentheses. To account for multiple observations per participant, day number was nested within participant as a random intercept. In total, 82 participants (1865 observations) were included in these models. Estimates reported below are unstandardized and reflect the difference between each factor level and the intercept (grand mean of all conditions). These results are summarized in Fig. S3 (see Tables S11-S13 for ANOVA output, parameter estimates, and the variance explained by random effects). It is worth noting that the cells of this analysis were unbalanced, with fewer observations for interacting—particularly virtually—compared to not interacting at all (see Table S14 for the number of observations per interaction type for each age group), so these results should be interpreted with caution.

Example model formula: lmer(Thought component x ~ Interaction type * Age group + (1|Participant/Day number))

Model 1: Future-directed problem solving

There was a significant main effect of interaction type ($F(3, 1830) = 10.39$, $p < .001$). Pairwise comparisons (Bonferroni adjusted for 6 tests) revealed that future-directed problem solving was significantly lower when 'physically interacting' compared to 'virtually interacting' ($b = -0.42$, 95% CI [-0.63, -0.12], $t(1833) = -5.11$, $p < .001$) and 'no interaction' ($b = -0.28$, 95% CI [-0.44, -0.12], $t(1836) = -4.66$, $p < .001$).

Model 2: Pleasant engagement

There were no significant main effects or interactions for levels of pleasant engagement ($p > .05$).

Model 3: Episodic social cognition

There was a significant main effect of interaction type ($F(3, 1834) = 29.05$, $p < .001$). Pairwise comparisons (Bonferroni adjusted for 6 tests) revealed that episodic social cognition was significantly higher: 1) when 'physically interacting' compared to 'no interaction' ($b = 0.44$, 95% CI [0.29, 0.60], $t(1829) = 7.54$, $p < .001$), 2) when 'virtually interacting' compared to 'no interaction' ($b = 0.37$, 95% CI [0.19, 0.55], $t(1829) = 5.34$, $p < .001$), and 3) when 'interacting both virtually and physically' compared to 'no interaction' ($b = 0.46$, 95% CI [0.26, 0.66], $t(1829) = 6.13$, $p < .001$).

Model 4: Imagery

While it did not pass the Bonferroni cut-off ($p > .01$), there was a main effect of interaction type ($F(3, 1795) = 2.62$, $p = .049$) and a two-way interaction between interaction type and age group ($F(3, 1795) = 2.83$, $p = .037$). While it did not reach significance, for completeness, pairwise comparisons (Bonferroni adjusted for 6 tests) indicated that imagery tended to be lower when ‘physically interacting’ compared to ‘virtually interacting’ ($b = -0.19$, 95% CI [-0.40, 0.02], $p = .096$). Furthermore, while it did not reach significance, for completeness, pairwise comparisons (Bonferroni adjusted for 12 tests) indicated that imagery tended to be lower when ‘physically interacting’ compared to ‘virtually interacting’ for younger participants only ($b = -0.26$, 95% CI [-0.53, 0.01], $p = .070$).

Model 5: Detailed task focus

There was a significant main effect of interaction type ($F(3, 1835) = 6.10$, $p < .001$). Pairwise comparisons (Bonferroni adjusted for 6 tests) revealed that detailed task focus was significantly higher when ‘virtually interacting’ compared to 1) ‘interacting both virtually and physically’ ($b = 0.28$, 95% CI = [0.04,0.51], $t(1827) = 3.08$, $p = .013$), and 2) ‘no interaction’ ($b = 0.28$, 95% CI = [0.10,0.45], $t(1826) = 4.13$, $p < .001$). There was also a significant two-way interaction between interaction type and age group ($F(3, 1835) = 4.29$, $p = .005$). Pairwise comparisons (Bonferroni adjusted for 12 tests) revealed that for older participants, but not younger participants, detailed task focus was significantly higher when ‘virtually interacting’ compared to 1) ‘physically interacting’ ($b = 0.39$, 95% CI = [0.03, 0.76], $t(1831) = 3.15$, $p = .020$), 2) ‘interacting both virtually and physically’ ($b = 0.53$, 95% CI = [0.13,0.92], $t(1826) = 3.80$, $p = .002$), and 3) ‘no interaction’ ($b = 0.50$, 95% CI = [0.20,0.81], $t(1815) = 4.68$, $p < .001$).

Principal Components Analysis (PCA) applied to State Affect Data from Pre- and during Lockdown Samples

To identify common patterns of state affect across both samples (pre- and during lockdown), PCA with varimax rotation was applied to the combined z-scored affect data from both samples (12 items which asked about current affect; see Table S15) using IBM SPSS Statistics (Version 26). PCA was applied at the observation level in the same manner as the PCA applied to the thought data. The Kaiser-Meyer-Olkin measure of sampling adequacy was .88, above the commonly recommended value of .6, and Bartlett’s test of sphericity was significant ($\chi2(66) = 26070.84$, $p < .001$). Based on an eigenvalues >1, two components — explaining 57% of the variance — were retained for inclusion as 1) nuisance covariates and 2) outcome variables in LMMs (see Fig. S4. for scree plot): 1) ‘Negative affect’- with the highest loadings on ‘Sad,’ ‘Negative,’ ‘Anxious,’ and ‘Lonely,’ and 2) ‘Positive affect’- with the highest loadings on ‘Excited,’ ‘Happy,’ ‘Positive,’ and ‘Energized’. Item loadings on these components are presented as word clouds in the left-hand side of Fig. S6, and see Table S16 for exact component loadings. To ensure that the affect patterns identified across samples were present in both samples separately, we ran a PCA on each sample separately (specified two components for extraction) and correlated each participant’s PCA score from this analysis with their PCA score from the combined analysis (see Fig. S5 for scatterplots).

Including Affect Components as Nuisance Covariates when Comparing Thought Patterns between 1) Samples, 2) Age Groups, and 3) Social Environments

To examine whether the lockdown-related changes in ongoing thought identified in our prior analysis were independent of changes in affect, we ran an additional analysis in which the two affect components (positive and negative) derived from the PCA across both samples were included as nuisance covariates. We ran 5 LMMs — one with each thought component as the outcome variable — modelling the following fixed effects and their interactions: 1) ‘sample’ (2 levels: pre- and during lockdown), 2) ‘age group’ (2 levels: younger and older) and 3) ‘social environment’ (3 levels: alone, around people but not interacting, around people and interacting). Age group mean-centered age and the two affect components (negative and positive) were included in all models as nuisance covariates. To account for multiple observations per participant, day number was nested within participant as a random intercept. In total, 195 participants (4850 observations) were included in these models. The alpha level was set to < .01 (two-tailed) to account for family-wise error emerging from conducting five models (i.e., .05/5). Importantly, the significant effects relating to lockdown (i.e., changes to future-directed problem-solving, episodic social cognition and imagery) held when we controlled for state affect. Differences in the results are summarized below and see Tables S17-S19 for ANOVA output, parameter estimates, and the variance explained by random effects.

Example model formula: lmer(Thought component x ~ Sample * Age group * Social environment + Negative affect + Positive affect + Age group mean-centered age + (1|Participant/Day number))

With the inclusion of the two affect covariates, the main effects of age group for models 1-3 were no longer significant ($P > .05$). However, it is worth noting that the effect of age group on levels of future-directed problem-solving still approached significance ($p = .071$). A new effect of sample (pre- vs during lockdown) emerged for pleasant engagement ($p = .003$), with pleasant engagement significantly higher in the lockdown sample compared to prelockdown. Without controlling for affect, this effect approached significance (p = .067). In addition, the two-way interaction between age group and social environment for pleasant engagement no longer passed the Bonferroni-adjusted alpha level (p = .026). Pairwise comparisons (Bonferroni adjusted for 6 tests) indicated that the interpretation of this interaction also differed. Older participants reported significantly higher levels of pleasant engagement when alone compared to when interacting ($b = 0.15$, p = .013). Whereas, for younger participants, there was no significant difference (b = 0.06, p = .738). Without controlling for affect, this interaction indicated that younger individuals reported significantly higher levels of pleasant engagement when interacting with others compared to when alone, while levels of pleasant engagement did not differ significantly between social environments for older individuals.

Furthermore, while the two-way interaction between sample (pre- vs during lockdown) and social environment for episodic social cognition remained significant (p < .001), the interpretation of this interaction varied slightly. In the prelockdown sample, there was no significant effect of social environment on levels of episodic social cognition (p > .05). Whereas, during lockdown, there was a significant effect of social environment (significantly higher when 'interacting' compared to when 'alone' or 'around people but not interacting'). Without controlling for affect, this interaction indicated that although there was an effect of social environment in both samples, the increase in episodic social cognition between 'interacting' with both 'alone' and 'not interacting' was greater in the lockdown sample. Therefore, in both cases, social interactions promoted a greater increase in episodic social cognition during lockdown than prelockdown. In addition, while it did not pass the Bonferroni correction of p < .01, there was also a new three-way interaction for episodic social cognition (p = .025). This interaction indicated that the effect of social environment on episodic social cognition was present for younger participants, and not older participants, in the lockdown sample when controlling for state affect.

Finally, while the three-way interaction between sample, age group and social environment for imagery remained significant, the breakdown of this interaction changed such that the effect of social environment on imagery was only present for young participants in the lockdown sample (higher when alone compared to when interacting). Without controlling for affect, for younger participants, the direction of the effect of social environment on levels of imagery differed between samples: 1) prelockdown, younger participants reported significantly less imagery when they were alone compared to when they were interacting with others, 2) during lockdown, younger participants reported significantly more imagery when they were alone compared to when they were interacting with others. In both cases, therefore, younger participants reported significantly higher levels of imagery when alone compared to when interacting during lockdown.

Comparing State Affect between 1) Samples, 2) Age Groups, and 3) Social Environments

To examine the influence that lockdown had on state affect, we performed a series of LMMs with each of the two affect components as the outcome measures. We modelled the following fixed effects and their interactions: 1) 'sample' (2 levels: pre- and during lockdown), 2) 'age group' (2 levels: younger and older), and 3) 'social environment' (3 levels: alone, around people but not interacting, around people and interacting). Age group mean-centered age was included in all models as a nuisance covariate to control for age differences, within age groups, between the two samples. Alpha level was set to < .025 (two-tailed) to account for family-wise error emerging from conducting two models (i.e., .05/2). The reported alpha levels below are unadjusted; main effects and interactions are considered significant only at the $p < .025$ level. When probing these significant main effects and interactions using pairwise comparisons, the alpha level was Bonferroni adjusted to account for the number of tests being conducted; here, the adjusted alpha levels are reported in parentheses. To account for multiple observations per participant, day number was nested within participant as a random intercept. In total, 195 participants (4926 observations) were included in these models. Estimates reported below are unstandardized and reflect the difference between each factor level and the intercept (grand mean of all conditions). These results are summarized in Fig. S6 (see Tables S20-S22 for ANOVA output, parameter estimates, and the variance explained by random effects). It is worth noting that the residual plots for model 1 indicated heteroskedasticity of the residuals (see Fig. S7), so these results should be interpreted with caution.

Example model formula: lmer(Affect component x ~ Sample * Age group * Social environment + Age Group mean-centered age + (1|Participant/Day number))

Model 1: Negative affect

There was a significant main effect of age group ($F(1, 188) = 33.61$, $p < .001$). Negative affect was higher in younger participants compared to older participants ($b = 0.34$, 95% CI

[0.23, 0.46], *t*(188) = 5.80, *p* < .001). There was also a significant interaction between age group and social environment (*F*(2, 4634) = 8.41, *p* < .001). Pairwise comparisons (Bonferroni adjusted for 6 tests) revealed that for younger participants, negative affect was significantly higher when alone compared to when interacting with others (*b* = 0.09, 95% CI [0.01, 0.17), *t*(4783) = 2.97, *p* = .018). Whereas, for older participants, negative affect was significantly lower when alone compared to when interacting with others (*b* = -0.12, 95% CI [-0.23, -0.01], *t*(4602) = -2.88, *p* = .024).

Model 2: Positive affect

There was a significant main effect of social environment (*F*(2, 4652) = 147.53, *p* < .001). Positive affect was lowest when alone (*b* = -0.19, 95% CI [-0.23, -0.16], *t*(4730) = -11.02, *p* < .001) and highest when interacting with others (*b* = 0.29, 95% CI [0.25, 0.32], *t*(4615) = 16.32, *p* < .001). There was also a significant interaction between sample (pre- vs during lockdown) and social environment (*F*(2, 4653) = 5.28, *p* = .005). This interaction indicated that although positive affect was highest when interacting with others in both the pre- and during lockdown samples, there was a smaller increase in positive affect between 'interacting' with both 'alone' (unadjusted, *b* = -0.18, 95% CI[-0.30, -0.06], *t*(4704) = -3.11, *p* = .002) and 'not interacting' (unadjusted, *b* = -0.15 , 95% CI[-0.28, -0.02], *t*(4572) = -2.23, *p* = .026) in the lockdown sample. During lockdown, therefore, social interactions promoted a smaller increase in positive affect than prelockdown. While it did not pass Bonferroni correction, there was also a three-way interaction between sample, age group, and social environment (*F*(2, 4653) = 3.12, *p* = .044). This interaction indicated that the difference in positive affect when 'interacting' compared to when 'alone' (unadjusted, *b* = -0.25, 95% CI [-0.38, -0.11], *t*(4812) = -3.58, *p* < .001) and 'not interacting' (unadjusted, *b* = -0.31, 95% CI [-0.48, -0.15], *t*(4647) = -3.74, *p* < .001) during lockdown was significantly reduced for younger participants only.

Comparing Thought Patterns between 1) Samples, 2) Age groups, and 3) Social Environments while Restricting the Young Age Group Range to 18-27 years in Both Samples

The age range of the young age group in the lockdown sample was greater than the age range of the young age group in the prelockdown sample. In the models reported in the main manuscript, we included age group mean-centred age as a nuisance covariate to account for these differences. However, to ensure that the lockdown-related differences observed were not due to differences in age between the two samples, we also re-ran these analyses while limiting the young age group age range to be 18-27 years in both samples. In total, 188 participants (4715 observations) were included in these analyses (7 participants removed). Removing these participants did not substantially change the results of the overall interpretations of the paper. See Tables S24-S26 for ANOVA output, parameter estimates, and the variance explained by random effects.

Supplementary Figures

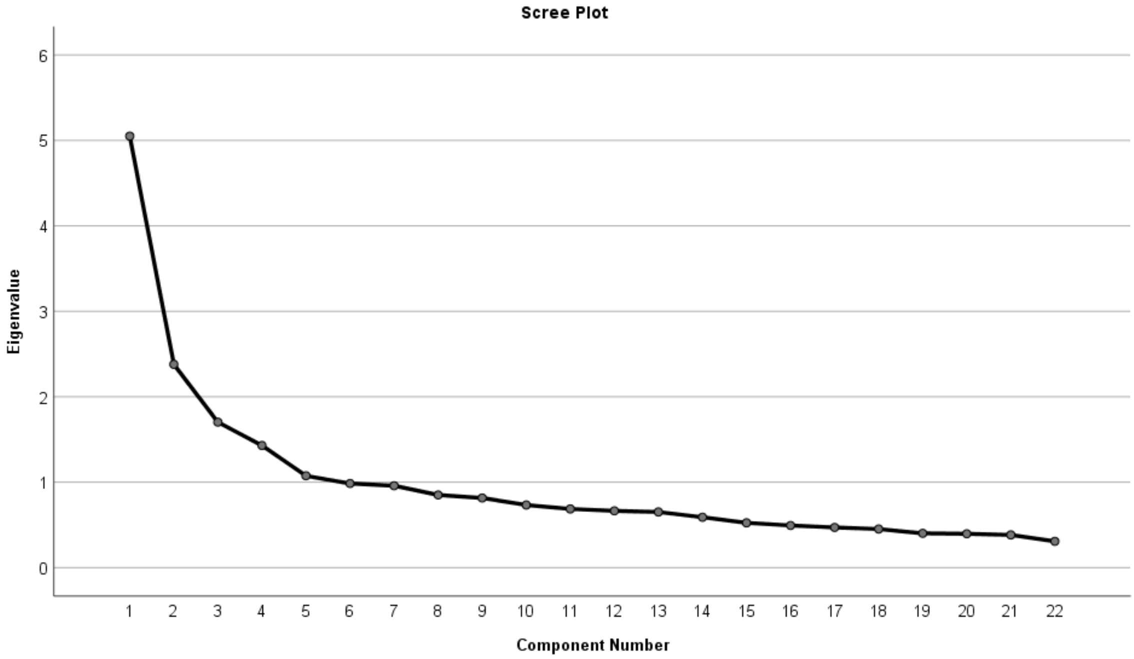

Fig. S1. Scree plot from the PCA applied to the thought data from both experience-sampling datasets (pre- and during lockdown) to identify common "patterns of thought" (x-axis = component number and y-axis = eigenvalue). Based on eigenvalues >1, five components were retained as outcome variables for LMM analyses. These five components accounted for 53% of the total variance. Component 1 (future-directed problem-solving) accounted for 23% of variance, component 2 (pleasant engagement) accounted for 11% of variance, component 3 (episodic social cognition) accounted for 8% of variance, component 4 (imagery) accounted for 6% of variance and component 5 (detailed task focus) accounted for 5% of variance.

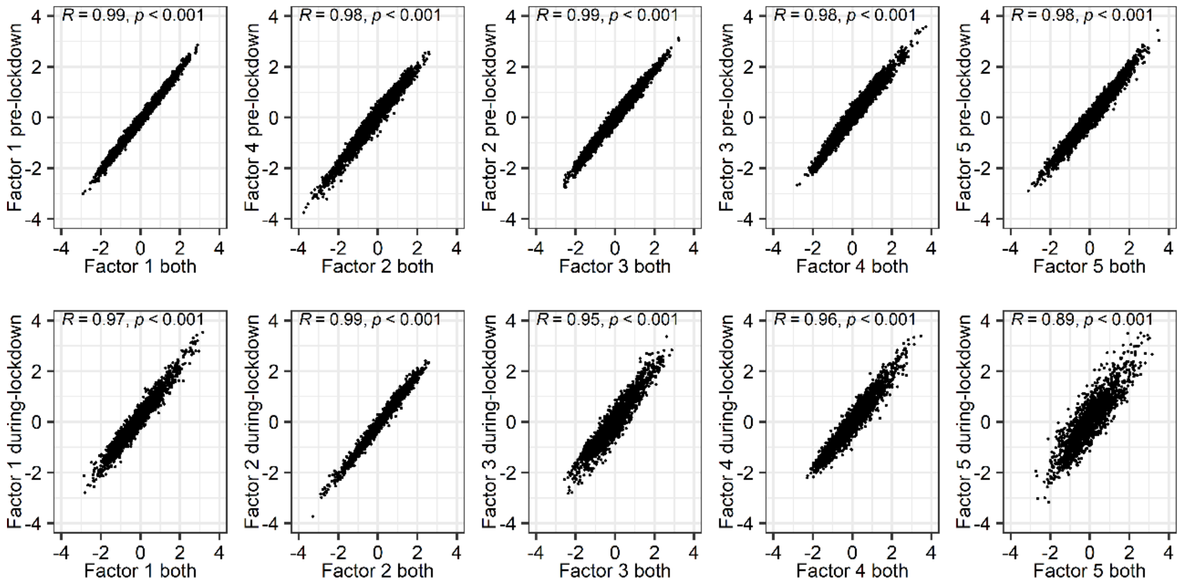

Fig. S2. Scatterplots demonstrating the high correspondence between PCA solutions (varimax rotated) applied to 1) combined thought datasets (pre- and during lockdown) and 2) each thought dataset separately (specifying five components for extraction). The top panel shows the correlation between PCA components using both samples (x-axis) and prelockdown sample only (y-axis) (N observations = 3005). The bottom panel shows the correlation between PCA components using both samples (x-axis) and during lockdown sample only (y-axis) (N observations = 1865). Pearson correlation R and p-values were calculated using the stat_cor function as part of the ggpubr R package (Kassambara, 2020).

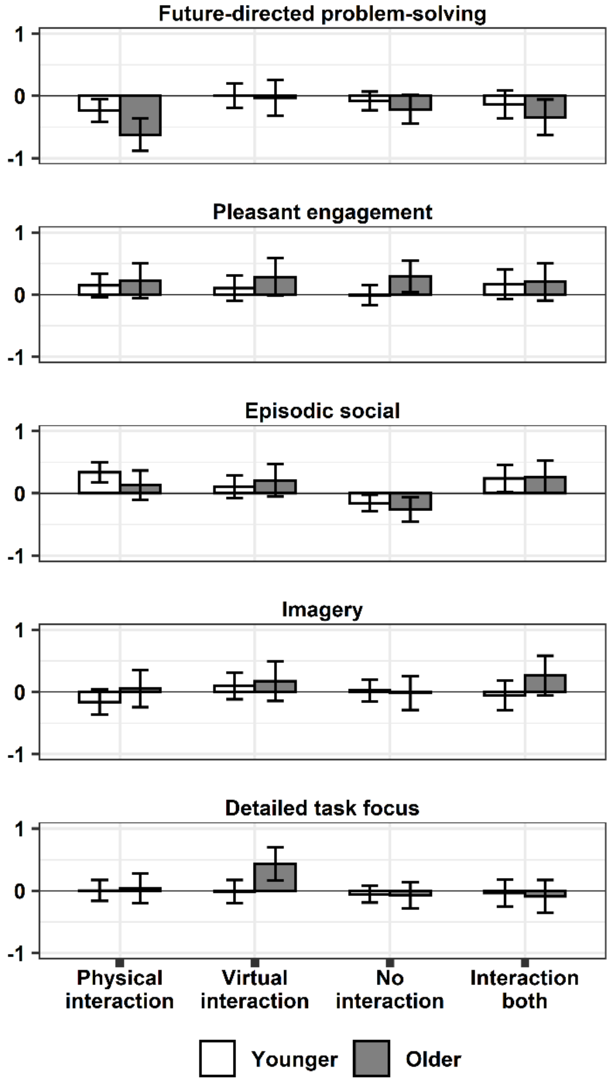

Fig. S3. A summary of the LMMs' results comparing the prevalence of each thought pattern between 1) interaction type and 2) age groups in the lockdown sample. The y-axis of each graph shows the predicted means for each thought pattern. The x-axis shows the four interaction types: 1) physical interaction only, 2) virtual interaction only, 3) no interaction, and 4) interacting both virtually and physically (see Table S10 for how this variable was coded). White bars represent young participants, and gray bars represent older participants. Error bars represent the 95% Confidence intervals for each predicted mean. In total, 82 participants (1865 observations) were included in this analysis. It is worth noting that the cells of this analysis were unbalanced, with fewer observations for interacting—particularly virtually—compared to not interacting at all (see Table S14 for the number of observations per factor level by age group), so these results should be interpreted with caution.

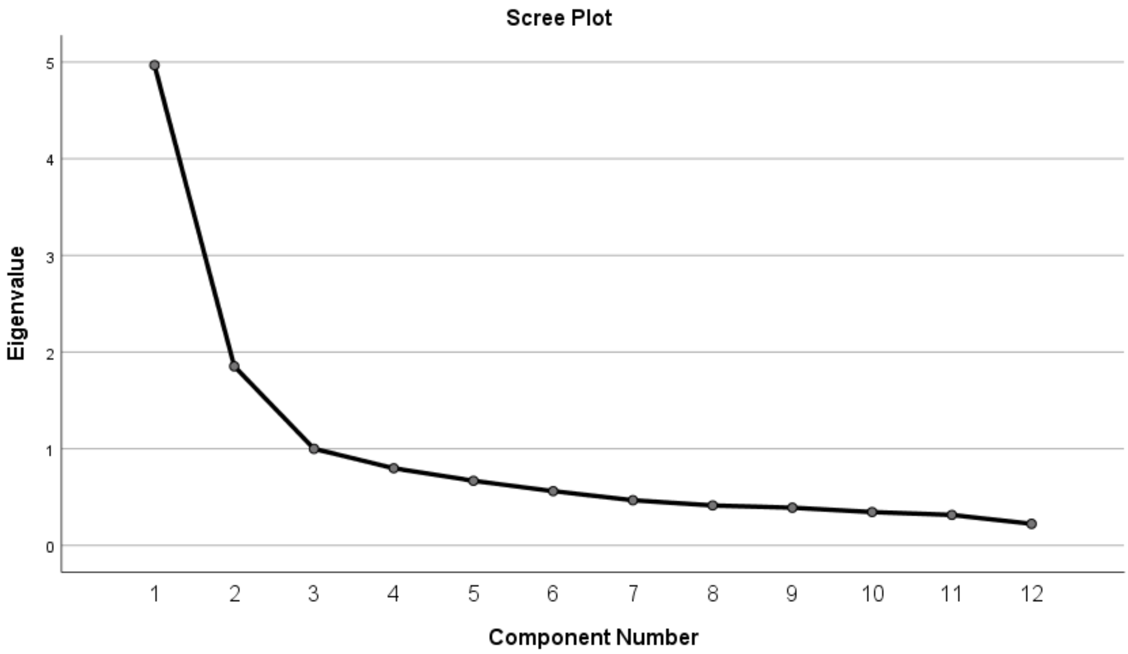

Fig. S4. Scree plot from the PCA applied to the affect data from both experience-sampling datasets (pre- and during lockdown) to identify common affect patterns (x-axis = component number and y-axis = eigenvalue). Based on eigenvalues >1, two components were retained as outcome variables and nuisance covariates for LMM analyses. These two components accounted for 57% of the total variance. Component 1 (negative affect) accounted for 41% of the variance, and component 2 (positive affect) accounted for 15% of the variance.

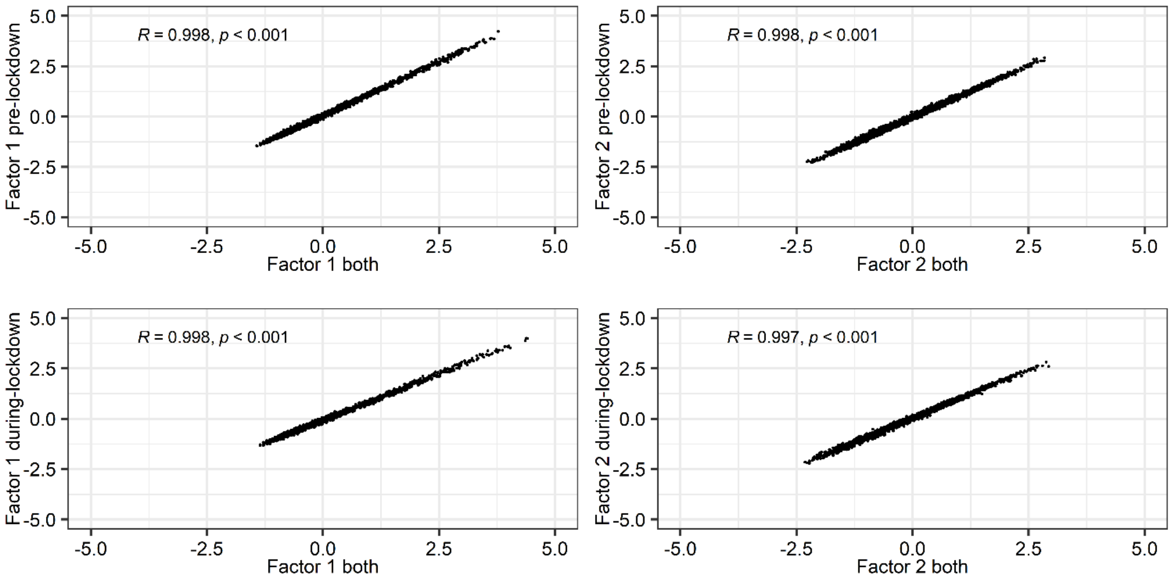

Fig. S5. Scatterplots demonstrating the high correspondence between PCA solutions (varimax rotated) applied to 1) combined affect datasets (pre- and during lockdown) and 2) each affect dataset separately (specifying two components for extraction). The top panel shows the correlation between PCA components using affect data from both samples (x-axis) and prelockdown sample only (y-axis) (N observations = 3061). The bottom panel shows the correlation between PCA components using both samples (x-axis) and during lockdown sample only (y-axis) (N observations = 1865). Pearson correlation R and p-values were calculated using the stat_cor function as part of the ggpubr R package (Kassambara, 2020).

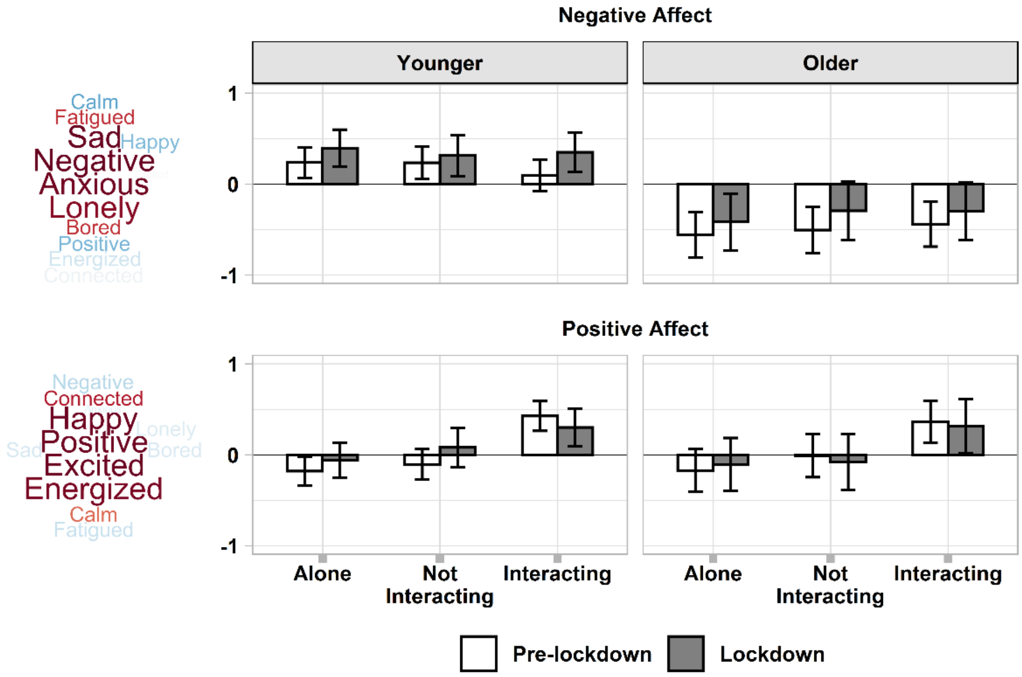

Fig. S6. A summary of the LMMs' results comparing the prevalence of each affect component between 1) pre- and during lockdown samples, 2) age groups and 3) social environments. Word clouds representing the item loadings on the two affect components identified in the affect data from both samples (pre- and during lockdown) using PCA are shown on the left-hand side (N observations = 4929). Each word represents an affect item (12 items; see Table S15). Font size represents the magnitude of the loading, and the color describes the direction. Warm colors reflect positive loadings, while cool colors reflect negative loadings (see Table S16 for exact component loadings). The y-axis of each graph shows the predicted means for each affect component. The x-axis shows the social environment options: 1) alone, 2) around people but not interacting, and 3) around people and interacting. White bars represent the prelockdown sample, and gray bars represent the lockdown sample. Each bar graph is split by age group, with young participants on the left and older on the right. Error bars represent the 95% confidence intervals for each predicted mean. In total, 195 participants (4926 observations) were included in this analysis.

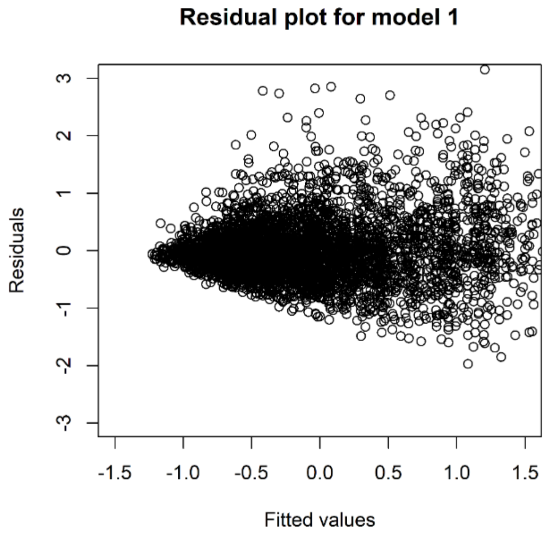

Fig. S7. Residual plot for LMM 1 assessing whether negative state affect significantly varied between 1) samples, 2) age groups, and 3) social environments, demonstrating heteroskedasticity of the residuals. The residuals are more varied at the positive end of fitted values than the negative end of fitted values. Accordingly, these results should be interpreted with caution.

Supplementary Tables

Table S1. Multidimensional experience-sampling (MDES) questions included in the PCA to identify common "patterns of thought" across both experience-sampling datasets (pre- and during lockdown).

Dimension	Wording	Low	High
Task	My thoughts were related to my current activity and/or external environment	Not at all	Completely
Conflicting	My thoughts were conflicting or interfering with what I am trying to achieve right now	Not at all	Completely
Current-goals	My thoughts were helpful for goals that I am trying to achieve right now	Not at all	Completely
Future-goals	My thoughts were helpful for goals that I am trying to achieve (or avoid) in the future	Not at all	Completely
Close-others	My thoughts involved other people close to me	Not at all	Completely
Distant-others	My thoughts involved other people NOT close to me	Not at all	Completely
Self	My thoughts involved myself	Not at all	Completely
Future	My thoughts were about the future	Not at all	Completely
Past	My thoughts were about the past	Not at all	Completely
Important	**Prelockdown:** The content of my thoughts is important to me (i.e., it deals with something important in my life) **Lockdown:** I was thinking about things that are important to me	Not at all	Completely
Controlled	I was trying to control the progression of my thoughts	Not at all	Completely
Wanted	I wanted to have my thoughts	Not at all	Completely
Evolving	My thoughts tended to evolve in a series of steps	Not at all	Completely
Normal	My thoughts had recurrent themes similar to those that I have had before	Not at all	Completely
Images	My thoughts were in the form of visual images	Not at all	Completely
Words	My thoughts were in the form of words	Not at all	Completely
Detailed	My thoughts were detailed and specific	Not at all	Completely
Vivid	My thoughts were vivid	Not at all	Completely
Positive	My thoughts were....	Very negative	Very positive
Deliberate	My thoughts were....	Completely spontaneous	Completely deliberate
Problem-Solving	**Prelockdown:** To what extent are your thoughts... -Focused on solving a problem? **Lockdown:** I was thinking about solutions to problems (or goals)	Not at all	Completely
Rehearsing-Future	**Prelockdown:** To what extent are your thoughts... -Focused on rehearsing or simulating a future situation? **Lockdown:** I was focused on rehearsing or simulating a future situation	Not at all	Completely

Note. The wording for 'Important', 'Problem-solving' and 'Rehearsing-future' differed slightly between pre- and during lockdown samples. All questions were answered on a 1 to 5 Likert scale, with the exception of 'Positive' and 'Deliberate' in the prelockdown sample (answered on a 1 to 7 scale; see main Methods for rescaling procedure). Participants were instructed as follows: "Below are several statements which people have used to describe their thoughts. We're interested in the extent to which your thoughts JUST BEFORE starting this survey relate to these statements. Please read each statement and then select the option which best describes what you were thinking about just before taking this survey. This can be hard so don't think too much about it - go with your initial reaction."

Table S2. Rotated component matrix for the PCA applied to the thought data (22 items; see Table S1) obtained from both samples (pre- and during lockdown).

Questionnaire item	**Component**				
	1 (future-directed problem-solving)	2 (pleasant engagement)	3 (episodic social)	4 (imagery)	5 (detailed task focus)
Task	0.08	0.51	-0.09	0.21	0.42
Conflicting	0.11	-0.63	0.16	0.13	0.03
Current-goals	0.50	0.54	0.05	0.03	0.29
Future-goals	0.67	0.24	0.27	-0.01	0.10
Close-others	-0.11	-0.01	0.70	0.09	-0.04
Distant-others	0.04	-0.22	-0.26	0.48	0.02
Self	0.18	0.00	0.60	-0.03	0.01
Future	0.53	-0.10	0.54	-0.05	-0.20
Past	-0.09	-0.38	0.27	0.39	0.11
Important	0.29	0.10	0.63	0.15	0.15
Controlled	0.60	-0.07	0.04	0.21	0.20
Wanted	0.28	0.66	0.14	0.27	0.13
Evolving	0.57	0.12	0.14	0.34	0.20
Normal	0.18	-0.03	0.46	0.18	0.21
Images	-0.02	0.18	0.13	0.68	-0.46
Words	0.19	-0.05	0.15	0.01	0.75
Detailed	0.35	0.26	0.19	0.51	0.28
Vivid	0.14	0.16	0.24	0.73	0.09
Positive	-0.01	0.70	0.18	0.05	-0.20
Deliberate	0.53	0.37	-0.09	0.06	0.04
Problem-solving	0.76	0.00	0.11	-0.04	0.09
Rehearsing-future	0.58	-0.19	0.39	0.02	-0.25

Note. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 10 iterations. Values indicate the item’s loading on each component.

Table S3. Type 3 Sum of Squares ANOVA table for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) samples (pre- vs during lockdown), 2) age groups (young vs older), and 3) social environments (alone, around people but not interacting and around people and interacting).

	Future-directed problem-solving				**Pleasant engagement**				**Episodic social**				**Imagery**				**Detailed task focus**			
Main effects & interactions	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*
Sample (pre- vs during lockdown)	12.12	1, 191	16.19	**<.001**	2.33	1, 193	3.38	.067	0.05	1, 196	0.07	.797	0.05	1, 193	0.09	.764	0.00	1, 196	0.00	.984
Age group	4.74	1, 188	6.33	**.013**	13.64	1, 191	19.82	**<.001**	4.43	1, 193	6.10	**.014**	0.33	1, 192	0.56	.455	0.63	1, 194	0.92	.338
Social environment	46.94	2, 4824	31.36	**<.001**	7.48	2, 4823	5.43	**.004**	51.15	2, 4827	35.20	**<.001**	1.52	2, 4777	1.28	.278	0.34	2, 4808	0.25	.782
Age group mean-centered age	0.30	1, 176	0.40	.529	0.29	1, 181	0.42	.518	4.46	1, 182	6.14	**.014**	1.41	1, 184	2.38	.125	0.58	1, 185	0.85	.358
Sample * Age group	0.14	1, 187	0.18	.669	2.44	1, 190	3.55	.061	0.05	1, 193	0.07	.789	0.03	1, 191	0.05	.818	0.45	1, 193	0.65	.420
Sample * Social environment	0.53	2, 4823	0.36	.701	3.02	2, 4823	2.20	.111	8.81	2, 4826	6.06	**.002**	2.41	2, 4777	2.02	.132	0.54	2, 4809	0.39	.677
Age group * Social environment	3.71	2, 4822	2.48	.084	7.71	2, 4823	5.60	**.004**	0.07	2, 4826	0.05	.956	3.81	2, 4778	3.20	.041	1.93	2, 4809	1.40	.246
Sample * Age group * Social environment	0.54	2, 4823	0.36	.699	3.21	2, 4823	2.33	.098	3.68	2, 4826	2.53	.080	6.95	2, 4778	5.85	**.003**	0.51	2, 4809	0.37	.692

Note. SS = Sum of Squares. DF = numerator and denominator degrees of freedom. P-values <.01 are in bold. Age group mean-centered age was included as a nuisance covariate in all models. Information in this table obtained using anova() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S4. Unstandardized parameter estimates for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) samples (pre- vs during lockdown), 2) age groups (young vs older), and 3) social environments (alone, around people but not interacting, around people and interacting).

	Future-directed problem-solving				**Pleasant engagement**				**Episodic social cognition**				**Imagery**				**Detailed task focus**			
Factor level	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*
(Intercept)	-0.07	-0.14 – 0.01	-1.81	.070	0.08	0.00 – 0.16	1.97	**.049**	-0.02	-0.09 – 0.06	-0.40	.691	0.01	-0.09 – 0.11	0.19	.849	-0.02	-0.11 – 0.07	-0.46	.649
Lockdown	-0.15	-0.23 – -0.08	-4.02	**<.001**	0.08	-0.00 – 0.16	1.84	.066	0.01	-0.07 – 0.09	0.26	.797	0.01	-0.08 – 0.11	0.30	.764	-0.00	-0.09 – 0.09	-0.02	.984
Younger	0.10	0.02 – 0.17	2.52	**.012**	-0.19	-0.27 – -0.10	-4.45	**<.001**	0.10	0.02 – 0.18	2.47	**.014**	-0.04	-0.13 – 0.06	-0.75	.454	0.04	-0.05 – 0.14	0.96	.336
Alone	0.11	0.07 – 0.15	5.01	**<.001**	-0.02	-0.06 – 0.02	-1.07	.286	-0.08	-0.12 – -0.03	-3.52	**<.001**	-0.03	-0.07 – 0.01	-1.46	.146	0.01	-0.03 – 0.06	0.65	.513
Interacting	-0.17	-0.21 – -0.12	-7.52	**<.001**	0.07	0.03 – 0.11	3.29	**.001**	0.19	0.14 – 0.23	8.37	**<.001**	0.02	-0.02 – 0.06	1.15	.249	-0.01	-0.05 – 0.03	-0.47	.636
Age group mean-centered age	0.00	-0.01 – 0.02	0.63	.528	0.01	-0.01 – 0.02	0.65	.518	-0.02	-0.03 – -0.00	-2.48	**.013**	-0.02	-0.03 – 0.00	-1.54	.123	-0.01	-0.03 – 0.01	-0.92	.357
Lockdown * Younger	-0.02	-0.10 – 0.06	-0.43	.668	0.08	-0.00 – 0.17	1.88	.060	0.01	-0.07 – 0.09	0.27	.788	0.01	-0.09 – 0.11	0.23	.818	-0.04	-0.14 – 0.06	-0.81	.419
Lockdown * Alone	-0.01	-0.05 – 0.04	-0.27	.789	0.03	-0.01 – 0.07	1.54	.125	-0.06	-0.10 – -0.01	-2.51	**.012**	0.02	-0.02 – 0.06	0.86	.389	0.01	-0.03 – 0.05	0.40	.692
Lockdown * Interacting	0.02	-0.03 – 0.06	0.84	.400	-0.04	-0.08 – 0.00	-1.89	.059	0.07	0.03 – 0.11	3.16	**.002**	-0.04	-0.08 – -0.00	-2.01	**.045**	0.01	-0.03 – 0.05	0.59	.555
Younger * Alone	-0.02	-0.06 – 0.02	-0.93	.355	-0.04	-0.08 – 0.00	-1.73	.083	-0.00	-0.05 – 0.04	-0.12	.907	0.05	0.01 – 0.09	2.30	**.022**	-0.04	-0.08 – 0.01	-1.67	.095
Younger * Interacting	0.05	0.01 – 0.09	2.22	**.026**	0.07	0.03 – 0.11	3.30	**.001**	-0.00	-0.05 – 0.04	-0.22	.830	-0.04	-0.08 – 0.00	-1.83	.067	0.02	-0.03 – 0.06	0.74	.460
Lockdown * Younger * Alone	-0.02	-0.06 – 0.03	-0.81	.416	-0.04	-0.08 – 0.00	-1.90	.058	-0.05	-0.09 – -0.01	-2.25	**.024**	0.07	0.03 – 0.11	3.34	**.001**	0.01	-0.03 – 0.05	0.57	.566
Lockdown * Younger * Interacting	0.01	-0.03 – 0.06	0.51	.610	-0.01	-0.05 – 0.04	-0.28	.783	0.02	-0.03 – 0.06	0.79	.428	-0.04	-0.08 – 0.00	-1.92	.055	0.01	-0.03 – 0.05	0.38	.701

Note. Summed contrasts were used meaning that the intercept reflects the grand mean of all conditions for each model and each estimate (*b*) reflects the difference between the factor level and the intercept. P-values <.05 are in bold. Information in this table obtained using summary() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S5. A summary of the variance explained by random effects for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) samples (pre- vs during lockdown), 2) age groups (young vs older), and 3) social environments (alone, around people but not interacting, around people and interacting).

	Future-directed problem-solving	**Pleasant engagement**	**Episodic social**	**Imagery**	**Detailed task focus**
σ^2	0.75	0.69	0.73	0.59	0.69
τ_{00}	0.05 $_{DAY:IDNO}$	0.03 $_{DAY:IDNO}$	0.05 $_{DAY:IDNO}$	0.07 $_{DAY:IDNO}$	0.03 $_{DAY:IDNO}$
	0.17 $_{IDNO}$	0.22 $_{IDNO}$	0.19 $_{IDNO}$	0.33 $_{IDNO}$	0.28 $_{IDNO}$
N	10 $_{DAY}$	10 $_{DAY}$	10 $_{DAY}$	10 $_{DAY}$	10 $_{DAY}$
	195 $_{IDNO}$	195 $_{IDNO}$	195 $_{IDNO}$	195 $_{IDNO}$	195 $_{IDNO}$
Observations	4870	4870	4870	4870	4870

Note. σ^2 = population variance, τ_{00} = random intercept variance. IDNO = participant identifier, DAY = day number. Information in this table obtained using summary() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S6. Number of observations per higher-order activity category split by age group in the lockdown sample.

Age group			**Activity category**		
	Working	Social interactions	Media consumption	Leisure activities	Essential tasks
Younger	186	82	380	228	326
Older	26	70	169	147	163

Table S7. Type 3 Sum of Squares ANOVA tables for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) current activities (work, leisure, social, media, and essentials) and 2) age groups (young vs older) in the lockdown sample.

	Future-directed problem-solving				**Pleasant engagement**				**Episodic social**				**Imagery**				**Detailed task focus**			
Main effects & interactions	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*
Activity	78.00	4, 1712	33.67	**<.001**	45.37	4, 1699	18.93	**<.001**	62.93	4, 1718	25.58	**<.001**	15.17	4, 1690	6.52	**<.001**	31.30	4, 1713	13.39	**<.001**
Age Group	0.45	1, 83	0.77	.383	1.77	1, 81	2.96	.089	1.03	1, 87	1.67	.200	0.05	1, 80	0.08	.778	0.47	1, 86	0.80	.373
Activity * Age Group	5.88	4, 1712	2.54	.038	13.69	4, 1699	5.71	**<.001**	2.08	4, 1718	0.85	.497	3.88	4, 1690	1.67	.155	11.80	4, 1713	5.04	**<.001**

Note. SS = Sum of Squares. DF = numerator and denominator degrees of freedom. P-values <.01 are in bold. Information in this table obtained using anova() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S8. Unstandardized parameter estimates for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) current activities (work, leisure, social, media and essentials) and 2) age groups (young vs older) in the lockdown sample.

	Future-directed problem-solving				**Pleasant engagement**				**Episodic social cognition**				**Imagery**				**Detailed task focus**			
Factor level	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*
(Intercept)	-0.12	-0.25 – 0.01	-1.86	.063	0.19	0.03 – 0.34	2.40	**.017**	-0.01	-0.13 – 0.11	-0.11	.914	-0.00	-0.16 – 0.16	-0.01	.990	0.05	-0.07 – 0.18	0.85	.394
Working	0.62	0.48 – 0.77	8.62	**<.001**	0.13	-0.01 – 0.27	1.76	.078	-0.35	-0.50 – -0.20	-4.68	**<.001**	-0.12	-0.26 – 0.03	-1.59	.113	0.39	0.25 – 0.53	5.44	**<.001**
Leisure	0.06	-0.03 – 0.14	1.34	.181	0.27	0.19 – 0.36	6.36	**<.001**	0.00	-0.08 – 0.09	0.04	.969	0.06	-0.03 – 0.14	1.38	.168	-0.19	-0.27 – -0.11	-4.48	**<.001**
Social	-0.10	-0.21 – 0.02	-1.67	.094	-0.12	-0.23 – -0.00	-2.02	**.043**	0.52	0.40 – 0.64	8.72	**<.001**	-0.02	-0.14 – 0.09	-0.37	.714	0.13	0.02 – 0.24	2.30	**.021**
Media	-0.36	-0.44 – -0.28	-8.92	**<.001**	-0.21	-0.29 – -0.13	-5.14	**<.001**	-0.23	-0.31 – -0.14	-5.42	**<.001**	0.17	0.09 – 0.26	4.21	**<.001**	-0.17	-0.25 – -0.09	-4.23	**<.001**
Younger	0.06	-0.07 – 0.18	0.88	.381	-0.13	-0.28 – 0.02	-1.72	.086	0.08	-0.04 – 0.20	1.29	.197	-0.02	-0.18 – 0.14	-0.28	.777	-0.06	-0.18 – 0.07	-0.89	.371
Working * Younger	0.03	-0.11 – 0.17	0.43	.665	-0.26	-0.40 – -0.11	-3.52	**<.001**	0.04	-0.11 – 0.18	0.48	.632	0.08	-0.07 – 0.22	1.01	.315	0.04	-0.10 – 0.18	0.60	.549
Leisure * Younger	-0.05	-0.14 – 0.03	-1.24	.215	0.00	-0.08 – 0.09	0.06	.953	0.05	-0.03 – 0.14	1.19	.234	-0.02	-0.11 – 0.06	-0.51	.608	0.15	0.06 – 0.23	3.47	**.001**
Social * Younger	-0.09	-0.20 – 0.03	-1.50	.134	0.14	0.02 – 0.25	2.35	**.019**	-0.01	-0.13 – 0.11	-0.14	.891	-0.04	-0.16 – 0.08	-0.65	.513	-0.18	-0.30 – -0.07	-3.18	**.001**
Media * Younger	0.11	0.03 – 0.19	2.63	**.009**	0.14	0.06 – 0.22	3.36	**.001**	-0.05	-0.13 – 0.04	-1.09	.276	-0.07	-0.15 – 0.01	-1.76	.078	-0.03	-0.11 – 0.04	-0.85	.398

Note. Summed contrasts were used meaning that the intercept reflects the grand mean of all conditions for each model and each estimate (*b*) reflects the difference between the factor level and the intercept. P-values <.05 are in bold. Information in this table obtained using summary() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S9. A summary of the variance explained by random effects for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) current activities (work, leisure, social, media and essentials) and 2) age groups (young vs older) in the lockdown sample**.**

	Future-directed problem-solving	**Pleasant engagement**	**Episodic social**	**Imagery**	**Detailed task focus**
σ^2	0.58	0.60	0.62	0.58	0.58
τ_{00}	0.04 $_{\text{DAY: IDNO}}$	0.03 $_{\text{DAY: IDNO}}$	0.04 $_{\text{DAY: IDNO}}$	0.07 $_{\text{DAY: IDNO}}$	0.01 $_{\text{DAY: IDNO}}$
	0.22 $_{\text{IDNO}}$	0.33 $_{\text{IDNO}}$	0.18 $_{\text{IDNO}}$	0.36 $_{\text{IDNO}}$	0.20 $_{\text{IDNO}}$
N	7 $_{\text{DAY}}$	7 $_{\text{DAY}}$	7 $_{\text{DAY}}$	7 $_{\text{DAY}}$	7 $_{\text{DAY}}$
	81 $_{\text{IDNO}}$	81 $_{\text{IDNO}}$	81 $_{\text{IDNO}}$	81 $_{\text{IDNO}}$	81 $_{\text{IDNO}}$
Observations	1777	1777	1777	1777	1777

Note. σ^2 = population variance, τ_{00} = random intercept variance. IDNO = participant identifier, DAY = day number. Information in this table obtained using summary() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S10. Demonstration of how the 'interaction type' variable was coded for the LMMs examining whether each thought pattern varied significantly between 1) interaction type and 2) age groups in the lockdown sample.

Original variables		**Recoded variable**
Physical social environment	Virtual social environment	Interaction type
Alone	Alone	No interaction
Around people but NOT interacting	Around people but NOT interacting	No interaction
Alone	Around people but NOT interacting	No interaction
Around people but NOT interacting	Alone	No interaction
Alone	Around people and interacting with them	Virtual interaction
Around people but NOT interacting	Around people and interacting with them	Virtual interaction
Around people and interacting with them	Alone	Physical interaction
Around people and interacting with them	Around people but NOT interacting	Physical interaction
Around people and interacting with them	Around people and interacting with them	Interaction both

Table S11. Type 3 Sum of Squares ANOVA table for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) interaction type (physical interaction, virtual interaction, no interaction, and interaction both) and 2) age group (younger vs older) in the lockdown sample.

	Future-directed problem-solving				**Pleasant engagement**				**Episodic social**				**Imagery**				**Detailed task focus**			
Main effects & interactions	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*
Interaction type	20.31	3, 1830	10.39	**<.001**	0.65	3, 1822	0.35	.792	54.34	3, 1834	29.05	**<.001**	4.57	3, 1795	2.62	.049	10.95	3, 1835	6.10	**<.001**
Age group	1.31	1, 85	2.01	.160	0.63	1, 84	1.01	.319	0.10	1, 89	0.16	.694	0.45	1, 82	0.78	.380	0.40	1, 89	0.66	.418
Interaction type * Age group	3.75	3, 1830	1.92	.125	3.45	3, 1822	1.83	.140	2.86	3, 1834	1.53	.205	4.93	3, 1795	2.83	.037	7.70	3, 1835	4.29	**.005**

Note. SS = Sum of Squares. DF = numerator and denominator degrees of freedom. P-values <.01 are in bold. Information in this table obtained using anova() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S12. Unstandardized parameter estimates for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) interaction type (physical interaction, virtual interaction, no interaction, and interaction both) and 2) age group (younger vs older) in the lockdown sample.

	Future-directed problem-solving				**Pleasant engagement**				**Episodic social**				**Imagery**				**Detailed task focus**			
Factor levels	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*
(Intercept)	-0.21	-0.34 – -0.08	-3.06	**.002**	0.18	0.03 – 0.32	2.38	**.017**	0.11	-0.01 – 0.22	1.84	.066	0.05	-0.11 – 0.21	0.61	.545	0.02	-0.10 – 0.15	0.39	.693
Physical interaction	-0.22	-0.31 – -0.13	-4.86	**<.001**	0.01	-0.08 – 0.09	0.16	.873	0.13	0.04 – 0.21	2.84	**.004**	-0.10	-0.19 – -0.02	-2.31	**.021**	-0.00	-0.09 – 0.08	-0.11	.915
Virtual interaction	0.20	0.09 – 0.30	3.73	**<.001**	0.02	-0.08 – 0.12	0.34	.732	0.05	-0.05 – 0.15	0.93	.354	0.09	-0.01 – 0.19	1.75	.080	0.18	0.09 – 0.28	3.69	**<.001**
No interaction	0.06	-0.01 – 0.13	1.66	.097	-0.04	-0.10 – 0.03	-1.00	.317	-0.32	-0.39 – -0.25	-9.09	**<.001**	-0.04	-0.11 – 0.02	-1.29	.197	-0.09	-0.16 – -0.02	-2.64	**.008**
Younger	0.10	-0.04 – 0.23	1.42	.156	-0.07	-0.22 – 0.07	-1.00	.316	0.02	-0.09 – 0.14	0.39	.693	-0.07	-0.23 – 0.09	-0.88	.378	-0.05	-0.17 – 0.07	-0.81	.416
Physical interaction * Younger	0.10	0.01 – 0.19	2.14	**.033**	0.04	-0.05 – 0.13	0.84	.399	0.08	-0.01 – 0.17	1.80	.072	-0.04	-0.12 – 0.05	-0.80	.426	0.03	-0.05 – 0.12	0.78	.435
Virtual interaction * Younger	-0.08	-0.18 – 0.03	-1.48	.139	-0.02	-0.12 – 0.09	-0.29	.769	-0.07	-0.18 – 0.03	-1.45	.147	0.03	-0.07 – 0.13	0.66	.509	-0.17	-0.27 – -0.07	-3.42	**.001**
No interaction * Younger	-0.03	-0.10 – 0.04	-0.78	.438	-0.08	-0.15 – -0.01	-2.18	**.029**	0.03	-0.04 – 0.10	0.86	.390	0.09	0.02 – 0.16	2.62	**.009**	0.06	-0.01 – 0.13	1.73	.084

Note. Summed contrasts were used meaning that the intercept reflects the grand mean of all conditions for each model and each estimate (*b*) reflects the difference between the factor level and the intercept. P-values <.05 are in bold. Information in this table obtained using summary() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S13. A summary of the variance explained by random effects for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) interaction type (physical interaction, virtual interaction, no interaction, and interaction both) and 2) age group (younger vs older) in the lockdown sample.

	Future-directed problem-solving	**Pleasant engagement**	**Episodic social**	**Imagery**	**Detailed task focus**
σ^2	0.65	0.63	0.62	0.58	0.60
τ_{00}	0.04 $_{DAY: IDNO}$	0.04 $_{DAY: IDNO}$	0.05 $_{DAY: IDNO}$	0.07 $_{DAY: IDNO}$	0.03 $_{DAY: IDNO}$
	0.24 $_{IDNO}$	0.30 $_{IDNO}$	0.16 $_{IDNO}$	0.36 $_{IDNO}$	0.20 $_{IDNO}$
N	7 $_{DAY}$	7 $_{DAY}$	7 $_{DAY}$	7 $_{DAY}$	7 $_{DAY}$
	82 $_{IDNO}$	82 $_{IDNO}$	82 $_{IDNO}$	82 $_{IDNO}$	82 $_{IDNO}$
Observations	1865	1865	1865	1865	1865

Note. σ2 = population variance, τ00 = random intercept variance. IDNO = participant identifier, DAY = day number. Information in this table obtained using summary() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S14. Number of observations for each level of the variable 'interaction type' by levels of age group.

Age group	**Interaction type**			
	Physical interaction	Virtual interaction	Interaction both	No interaction
Younger	224	141	86	805
Older	125	71	73	340

Table S15. All 12 affect items presented to participants in both samples included in the PCA to identify common patterns of affect.

Affect item	**Low**	**High**
Positive	Not at all	Extremely
Calm	Not at all	Extremely
Happy	Not at all	Extremely
Fatigued	Not at all	Extremely
Excited	Not at all	Extremely
Lonely	Not at all	Extremely
Anxious	Not at all	Extremely
Energized	Not at all	Extremely
Negative	Not at all	Extremely
Sad	Not at all	Extremely
Connected with other people	Not at all	Extremely
Bored	Not at all	Extremely

Note. Participants were instructed as follows: “Below are a list of different types of emotions and feelings. For each emotion or feeling, please select the option which best describes how you were feeling just before taking this survey.” All questions were answered on a 1-5 Likert scale.

Table S16. Rotated component matrix for the PCA applied to the affect data (12 items; see Table S15) obtained from both samples (pre- and during lockdown).

Questionnaire items	Components	
	1 (negative)	2 (positive)
Positive	-0.37	0.79
Negative	0.80	-0.23
Happy	-0.36	0.79
Sad	0.80	-0.13
Anxious	0.78	-0.10
Calm	-0.43	0.46
Excited	0.00	0.79
Bored	0.58	-0.12
Energized	-0.17	0.76
Fatigued	0.59	-0.19
Connected	-0.04	0.65
Lonely	0.73	-0.11

Note. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 3 iterations. Values indicate the item's loading on each component.

Table S17. Type 3 Sum of Squares ANOVA table for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) samples (pre- vs during lockdown), 2) age groups (young vs older), and 3) social environments (alone, around people but not interacting and around people and interacting) while including negative and positive affect components as nuisance covariates to control for state affect.

	Future-directed problem-solving				**Pleasant engagement**				**Episodic social**				**Imagery**				**Detailed task focus**			
Main effects & Interactions	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*
Sample	14.22	1, 190	18.98	**<.001**	4.50	1, 194	8.92	**.003**	0.02	1, 196	0.04	.851	0.02	1, 191	0.03	.871	0.03	1, 195	0.04	.840
Age group	2.47	1, 196	3.30	.071	0.43	1, 198	0.84	.359	0.55	1, 202	0.82	.366	0.99	1, 195	1.69	.195	0.00	1, 198	0.01	.945
Social environment	50.67	2, 4790	33.80	**<.001**	5.71	2, 4797	5.67	**.003**	12.59	2, 4789	9.37	**<.001**	0.90	2, 4771	0.76	.467	0.18	2, 4779	0.13	.875
Negative affect	15.91	1, 3070	21.23	**<.001**	440.07	1, 3731	872.99	**<.001**	74.52	1, 3084	110.95	**<.001**	7.38	1, 4290	12.55	**<.001**	30.89	1, 4124	45.58	**<.001**
Positive affect	6.95	1, 3837	9.27	**.002**	380.81	1, 4250	755.43	**<.001**	281.02	1, 3844	418.38	**<.001**	60.99	1, 4603	103.80	**<.001**	11.97	1, 4426	17.67	**<.001**
Age group mean-centered age	0.59	1, 175	0.79	.377	0.70	1, 182	1.40	.239	1.62	1, 181	2.42	.122	0.90	1, 181	1.54	.216	0.55	1, 185	0.81	.368
Sample * Age group	0.13	1, 187	0.17	.678	1.93	1, 191	3.83	.052	0.07	1, 193	0.10	.750	0.03	1, 188	0.06	.811	0.38	1, 192	0.55	.458
Sample * Social environment	0.53	2, 4796	0.35	.705	0.57	2, 4801	0.56	.569	14.01	2, 4796	10.43	**<.001**	1.37	2, 4769	1.16	.312	0.42	2, 4782	0.31	.734
Age group * Social environment	4.15	2, 4796	2.77	.063	3.68	2, 4802	3.65	.026	0.38	2, 4796	0.28	.756	3.14	2, 4769	2.67	.069	2.95	2, 4783	2.18	.113
Sample * Age group * Social environment	0.79	2, 4795	0.53	.589	2.08	2, 4801	2.07	.127	4.95	2, 4795	3.69	.025	6.53	2, 4771	5.55	**.004**	0.23	2, 4782	0.17	.846

Note. SS = Sum of Squares. DF = numerator and denominator degrees of freedom. P-values <.01 are in bold. Age group mean-centered age was included as a nuisance covariate in all models. Information in this table obtained using anova() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S18. Unstandardized parameter estimates for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) samples (pre- vs during- lockdown), 2) age groups (younger vs older), and 3) social environments (alone, around people but not interacting, around people and interacting) while including negative and positive affect components as nuisance covariates to control for state affect.

	Future-directed problem-solving				**Pleasant engagement**				**Episodic social**				**Imagery**				**Detailed task focus**			
Factor levels & continuous predictors	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*
(Intercept)	-0.06	-0.14 – 0.01	-1.76	.078	0.02	-0.05 – 0.09	0.60	.548	-0.02	-0.08 – 0.05	-0.45	.652	0.01	-0.08 – 0.10	0.13	.897	-0.01	-0.10 – 0.08	-0.15	.884
Lockdown	-0.16	-0.23 – -0.09	-4.36	**<.001**	0.11	0.04 – 0.17	2.99	**.003**	-0.01	-0.07 – 0.06	-0.19	.850	0.01	-0.08 – 0.10	0.16	.871	-0.01	-0.10 – 0.08	-0.20	.840
Younger	0.07	-0.01 – 0.14	1.82	.070	-0.03	-0.10 – 0.04	-0.92	.358	0.03	-0.04 – 0.10	0.91	.365	-0.06	-0.15 – 0.03	-1.30	.193	0.00	-0.09 – 0.10	0.07	.945
Alone	0.12	0.07 – 0.16	5.25	**<.001**	0.05	0.02 – 0.09	2.94	**.003**	-0.01	-0.06 – 0.03	-0.69	.492	0.00	-0.04 – 0.04	0.04	.964	0.00	-0.04 – 0.04	0.01	.992
Interacting	-0.18	-0.23 – -0.14	-7.85	**<.001**	-0.05	-0.09 – -0.01	-2.64	**.008**	0.09	0.05 – 0.13	4.22	**<.001**	-0.02	-0.07 – 0.02	-1.16	.248	0.01	-0.03 – 0.05	0.47	.636
Negative affect	0.09	0.05 – 0.12	4.61	**<.001**	-0.46	-0.49 – -0.43	-29.55	**<.001**	0.19	0.15 – 0.22	10.53	**<.001**	0.06	0.03 – 0.10	3.54	**<.001**	0.12	0.09 – 0.16	6.75	**<.001**
Positive affect	0.05	0.02 – 0.09	3.05	**.002**	0.39	0.37 – 0.42	27.49	**<.001**	0.33	0.30 – 0.36	20.45	**<.001**	0.16	0.13 – 0.20	10.19	**<.001**	-0.07	-0.10 – -0.04	-4.20	**<.001**
Age group mean-centered age	0.01	-0.01 – 0.02	0.89	.375	0.01	-0.01 – 0.02	1.18	.237	-0.01	-0.02 – 0.00	-1.55	.120	-0.01	-0.03 – 0.01	-1.24	.215	-0.01	-0.03 – 0.01	-0.90	.367
Lockdown * Younger	-0.02	-0.09 – 0.06	-0.42	.677	0.07	-0.00 – 0.15	1.96	.050	0.01	-0.06 – 0.08	0.32	.750	0.01	-0.08 – 0.11	0.24	.811	-0.04	-0.13 – 0.06	-0.74	.457
Lockdown * Alone	-0.01	-0.05 – 0.04	-0.28	.777	0.02	-0.02 – 0.06	1.06	.288	-0.07	-0.11 – -0.03	-3.29	**.001**	0.01	-0.03 – 0.05	0.66	.511	0.01	-0.03 – 0.05	0.57	.568
Lockdown * Interacting	0.02	-0.03 – 0.06	0.84	.403	-0.01	-0.04 – 0.03	-0.36	.719	0.09	0.05 – 0.13	4.13	**<.001**	-0.03	-0.07 – 0.01	-1.52	.128	0.01	-0.04 – 0.05	0.29	.768
Younger * Alone	-0.02	-0.07 – 0.02	-1.07	.286	-0.00	-0.04 – 0.03	-0.10	.922	-0.02	-0.06 – 0.03	-0.75	.455	0.04	0.00 – 0.08	2.17	**.030**	-0.04	-0.09 – -0.00	-2.06	**.039**
Younger * Interacting	0.05	0.01 – 0.10	2.34	**.019**	0.05	0.01 – 0.08	2.55	**.011**	0.01	-0.04 – 0.05	0.27	.791	-0.03	-0.07 – 0.01	-1.54	.123	0.02	-0.02 – 0.06	1.07	.286
Lockdown * Younger * Alone	-0.02	-0.07 – 0.02	-0.99	.325	-0.04	-0.07 – -0.00	-2.02	**.044**	-0.06	-0.10 – -0.01	-2.66	**.008**	0.07	0.03 – 0.11	3.28	**.001**	0.01	-0.03 – 0.05	0.47	.638
Lockdown * Younger * Interacting	0.01	-0.03 – 0.06	0.63	.528	0.02	-0.02 – 0.05	0.97	.334	0.03	-0.01 – 0.07	1.45	.148	-0.04	-0.08 – 0.00	-1.74	.082	0.00	-0.04 – 0.04	0.14	.888

Note. Summed contrasts were used meaning that the intercept reflects the grand mean of all conditions for each model and each estimate (*b*) reflects the difference between the factor level and the intercept. P-values <.05 are in bold. Information in this table obtained using summary() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S19. A summary of the variance explained by random effects for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) samples (pre- vs during- lockdown), 2) age groups (younger vs older), and 3) social environments (alone, around people but not interacting, around people and interacting) while including negative and positive affect components as nuisance covariates to control for state affect.

	Future-directed problem-solving	**Pleasant engagement**	**Episodic social**	**Imagery**	**Detailed task focus**
σ^2	0.75	0.50	0.67	0.59	0.68
τ_{00}	0.04 $_{DAY: IDNO}$	0.03 $_{DAY: IDNO}$	0.04 $_{DAY: IDNO}$	0.07 $_{DAY: IDNO}$	0.03 $_{DAY: IDNO}$
	0.16 $_{IDNO}$	0.16 $_{IDNO}$	0.14 $_{IDNO}$	0.28 $_{IDNO}$	0.29 $_{IDNO}$
N	10 $_{DAY}$	10 $_{DAY}$	10 $_{DAY}$	10 $_{DAY}$	10 $_{DAY}$
	195 $_{IDNO}$	195 $_{IDNO}$	195 $_{IDNO}$	195 $_{IDNO}$	195 $_{IDNO}$
Observations	4850	4850	4850	4850	4850

Note. σ2 = population variance, τ00 = random intercept variance, IDNO = participant identifier, DAY = day number. Information in this table obtained using summary() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S20. Type 3 Sum of Squares ANOVA table for LMMs 1-5 assessing whether each affect component varied significantly between 1) samples (pre- vs during lockdown), 2) age groups (young vs older), and 3) social environments (alone, around people but not interacting and around people and interacting).

	Negative Affect				**Positive Affect**			
Main effects & interactions	SS	DF	*F*	*p*	SS	DF	*F*	*p*
Sample	0.65	1, 189	1.96	.163	0.02	1, 185	0.04	.848
Age group	11.16	1, 188	33.62	**<.001**	0.02	1, 184	0.05	.817
Social environment	0.25	2, 4634	0.38	.683	123.10	2, 4652	147.53	**<.001**
Age-Group mean centered age	0.40	1, 184	1.20	.276	1.36	1, 179	3.27	.072
Sample * Age group	0.00	1, 188	0.00	.991	0.05	1, 184	0.11	.738
Sample * Social environment	0.38	2, 4634	0.58	.561	4.41	2, 4653	5.28	**.005**
Age group * Social environment	5.58	2, 4634	8.41	**<.001**	0.01	2, 4653	0.01	.990
Sample * Age group * Social environment	1.40	2, 4634	2.10	.122	2.60	2, 4653	3.12	.044

Note. SS = Sum of Squares. DF = numerator and denominator degrees of freedom. P-values <.01 are in bold. Age group mean-centered age was included as a nuisance covariate in all models. Information in this table obtained using anova() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S21. Unstandardized parameter estimates for LMMs 1-5 assessing whether each affect component varied significantly between 1) samples (pre- vs during lockdown), 2) age groups (young vs older), and 3) social environments (alone, around people but not interacting, around people and interacting).

	Negative Affect				**Positive Affect**			
Factor level	*b*	95% CI	*t*	*p*	*b*	95% CI	*t*	*p*
(Intercept)	-0.07	-0.19 – 0.04	-1.26	.208	0.07	-0.04 – 0.17	1.20	.231
Lockdown	0.08	-0.03 – 0.20	1.40	.161	0.01	-0.10 – 0.12	0.19	.848
Younger	0.34	0.23 – 0.46	5.80	**<.001**	0.01	-0.10 – 0.12	0.23	.816
Alone	-0.01	-0.04 – 0.02	-0.84	.400	-0.19	-0.23 – -0.16	-11.02	**<.001**
Interacting	0.00	-0.03 – 0.03	0.09	.925	0.29	0.25 – 0.32	16.32	**<.001**
Age group mean-centered age	-0.01	-0.04 – 0.01	-1.09	.274	-0.02	-0.04 – 0.00	-1.81	.071
Lockdown * Younger	-0.00	-0.12 – 0.12	-0.01	.991	0.02	-0.09 – 0.13	0.33	.738
Lockdown * Alone	-0.01	-0.04 – 0.02	-0.47	.637	0.04	0.00 – 0.07	2.04	**.041**
Lockdown * Interacting	0.02	-0.01 – 0.05	1.07	.284	-0.05	-0.09 – -0.02	-3.11	**.002**
Younger * Alone	0.06	0.03 – 0.09	3.63	**<.001**	-0.00	-0.04 – 0.03	-0.10	.919
Younger * Interacting	-0.05	-0.08 – -0.02	-3.12	**.002**	-0.00	-0.04 – 0.03	-0.05	.959
Lockdown * Younger * Alone	0.00	-0.03 – 0.04	0.29	.770	-0.01	-0.04 – 0.03	-0.32	.750
Lockdown * Younger * Interacting	0.03	-0.00 – 0.06	1.78	.076	-0.04	-0.07 – -0.00	-2.18	**.029**

Note. Summed contrasts were used meaning that the intercept reflects the grand mean of all conditions for each model and each estimate (*b*) reflects the difference between the factor level and the intercept. P-values <.05 are in bold. Information in this table obtained using summary() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S22. A summary of the variance explained by random effects for LMMs 1-5 assessing whether each affect component varied significantly between 1) samples (pre- vs during lockdown), 2) age groups (young vs older), and 3) social environments (alone, around people but not interacting, around people and interacting).

	Negative Affect	**Positive Affect**
σ^2	0.33	0.42
τ_{00}	0.09 $_{\text{DAY: IDNO}}$	0.11 $_{\text{DAY: IDNO}}$
	0.50 $_{\text{IDNO}}$	0.42 $_{\text{IDNO}}$
N	10 $_{\text{DAY}}$	10 $_{\text{DAY}}$
	195 $_{\text{IDNO}}$	195 $_{\text{IDNO}}$
Observations	4926	4926

Note. σ^2 = population variance, τ_{00} = random intercept variance. IDNO = participant identifier, DAY = day number. Information in this table obtained using summary() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S23. Additional experience-sampling questions (beyond those assessing thoughts and affect) reported in the main manuscript.

Measure name	Question phrasing	Sample	Possible responses
Social environment	“Were you alone or with other people (physically and not virtually) just before taking this survey?”	Both (pre- and during lockdown)	“Alone”, “Around people but not interacting”, “Around people and interacting”
Virtual social environment	“Virtually, were you alone or with other people just before taking this survey? Interacting = direct communication with another person/people by text, instant messaging, calling, or video calling etc. Around but not interacting = reading messages but not replying, being on a video call but not talking/participating etc.”	During lockdown only	“Alone”, “Around people but not interacting”, “Around people and interacting”
Location	“WHERE were you just before taking this survey?”	During lockdown only	“Inside at home”, “Inside at workplace”, “Inside shop”, “Outside in nature”, “Outside in town/city”, “Outside (other)”, “Inside (other)”
Activity	“What were you DOING just before taking this survey? If you were doing more than one thing, please select your PRIMARY activity…”	During lockdown only	"Caring for an adult(s)", "Childcare", "Cooking", "Eating and/or drinking", "Exercising", "Getting ready for bed", "Getting ready for the day", "Household chores", "Leisure: arts and crafts", "Leisure: gardening", "Leisure: listening to music", "Leisure: listening to radio/podcast", "Leisure: other", "Leisure: playing a game", "Leisure: reading for pleasure", "Leisure: watching TV/film", "Reading/listening to/watching the news", "Shopping", "Sleeping", "Social media", "Talking/conversation (in person)", "Talking/conversation (virtually)", "Working", "Other"

Note. At the beginning of the survey, participants were told: “This survey will ask you what you were thinking, feeling, and doing JUST BEFORE you were signalled via text to complete this survey. There are no right or wrong answers. Please answer as honestly as possible and don't spend too long on each question. This survey should take no longer than 3-4 minutes to complete.”

Table S24. Type 3 Sum of Squares ANOVA table for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) samples (pre- vs during lockdown), 2) age groups (young vs older), and 3) social environments (alone, around people but not interacting and around people and interacting) while limiting age range of young age group to 18-27 in both samples (N= 188).

	Future-directed problem-solving				**Pleasant engagement**				**Episodic social**				**Imagery**				**Detailed task focus**			
Main effects and interactions	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*	SS	DF	*F*	*p*
Sample	11.69	1, 186	15.43	**<.001**	2.59	1, 189	3.74	.055	0.12	1, 191	0.17	.685	0.08	1, 187	0.14	.711	0.01	1, 190	0.01	.925
Age group	4.72	1, 184	6.23	**.013**	12.90	1, 187	18.63	**<.001**	4.86	1, 189	6.67	**.011**	0.29	1, 186	0.48	.491	0.54	1, 189	0.78	.379
Social environment	49.16	2, 4670	32.45	**<.001**	7.61	2, 4670	5.50	**.004**	46.72	2, 4674	32.10	**<.001**	0.79	2, 4626	0.66	.518	0.63	2, 4658	0.46	.634
Age group mean-centered age	0.06	1, 169	0.09	.771	0.50	1, 174	0.73	.395	3.68	1, 174	5.05	.026	0.82	1, 177	1.37	.244	0.60	1, 177	0.88	.351
Sample * Age group	0.09	1, 182	0.11	.737	2.55	1, 185	3.69	.056	0.12	1, 187	0.17	.683	0.03	1, 185	0.05	.818	0.50	1, 187	0.72	.396
Sample: * Social environment	0.15	2, 4670	0.10	.904	2.44	2, 4670	1.76	.171	8.46	2, 4674	5.81	**.003**	3.53	2, 4626	2.96	.052	0.94	2, 4658	0.68	.506
Age group * Social environment	2.36	2, 4670	1.56	.211	8.08	2, 4670	5.84	**.003**	0.39	2, 4674	0.27	.765	5.13	2, 4626	4.30	**.014**	1.28	2, 4658	0.93	.395
Sample * Age group * Social environment	0.72	2, 4670	0.48	.622	3.55	2, 4670	2.57	.077	4.68	2, 4674	3.22	.040	8.42	2, 4626	7.05	**.001**	0.95	2, 4658	0.69	.502

Note. SS = Sum of Squares. DF = numerator and denominator degrees of freedom. P-values <.01 are in bold. Age group mean-centered age was included as a nuisance covariate in all models. Information in this table obtained using anova() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S25. Unstandardized parameter estimates for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) samples (pre- vs during lockdown), 2) age groups (young vs older) and 3) social environments (alone, around people but not interacting, around people and interacting) while limiting age range of young age group to 18-27 in both samples (N = 188).

	Future-directed problem-solving				**Pleasant engagement**				**Episodic social**				**Imagery**				**Detailed task focus**			
Factor level	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*
(Intercept)	-0.07	-0.15 – 0.01	-1.79	.073	0.09	0.01 – 0.17	2.08	**.037**	-0.01	-0.09 – 0.07	-0.23	.817	0.01	-0.08 – 0.11	0.30	.766	-0.02	-0.12 – 0.07	-0.53	.595
Lockdown	-0.15	-0.23 – -0.08	-3.93	**<.001**	0.08	-0.00 – 0.16	1.93	.053	0.02	-0.06 – 0.09	0.41	.685	0.02	-0.08 – 0.12	0.37	.711	-0.00	-0.10 – 0.09	-0.09	.925
Younger	0.10	0.02 – 0.17	2.50	**.013**	-0.18	-0.26 – -0.10	-4.32	**<.001**	0.10	0.03 – 0.18	2.58	**.010**	-0.03	-0.13 – 0.06	-0.69	.490	0.04	-0.05 – 0.13	0.88	.377
Alone	0.11	0.06 – 0.15	4.77	**<.001**	-0.03	-0.07 – 0.02	-1.26	.209	-0.08	-0.13 – -0.04	-3.77	**<.001**	-0.02	-0.06 – 0.02	-1.11	.267	0.02	-0.02 – 0.06	0.95	.341
Interacting	-0.18	-0.23 – -0.13	-7.74	**<.001**	0.07	0.03 – 0.12	3.31	**.001**	0.18	0.14 – 0.23	7.94	**<.001**	0.01	-0.03 – 0.06	0.66	.511	-0.01	-0.05 – 0.03	-0.40	.686
Age group mean-centered age	0.00	-0.01 – 0.02	0.29	.771	0.01	-0.01 – 0.02	0.85	.394	-0.02	-0.04 – -0.00	-2.25	**.025**	-0.01	-0.03 – 0.01	-1.17	.242	-0.01	-0.03 – 0.01	-0.94	.350
Lockdown * Younger	-0.01	-0.09 – 0.07	-0.34	.737	0.08	-0.00 – 0.17	1.92	.055	0.02	-0.07 – 0.10	0.41	.683	0.01	-0.09 – 0.11	0.23	.818	-0.04	-0.14 – 0.05	-0.85	.395
Lockdown * Alone	-0.01	-0.05 – 0.04	-0.38	.703	0.03	-0.01 – 0.07	1.29	.196	-0.06	-0.11 – -0.02	-2.75	**.006**	0.02	-0.02 – 0.06	1.15	.248	0.02	-0.03 – 0.06	0.70	.482
Lockdown * Interacting	0.01	-0.04 – 0.05	0.36	.722	-0.04	-0.08 – 0.01	-1.73	.084	0.06	0.02 – 0.11	2.84	**.005**	-0.05	-0.09 – -0.01	-2.41	**.016**	0.01	-0.03 – 0.06	0.63	.529
Younger * Alone	-0.02	-0.07 – 0.02	-1.03	.303	-0.04	-0.08 – 0.00	-1.91	.056	-0.01	-0.05 – 0.03	-0.41	.682	0.05	0.01 – 0.09	2.56	**.011**	-0.03	-0.07 – 0.01	-1.32	.187
Younger * Interacting	0.04	-0.01 – 0.08	1.70	.090	0.07	0.03 – 0.12	3.32	**.001**	-0.01	-0.05 – 0.03	-0.43	.667	-0.05	-0.09 – -0.01	-2.24	**.025**	0.02	-0.03 – 0.06	0.78	.438
Lockdown * Younger * Alone	-0.02	-0.07 – 0.02	-0.93	.353	-0.05	-0.09 – -0.00	-2.07	**.038**	-0.06	-0.10 – -0.01	-2.52	**.012**	0.07	0.03 – 0.12	3.58	**<.001**	0.02	-0.02 – 0.06	0.88	.381
Lockdown * Younger * Interacting	0.00	-0.04 – 0.05	0.04	.970	-0.00	-0.05 – 0.04	-0.15	.883	0.01	-0.03 – 0.06	0.56	.574	-0.05	-0.09 – -0.01	-2.32	**.020**	0.01	-0.03 – 0.05	0.43	.668

Note. Summed contrasts were used meaning that the intercept reflects the grand mean of all conditions for each model and each estimate (*b*) reflects the difference between the factor level and the intercept. P-values <.05 are in bold. Information in this table obtained using summary() function as part of the lmerTest package (Kuznetsova et al., 2017).

Table S26. A summary of the variance explained by random effects for LMMs 1-5 assessing whether each thought pattern varied significantly between 1) samples (pre- vs during lockdown), 2) age groups (young vs older), and 3) social environments (alone, around people but not interacting, around people and interacting) while limiting age range of young age group to 18-27 in both samples (N = 188).

	Future-directed problem-solving	**Pleasant engagement**	**Episodic social**	**Imagery**	**Detailed task focus**
σ^2	0.76	0.69	0.73	0.60	0.69
τ_{00}	0.04 $_{\text{DAY: IDNO}}$	0.03 $_{\text{DAY: IDNO}}$	0.05 $_{\text{DAY: IDNO}}$	0.07 $_{\text{DAY: IDNO}}$	0.03 $_{\text{DAY: IDNO}}$
	0.18 $_{\text{IDNO}}$	0.22 $_{\text{IDNO}}$	0.19 $_{\text{IDNO}}$	0.32 $_{\text{IDNO}}$	0.28 $_{\text{IDNO}}$
N	10 $_{\text{DAY}}$	10 $_{\text{DAY}}$	10 $_{\text{DAY}}$	10 $_{\text{DAY}}$	10 $_{\text{DAY}}$
	188 $_{\text{IDNO}}$	188 $_{\text{IDNO}}$	188 $_{\text{IDNO}}$	188 $_{\text{IDNO}}$	188 $_{\text{IDNO}}$
Observations	4715	4715	4715	4715	4715

Note. σ2 = population variance, τ00 = random intercept variance. IDNO = participant identifier, DAY = day number. Information in this table obtained using summary() function as part of the lmerTest package (Kuznetsova et al., 2017).

A.2 Supplementary Materials: Chapter 3

This section contains the supplementary materials for Chapter 3 including:

- S1 Text
  - Supplementary Analysis
  - Tables A-I
  - Figures A-T
- S2 Text
  - Supplementary Analysis
  - Tables A-S
  - Figures A-I

S1 Text

Supplementary Analysis

Principal Components Analysis (PCA) on Separate Laboratory Samples

To ensure that the thought patterns identified across both laboratory samples (n = 119) were present in both samples separately, we ran a PCA on each sample separately (z-scored each sample separately and specified three components for extraction) and correlated each participant's PCA score from this analysis with their PCA score from the combined analysis. This analysis revealed a high correspondence between the two-sample and one-sample solutions (see Fig G for scatterplots). For laboratory Sample 1 (n = 70), the Kaiser–Meyer–Olkin measure of sampling adequacy was 0.72, above the commonly recommended value of 0.6, and Bartlett's test of sphericity was significant ($\chi 2[78] = 1582.26$, $p < .001$). The three components explained 46% of the total variance and see Fig E for scree plot and Table C for component loadings. For laboratory Sample 2 (n = 49), the Kaiser–Meyer–Olkin measure of sampling adequacy was 0.73 and Bartlett's test of sphericity was significant ($\chi 2[78] = 1618.08$, $p < .001$). The three components explained 51% of the total variance and see Fig F for scree plot and Table D for component loadings.

Correspondence between 13-item, 11-item, and 8-item PCAs in Combined Laboratory Samples

To support the validity of the projection of laboratory patterns on to daily life data using only 11 items, we ran a PCA on these 11 items in the combined laboratory data (specified three components for extraction; see Fig M for scree plot and Table E for component loadings) and correlated each participant's PCA score from this analysis with their 13-item PCA score. This analysis revealed a high correspondence between the 11-item and 13-item patterns (see Fig N for scatterplots). The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.68, above the commonly recommended value of 0.6, and Bartlett's test of sphericity was significant ($\chi 2[55] = 2165.67$, $p < .001$). The three components explained 50% of the total variance.

In addition, we ran a PCA on the 8 items in the combined laboratory data that had like-for-like equivalents in the laboratory and daily life (specified three components for extraction; see Fig M for scree plot and Table F for component loadings) and correlated each participant's PCA score from this analysis with their 13-item PCA score. This analysis revealed a high correspondence between the 8-item and 13-item patterns (see Fig N for scatterplots). The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.64, above the commonly recommended value of 0.6, and Bartlett's test of sphericity was significant ($\chi 2[28] = 1277.87$, $p < .001$). The three components explained 60% of the total variance.

Correspondence between Projected and Direct PCA solutions in Daily Life Data

To understand how the projected laboratory patterns related to patterns present in the daily life data, we ran a PCA on the combined daily life thought datasets (11 items; specified three components for extraction) and correlated each participant's PCA score from this analysis with their projected PCA score (see Fig P for scatterplots). The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.67, above the commonly recommended value of 0.6, and Bartlett's test of sphericity was significant ($\chi 2[55] = 5471.21$, $p < .001$). The three components explained 49% of the total variance and see Fig O for scree plot and Table G for component loadings.

In addition, we ran a PCA on each daily life sample separately (before- and during-COVID; specified three components for extraction) and correlated each participant's PCA score from this analysis with their projected PCA score (see Figs S and T for scatterplots). For the pre-COVID sample, the Kaiser–Meyer–Olkin measure of sampling adequacy was 0.61, above the commonly recommended value of 0.6, and Bartlett's test of sphericity was significant ($\chi 2[55] = 3314.90$, $p < .001$). The three components explained 48% of the total variance and see Fig Q for scree plot and Table H for component loadings. For the post-COVID sample, the Kaiser–Meyer–Olkin measure of sampling adequacy was 0.79, above the commonly recommended value of 0.6, and Bartlett's test of sphericity was significant ($\chi 2[55]$

= 2602.18, $p < .001$). The three components explained 53% of the total variance and see Fig R for scree plot and Table I for component loadings.

Supplementary Tables

Table A. Multidimensional experience-sampling items used in Principal Components Analyses (PCA).

Item	**Context**	**Wording**	**Low**	**High**
Task	All	**Lab:** My thoughts were focused on the task. **Daily Life:** My thoughts were related to my current activity and/or external environment.	Not at all	Completely
Future	All	**Lab:** My thoughts involved future events. **Daily Life:** My thoughts were about the future.	Not at all	Completely
Past	All	**Lab:** My thoughts involved past events. **Daily Life:** My thoughts were about the past.	Not at all	Completely
Self	All	My thoughts involved myself	Not at all	Completely
Person [1]	All	**Lab:** My thoughts involved other people **Daily Life:** My thoughts involved other people close to me **Daily Life:** My thoughts involved other people NOT close to me	Not at all	Completely
Positive	All	**Lab:** The emotion of my thoughts was… **Daily Life:** My thoughts were....	**Lab:** Negative **Daily Life:** Very negative	**Lab:** Positive **Daily Life:** Very positive
Words [2]	All	**Lab:** My thoughts were in the form of: **Daily Life:** My thoughts were in the form of words	**Lab:** Images **Daily Life:** Not at all	**Lab:** Words **Daily Life:** Completely
Detailed	All	My thoughts were detailed and specific	Not at all	Completely
Deliberate	All	My thoughts were…	**Lab:** Spontaneous **Daily Life:** Completely spontaneous	**Lab:** Deliberate **Daily Life:** Completely deliberate
Problem-Solving	All	**Lab & COVID:** I was thinking about solutions to problems (or goals): **Pre-COVID:** To what extent are your thoughts... Focused on solving a problem?	Not at all	Completely
Diverse	Lab, COVID	**Lab:** My thoughts were… **COVID:** My thoughts were about…	One topic	Many topics
Intrusive [3]	All	**Lab:** My thoughts were intrusive **Daily Life:** I wanted to have my thoughts	Not at all	Completely
Memory	Lab, COVID	**Lab:** My thoughts were linked to information from: **COVID:** My thoughts were linked to information from my…	Environment	Memory

Note. 'Context' column indicates which contexts the item was used in. 'Lab' refers to the laboratory samples. 'COVID' refers to the COVID daily life sample and 'Pre-COVID' refers to the Pre-COVID daily life sample. 1) Average of the two items from daily life data used as 'Person' item when projecting the PCA components derived from the combined laboratory thought datasets on to the daily life data. 2) In the laboratory data, the 'Words' item had 'images' and 'words' at either end of the scale, while in the daily life data, the 'Words' item had 'Not at all' and 'Completely' at either end of the scale. 'Words' items from daily life data used when projecting the PCA components derived from the combined laboratory thought datasets on to the daily life data. 3) Reverse scored 'Wanted' item from daily life data to use as 'Intrusive' item when projecting the PCA components derived from the combined laboratory thought datasets on to the daily life data.

Table B. Varimax rotated component matrix for the PCA applied to the thought data (13 items; see Table A) obtained from both laboratory samples (n = 119).

Questionnaire items		**Components**	
	1	2	3
Task	-0.35	0.22	0.12
Future	0.19	**0.43**	0.03
Past	**0.43**	0.08	-0.03
Self	**0.46**	0.07	-0.06
Person	0.03	**0.48**	-0.08
Emotion	0.29	-0.39	0.10
Words	0.07	-0.09	0.19
Detail	0.02	0.15	**0.60**
Deliberate	-0.02	-0.12	**0.69**
Problem	0.02	0.37	0.26
Diverse	0.38	0.08	-0.05
Intrusive	0.00	**0.42**	-0.08
Memory	**0.45**	-0.04	0.12

Note. Values greater than 0.4 and values less than -0.4 are in bold.

Table C. Varimax rotated component matrix for the PCA applied to the thought data (13 items; see Table A) obtained from laboratory Sample 1 (n = 70).

Questionnaire items		**Components**	
	1	2	3
Task	-0.36	-0.22	0.08
Future	0.12	**-0.46**	-0.03
Past	**0.42**	-0.08	0.03
Self	**0.48**	-0.05	-0.12
Person	-0.06	**-0.41**	-0.07
Emotion	0.32	0.26	0.19
Words	0.00	0.10	0.39
Detail	0.01	-0.34	**0.46**
Deliberate	0.00	0.05	**0.67**
Problem	-0.06	-0.43	0.22
Diverse	0.38	-0.20	-0.06
Intrusive	0.08	-0.38	-0.23
Memory	**0.44**	0.02	0.15

Note. Values greater than 0.4 and values less than -0.4 are in bold.

Table D. Varimax rotated component matrix for the PCA applied to the thought data (13 items; see Table A) obtained from laboratory Sample 2 (n = 49).

Questionnaire items		**Components**	
	1	2	3
Task	-0.32	-0.23	0.15
Future	0.27	-0.34	0.08
Past	**0.46**	-0.05	-0.08
Self	**0.46**	-0.05	0.00
Person	0.15	**-0.48**	-0.02
Emotion	0.20	**0.51**	0.09
Words	0.07	0.07	0.18
Detail	0.01	0.02	**0.67**
Deliberate	-0.04	0.06	**0.60**
Problem	0.08	-0.30	0.31
Diverse	0.36	0.07	-0.01
Intrusive	-0.01	**-0.48**	-0.06
Memory	**0.45**	0.05	0.08

Note. Values greater than 0.4 and values less than -0.4 are in bold.

Table E. Varimax rotated component matrix for the PCA applied to the 11 thought items that have approximate equivalents in the daily life data (see Table A) obtained from the combined laboratory samples (n = 119).

Questionnaire items	**Components**		
	1	2	3
Task	0.23	**-0.43**	0.08
Future	**0.42**	0.26	0.08
Past	0.09	**0.52**	-0.03
Self	0.07	**0.59**	-0.02
Person	**0.48**	0.05	-0.06
Emotion	**-0.40**	0.34	0.13
Words	-0.12	0.08	0.26
Detail	0.14	0.00	**0.60**
Deliberate	-0.13	-0.04	**0.67**
Problem	0.36	0.04	0.28
Intrusive	**0.43**	0.01	-0.08

Note. Values greater than 0.4 and values less than -0.4 are in bold.

Table F. Varimax rotated component matrix for the PCA applied to the 8 thought items that have like-for-like equivalents in the daily life data (see Table A) obtained from the combined laboratory samples (n = 119).

Questionnaire items	**Components**		
	1	2	3
Task	**-0.48**	0.22	0.02
Future	0.16	**0.59**	-0.08
Past	**0.49**	0.14	0.03
Self	**0.57**	0.21	-0.09
Emotion	**0.42**	-0.35	0.18
Detail	-0.03	0.28	**0.56**
Deliberate	0.00	-0.09	**0.80**
Problem	-0.04	0.57	0.07

Note. Values greater than 0.4 and values less than -0.4 are in bold.

Table G. Varimax rotated component matrix for the PCA applied to the thought data (11 items; see Table A) obtained from both daily life samples (pre- and during-COVID; n = 137).

Questionnaire items	**Components**		
	1	2	3
Task	0.05	-0.34	0.27
Future	**0.43**	0.28	-0.02
Past	0.02	**0.52**	-0.06
Self	0.31	0.25	-0.03
Emotion	-0.18	0.12	**0.64**
Detail	0.35	0.06	0.21
Deliberate	0.28	-0.18	0.30
Problem	**0.56**	-0.11	-0.11
Words	0.39	-0.11	-0.09
Person	-0.04	**0.63**	0.15
Intrusive	-0.11	0.02	-0.58

Note. Values greater than 0.4 and values less than -0.4 are in bold.

Table H. Varimax rotated component matrix for the PCA applied to the thought data (11 items; see Table A) obtained from the pre-COVID daily life sample (n = 78).

Questionnaire items		**Components**	
	1	2	3
Task	-0.28	-0.31	-0.21
Future	-0.05	**0.65**	0.02
Past	0.02	-0.06	**0.60**
Self	0.08	**0.56**	0.06
Emotion	-0.32	-0.05	0.16
Detail	**-0.45**	-0.01	0.22
Deliberate	**-0.44**	0.12	-0.17
Problem	-0.21	0.38	-0.27
Words	-0.22	-0.03	-0.03
Person	-0.06	0.08	**0.65**
Intrusive	**0.56**	0.01	-0.04

Note. Values greater than 0.4 and values less than -0.4 are in bold.

Table I. Varimax rotated component matrix for the PCA applied to the thought data (11 items; see Table A) obtained from the COVID daily life sample (n = 59).

Questionnaire items	**Components**		
	1	2	3
Task	0.00	-0.08	**0.44**
Future	**0.47**	0.12	-0.06
Past	0.08	**0.62**	-0.12
Self	0.36	-0.12	0.03
Emotion	-0.13	0.05	**0.61**
Detail	0.35	0.10	0.18
Deliberate	0.26	-0.17	0.23
Problem	**0.56**	-0.07	-0.11
Words	0.32	0.06	0.03
Person	-0.05	**0.73**	0.11
Intrusive	-0.07	-0.05	**-0.55**

Note. Values greater than 0.4 and values less than -0.4 are in bold.

Supplementary Figures

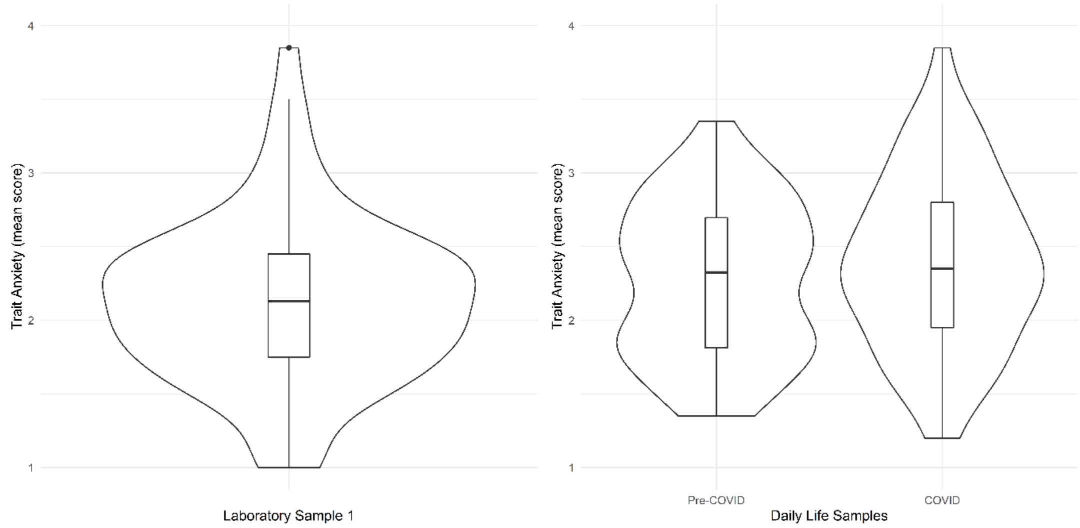

Fig A. Violin plots showing the distribution of trait anxiety (mean scores) in laboratory Sample 1 (left; n = 70) and in the pre- (n = 70) and post-COVID (n = 59) daily life samples (right). Within each violin plot, box plots are also presented. The middle line of each box plot represents the median value. The lower and upper hinges represent the first and third quartiles (25^{th} and 75^{th} percentiles). The upper whisker extends from the upper hinge to the largest value no further than 1.5 * inter-quartile range from the hinge and the lower whisker extends from the lower hinge to the smallest value at most 1.5 * inter-quartile range of the hinge. Data beyond the end of the whiskers are plotted individually.

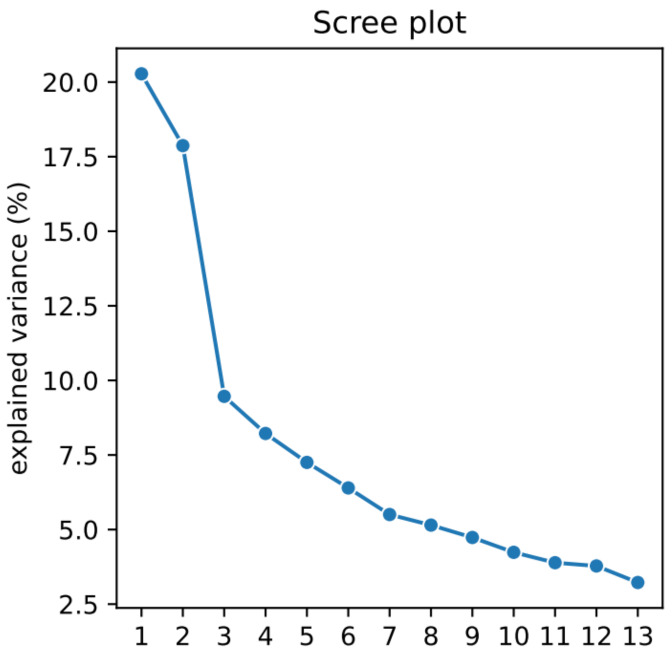

Fig B. Scree plot from the PCA applied to the thought data from both laboratory samples (n = 119; n observations = 1338) to identify common "patterns of thought" (x-axis = component number and y-axis = % variance explained by each component). Based on the elbow of the scree plot, three components were retained for further analysis.

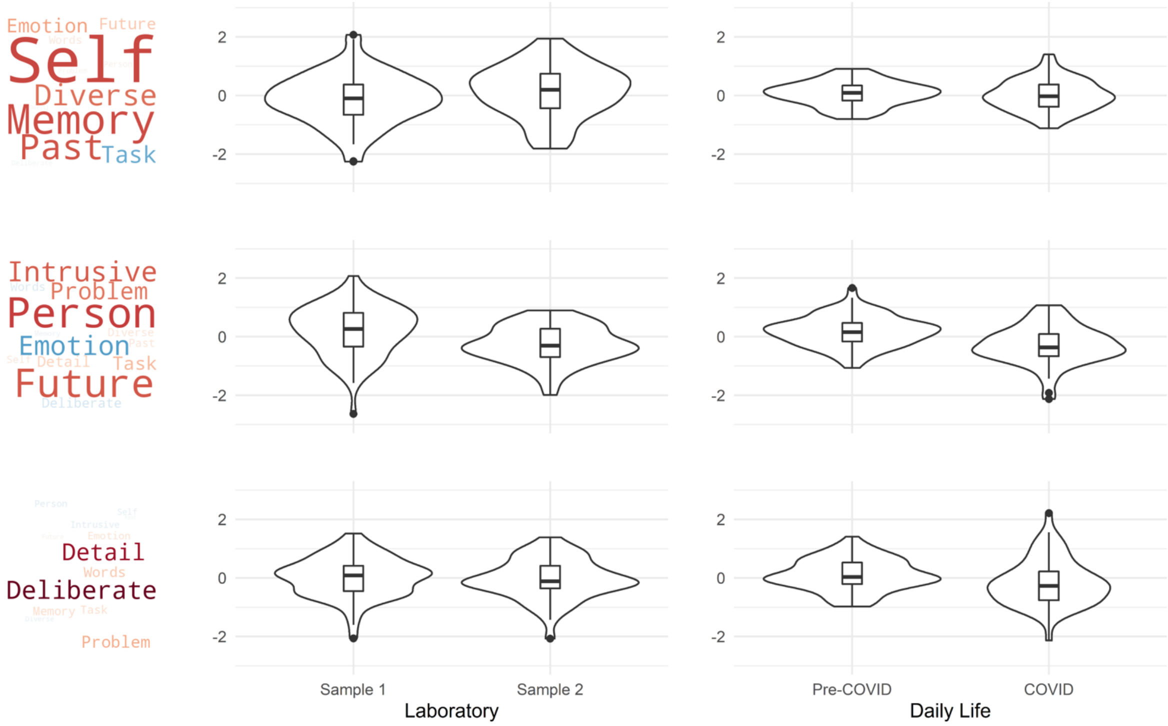

Fig C. Violin plots showing the distribution of each thought component in the laboratory samples (left) and in the daily life samples (right). Within each violin plot, box plots are also presented. The middle line of each box plot represents the median value. The lower and upper hinges represent the first and third quartiles (25^{th} and 75^{th} percentiles). The upper whisker extends from the upper hinge to the largest value no further than 1.5 * inter-quartile range from the hinge and the lower whisker extends from the lower hinge to the smallest value at most 1.5 * inter-quartile range of the hinge. Data beyond the end of the whiskers are plotted individually. There were 70 participants in laboratory Sample 1, 49 participants in laboratory Sample 2, 78 participants in the pre-COVID daily life sample, and 59 participants in the COVID daily life sample.

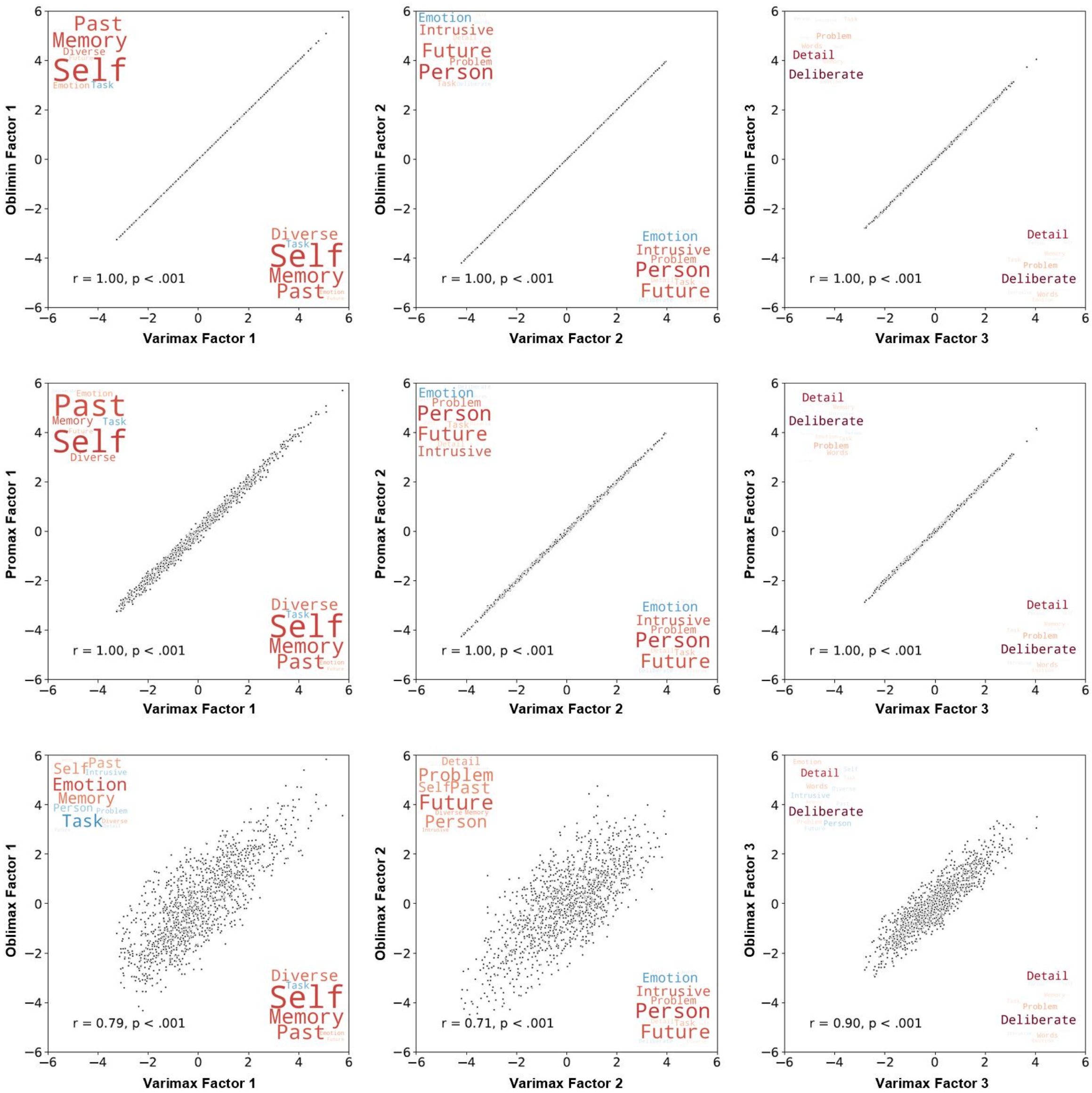

Fig D. Scatterplots and correlations demonstrating the high correspondence between varimax rotated PCA components (x-axis) and other rotation methods (y-axis). Top panel shows the correlation between varimax-rotated (orthogonal rotation) (x-axis) and oblimin-rotated (oblique rotation) (y-axis) PCA component scores. Middle panel shows the correlation between varimax-rotated (orthogonal rotation) (x-axis) and promax-rotated (oblique rotation) (y-axis) PCA component scores. Bottom panel shows the correlation between varimax-rotated (orthogonal rotation) (x-axis) and oblimax-rotated (orthogonal rotation) (y-axis) PCA component scores. Pearson correlation R and p-values were calculated using the 'pearsonr' function from the 'scipy' library (Virtanen et al., 2020). In each plot, the word clouds representing the PCA components on the y-axis are in the top left corner and the word clouds representing the PCA components on the x-axis are in the bottom right corner.

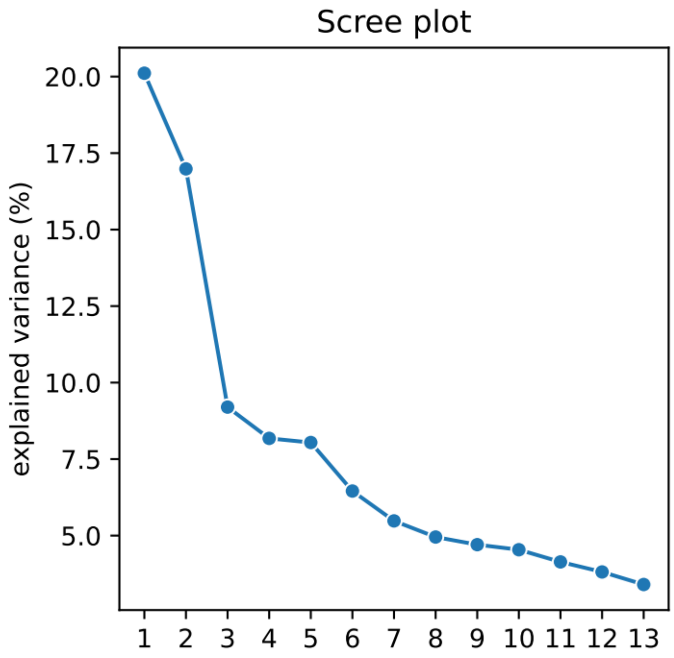

Fig E. Scree plot from the PCA applied to the thought data from laboratory Sample 1 (n = 70; n observations = 763) to identify "patterns of thought" (x-axis = component number and y-axis = % variance explained by each component).

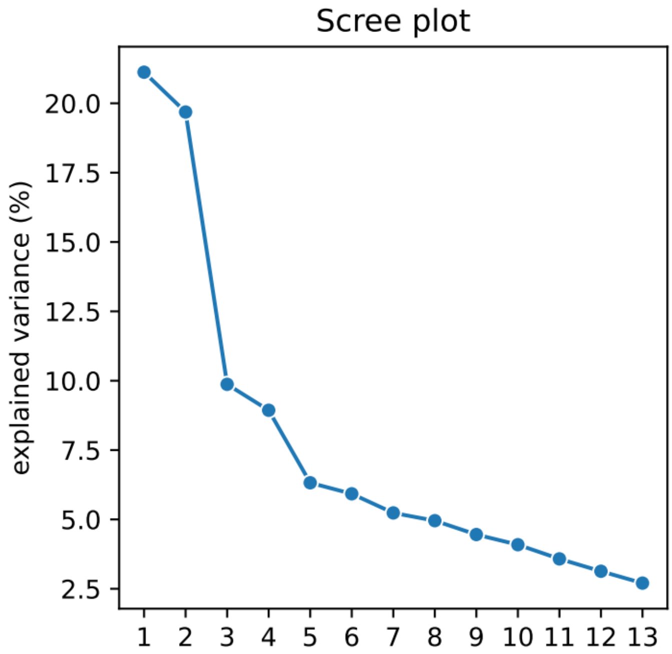

Fig F. Scree plot from the PCA applied to the thought data from laboratory Sample 2 (n = 49; n observations = 575) to identify "patterns of thought" (x-axis = component number and y-axis = % variance explained by each component).

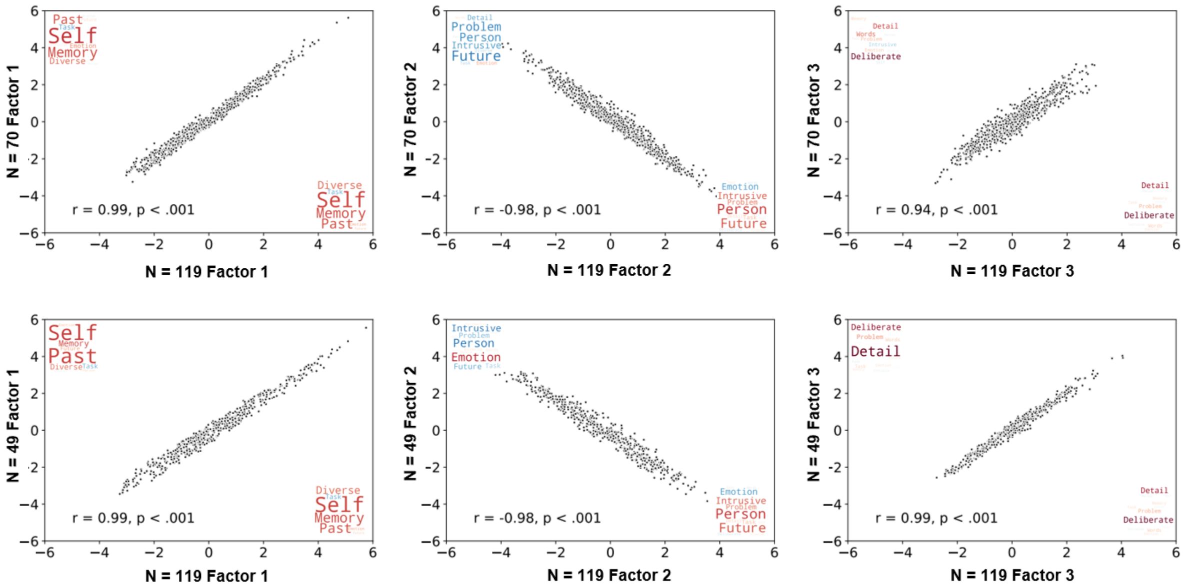

Fig G. Scatterplots and correlations demonstrating the high correspondence between PCA components (varimax rotated) derived from 1) combined laboratory thought datasets (n = 119; n observations = 1338) and 2) each laboratory thought dataset separately (n = 70 & n = 49; specified three components for extraction). Top panel shows the correlation between PCA components derived from combined laboratory thought datasets (x-axis) and laboratory Sample 1 only (y-axis; n = 70; n observations = 763). Bottom panel shows the correlation between PCA components derived from combined laboratory thought datasets (x-axis) and laboratory Sample 2 only (y-axis; n = 49; n observations = 575). Pearson correlation R and p-values were calculated using the ‘pearsonr’ function from the ‘scipy’ library (Virtanen et al., 2020). In each plot, the word clouds representing the PCA components on the y-axis are in the top left corner and the word clouds representing the PCA components on the x-axis are in the bottom right corner.

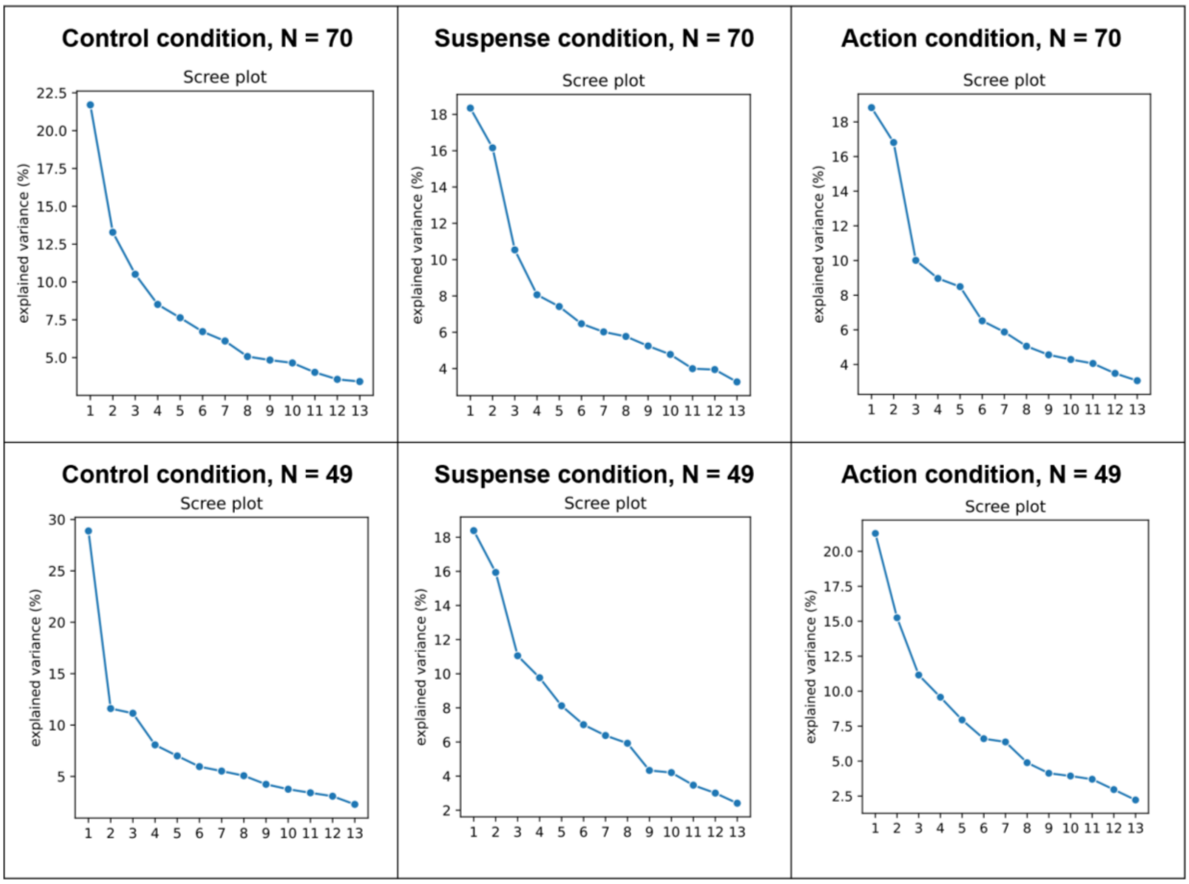

Fig H. Scree plots from the PCA applied to the thought data from each laboratory sample (n = 70 and n = 49) and video condition ('control', 'suspense' & 'action') separately to identify "patterns of thought" (specifying three components for extraction). In each plot, the x-axis reflects the component number, and the y-axis reflects the % variance explained by each component. The top panel shows the scree plots from laboratory Sample 1 (n = 70; n observations = 763) and the bottom panel shows the scree plots from laboratory Sample 2 (n = 49; n observations = 575).

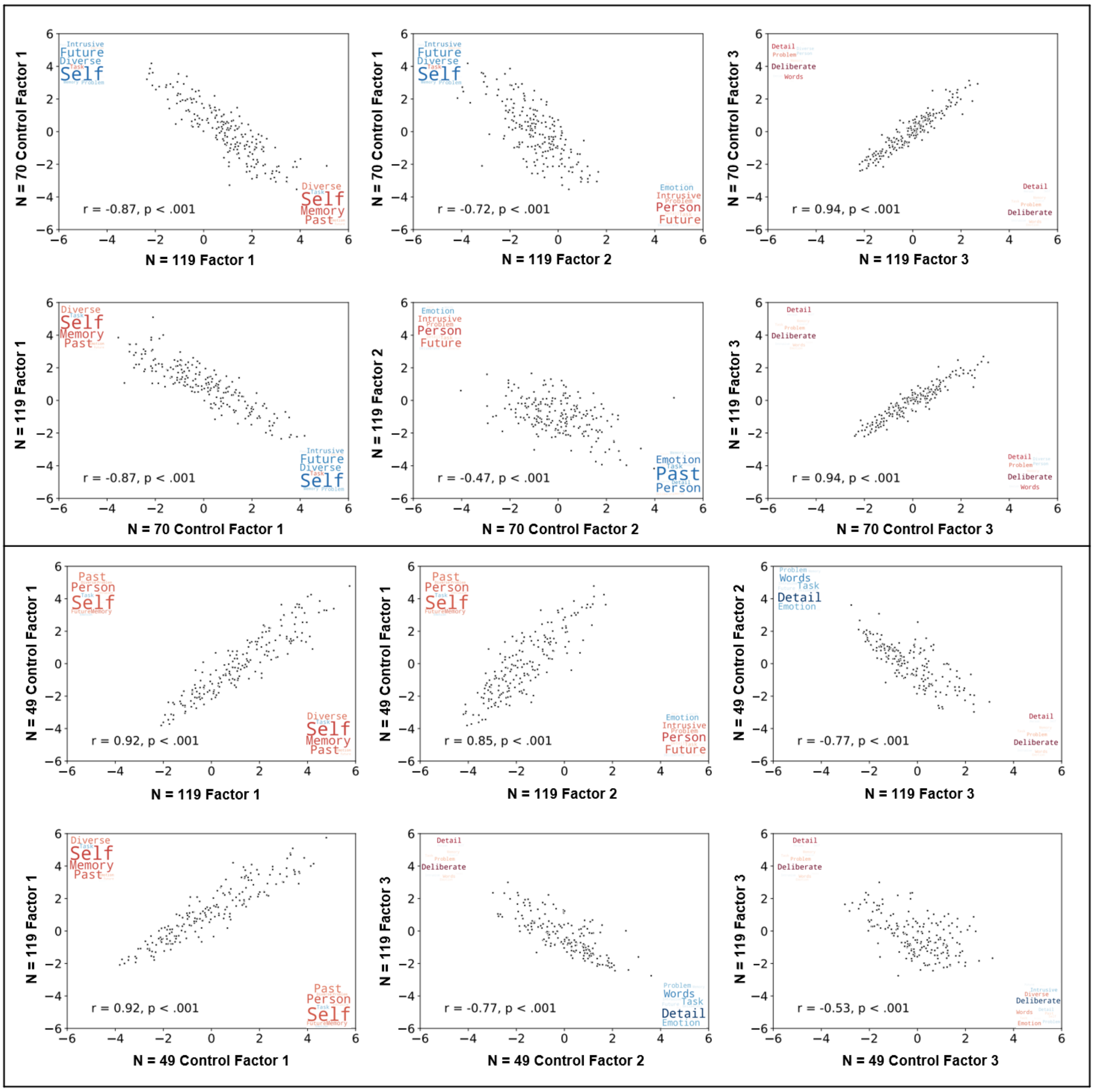

Fig I. Scatterplots demonstrating the correspondence between PCA components (varimax rotated**)** derived from 1) combined laboratory datasets (all video conditions; n = 119; n observations = 1338) and 2) the 'control' video condition in each laboratory thought sample separately (n = 70 & n = 49; specified three components for extraction). Top panel shows the highest correspondence between the combined components on the x-axis and laboratory Sample 1's 'control' condition components on the y-axis (n = 70, n observations = 210). Second panel shows the highest correspondence between laboratory Sample 1's 'control' condition components on the x-axis (n = 70; n observations = 210) and the combined components on the y-axis. Third panel shows the highest correspondence between the combined components on the x-axis and laboratory Sample 2's 'control' condition components on the y-axis (n = 49; n observations = 191). Fourth panel shows the highest correspondence between laboratory Sample 2's 'control' condition components on the x-axis (n = 49; n observations = 191) and the combined components on the y-axis. Pearson correlation R and p-values were calculated using the 'pearsonr' function from the 'scipy' library (Virtanen et al., 2020). In each plot, the word clouds representing the PCA components on the y-axis are in the top left corner and the word clouds representing the PCA components on the x-axis are in the bottom right corner.

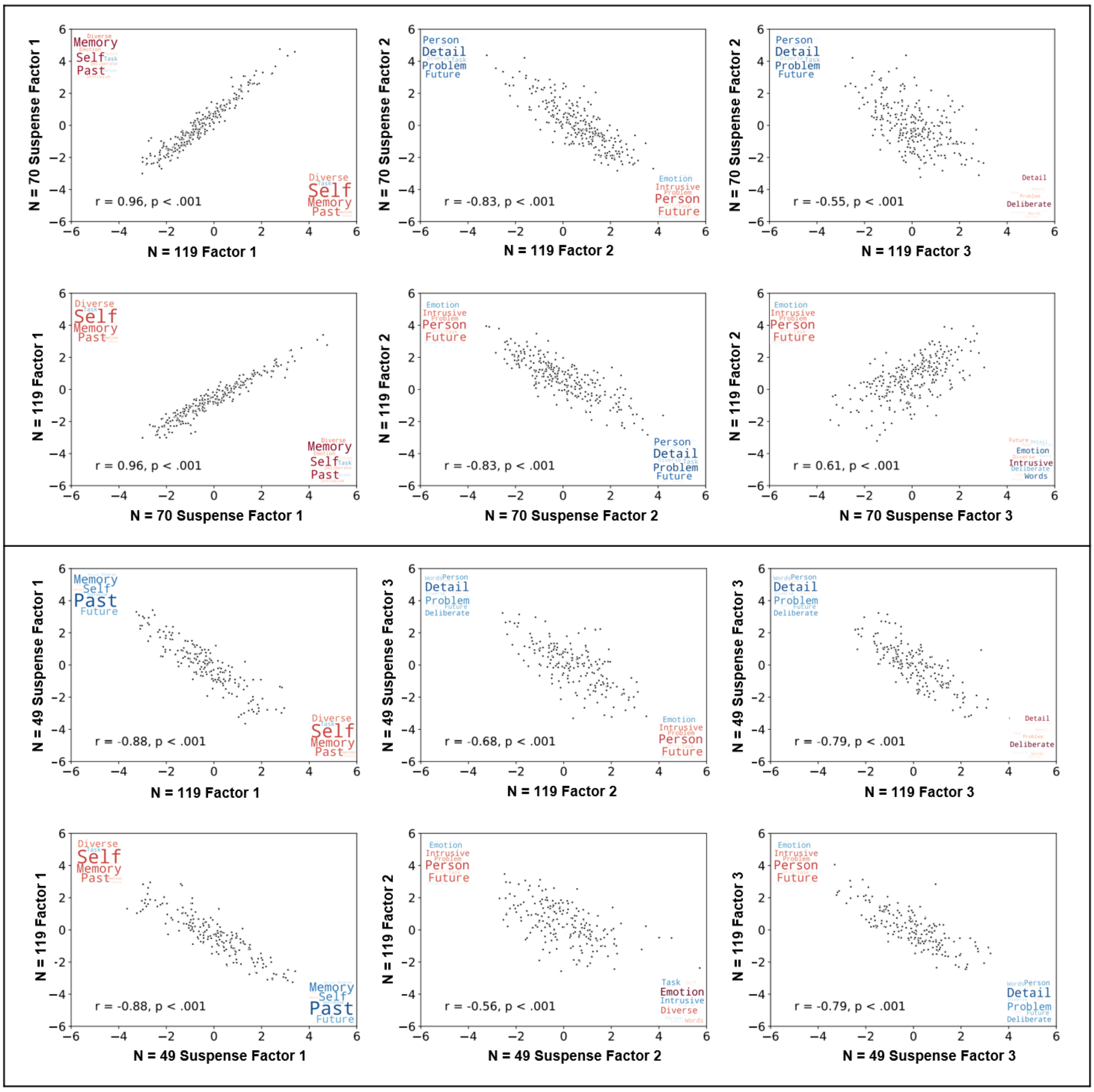

Fig J. Scatterplots and correlations demonstrating the correspondence between PCA components (varimax rotated**)** derived from 1) combined laboratory thought datasets (all video conditions; n = 119; n observations = 1338) and 2) the ‘suspense’ video condition in each laboratory thought sample separately (n = 70 & n = 49; specified three components for extraction). Top panel shows the highest correspondence between the combined components on the x-axis and laboratory Sample 1’s ‘suspense’ condition components on the y-axis (n = 70, n observations = 274). Second panel shows the highest correspondence between laboratory Sample 1’s ‘suspense’ condition components on the x-axis (n= 70; n observations = 274) and the combined components on the y-axis. Third panel shows the highest correspondence between the combined components on the x-axis and laboratory Sample 2’s ‘suspense’ condition components on the y-axis (n = 49; n observations = 192). Fourth panel shows the highest correspondence between laboratory Sample 2’s ‘suspense’ condition components on the x-axis (n = 49; n observations = 192) and the combined components on the y-axis. Pearson correlation R and p-values were calculated using the ‘pearsonr’ function from the ‘scipy’ library (Virtanen et al., 2020). In each plot, the word clouds representing the PCA components on the y-axis are in the top left corner and the word clouds representing the PCA components on the x-axis are in the bottom right corner.

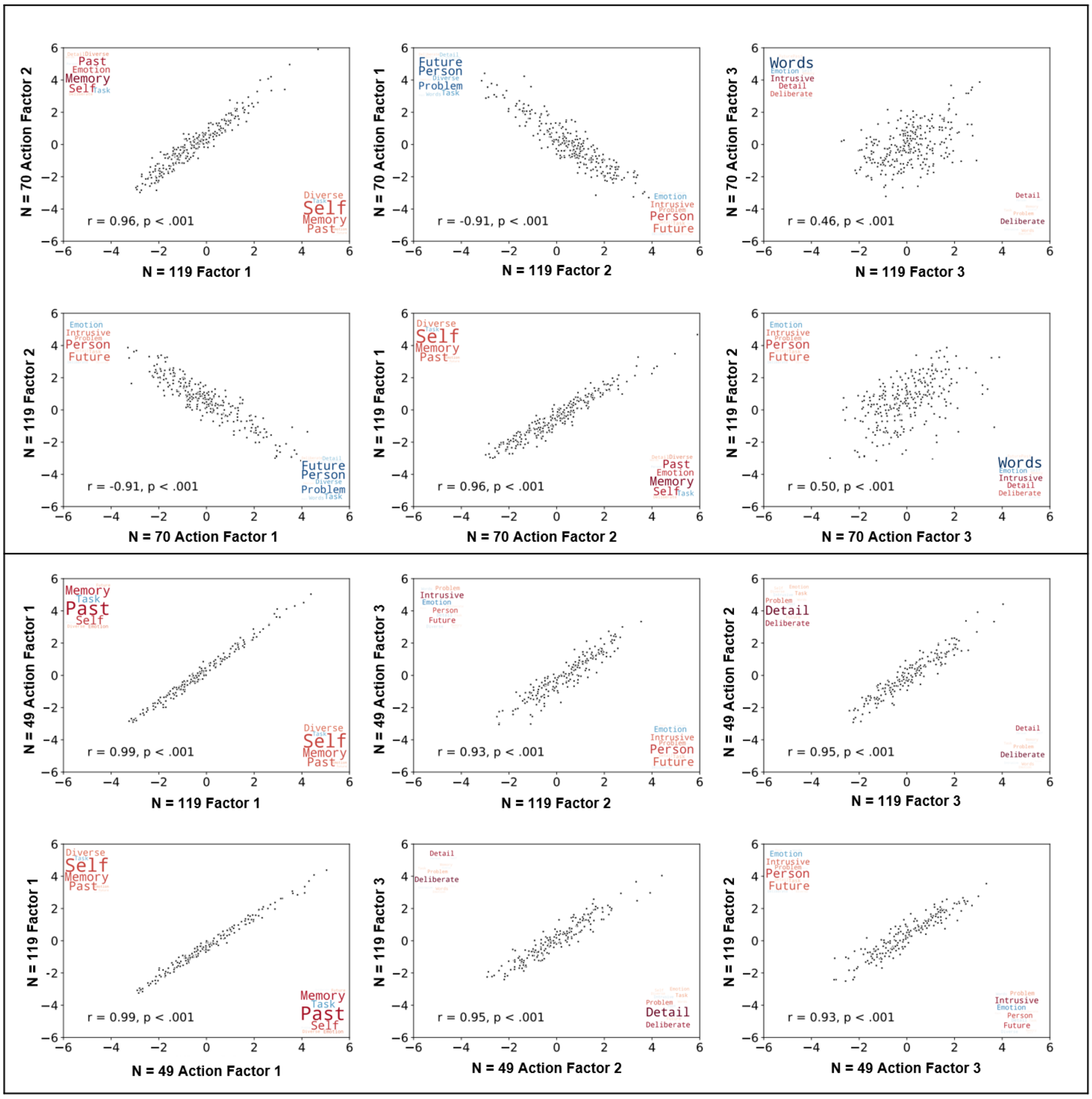

Fig K. Scatterplots and correlations demonstrating the correspondence between PCA components (varimax rotated**)** derived from 1) combined laboratory thought datasets (all video conditions; n = 119; n observations = 1338) and 2) the 'action' video condition in each laboratory thought sample separately (n = 70 & n = 49; specified three components for extraction). Top panel shows the highest correspondence between the combined components on the x-axis and laboratory Sample 1's 'action' condition components on the y-axis (n = 70, n observations = 279). Second panel shows the highest correspondence between laboratory Sample 1's 'action' condition components on the x-axis (n = 70; n observations = 279) and the combined components on the y-axis. Third panel shows the highest correspondence between the combined components on the x-axis and laboratory Sample 2's 'action' condition components on the y-axis (n = 49; n observations = 192). Fourth panel shows the highest correspondence between laboratory Sample 2's 'action' condition components on the x-axis (n = 49; n observations = 192) and the combined components on the y-axis. Pearson correlation R and p-values were calculated using the 'pearsonr' function from the 'scipy' library (Virtanen et al., 2020). In each plot, the word clouds representing the PCA components on the y-axis are in the top left corner and the word clouds representing the PCA components on the x-axis are in the bottom right corner.

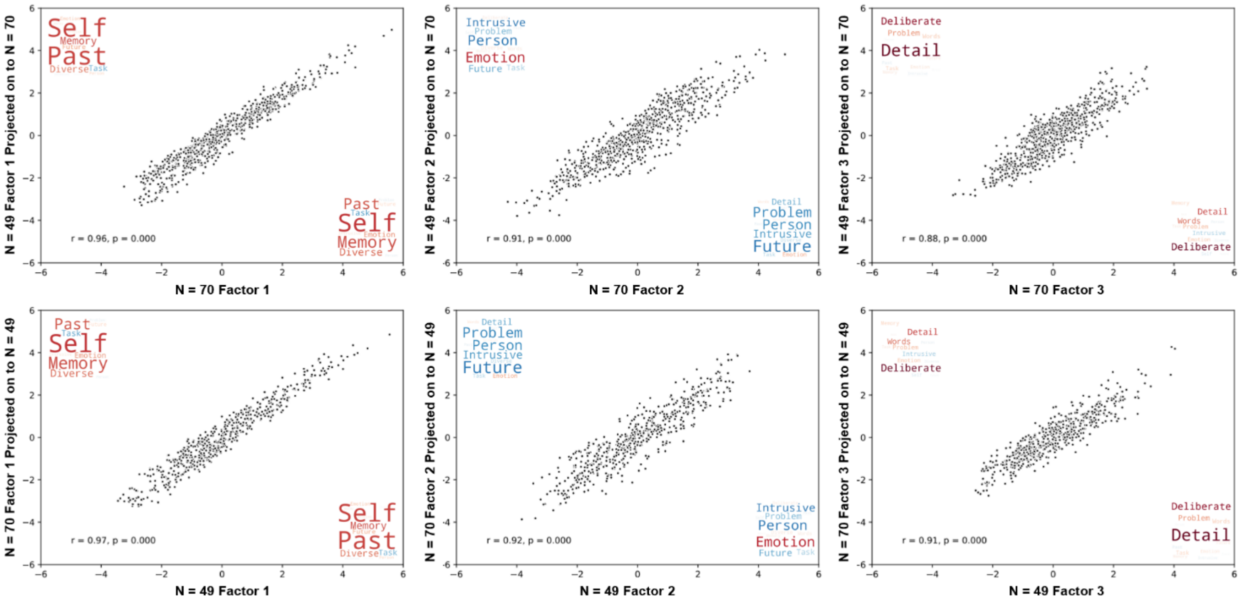

Fig L. Scatterplots and correlations demonstrating the correspondence between PCA components (varimax rotated) derived from 1) each laboratory thought dataset separately (n = 70 and n = 49; specifying three components for extraction) and 2) projecting components from one laboratory thought dataset to the other. Top panel shows the highest correspondence between PCA components derived from laboratory Sample 1 directly (x-axis; n = 70; n observations = 763) and PCA components derived from laboratory Sample 2 (n = 49; n observations = 575) in laboratory Sample 1 (y-axis; n = 70; n observations = 763). Bottom panel shows the highest correspondence between PCA components derived from laboratory Sample 2 directly (x-axis; n = 49; n observations = 575) and PCA components derived from laboratory Sample 1 (n = 70; n observations = 763) in laboratory Sample 2 (y-axis; n = 49; n observations = 575). Pearson correlation R and p-values were calculated using the ‘pearsonr’ function from the ‘scipy’ library (Virtanen et al., 2020). In each plot, the word clouds representing the PCA components on the y-axis are in the top left corner and the word clouds representing the PCA components on the x-axis are in the bottom right corner.

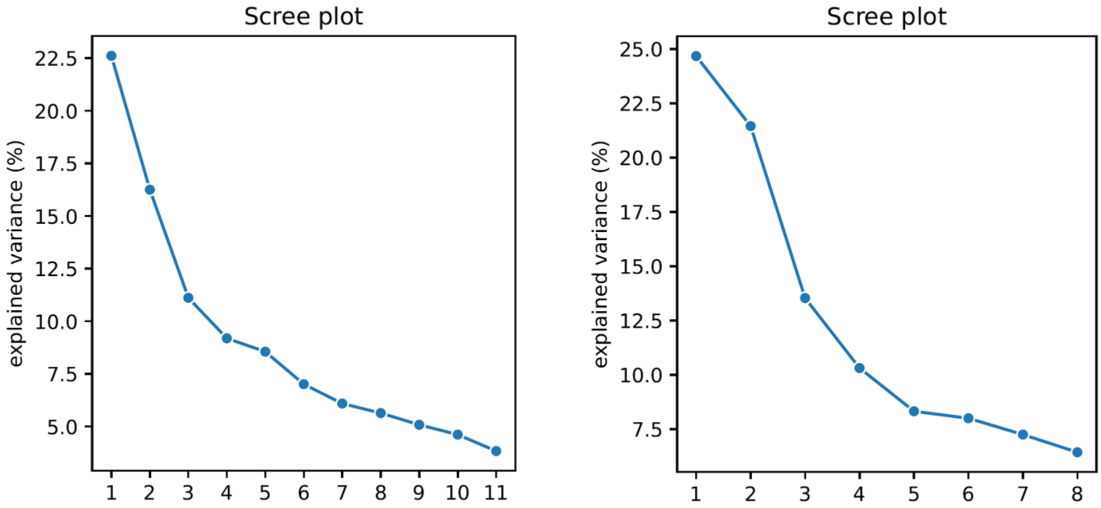

Fig M. Scree plots from the PCA applied to the 11-item (left) and 8-item (right) thought data from the combined laboratory samples (n = 119; n observations = 1338) to identify "patterns of thought" (x-axis = component number and y-axis = % variance explained by each component).

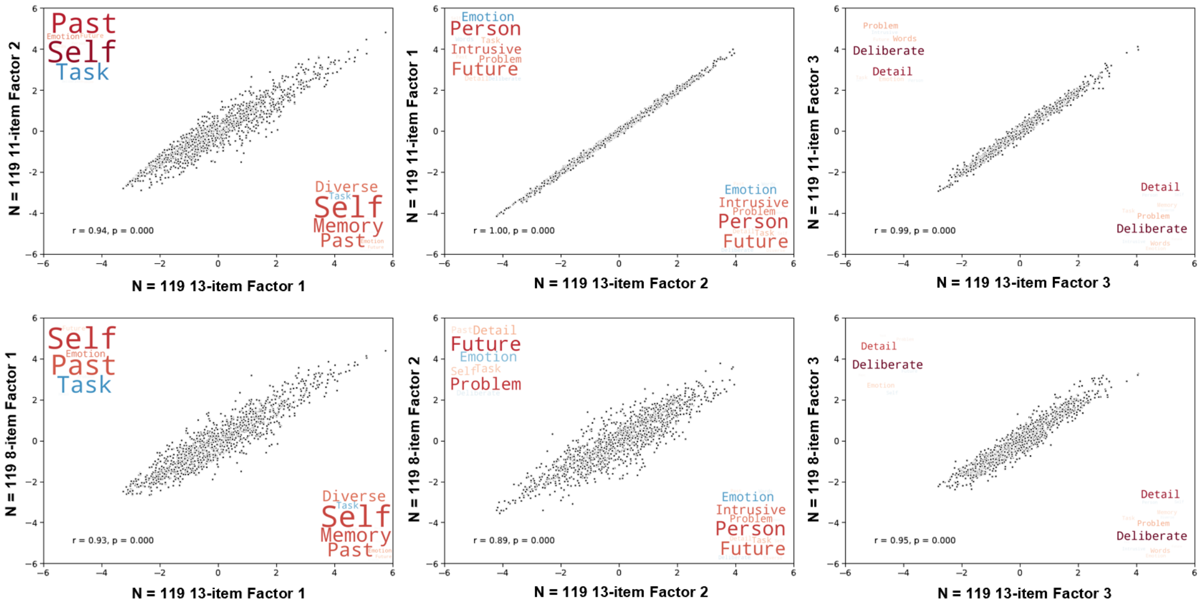

Fig N. Scatterplots and correlations demonstrating the high correspondence between PCA components (varimax rotated) derived from 1) 13-item combined laboratory samples and 2) 11- and 8-item combined laboratory samples (n = 119, n observations = 1338; specifying three components for extraction). Top panel shows the highest correspondence between PCA components derived from 13-item combined laboratory samples (x-axis; n = 119; n observations = 1338) and PCA components derived from 11-item combined laboratory samples (y-axis; n = 119; n observations = 1338). Bottom panel shows the highest correspondence between PCA components derived from 13-item combined laboratory samples (x-axis; n = 119; n observations = 1338) and PCA components derived from 8-item combined laboratory samples (y-axis; n = 119; n observations = 1338). Pearson correlation R and p-values were calculated using the ‘pearsonr’ function from the ‘scipy’ library (Virtanen et al., 2020). In each plot, the word clouds representing the PCA components on the y-axis are in the top left corner and the word clouds representing the PCA components on the x-axis are in the bottom right corner.

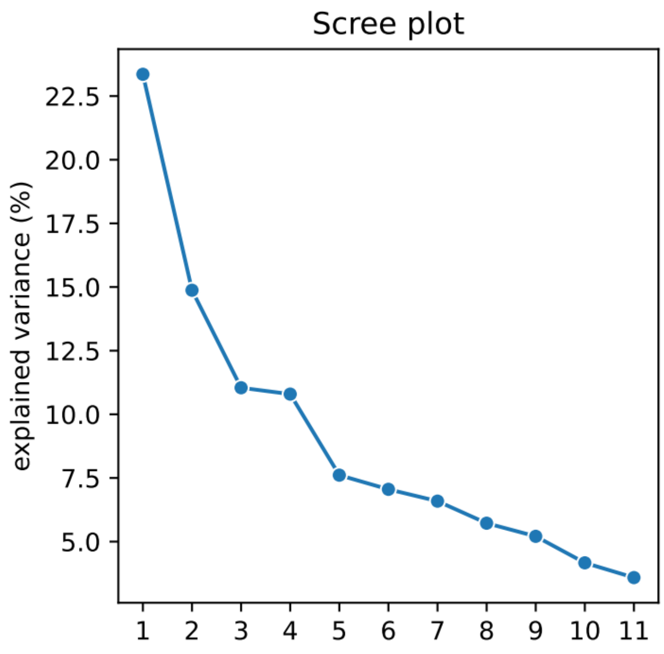

Fig O. Scree plot from the PCA applied to the thought data from both daily life samples (pre- and during-COVID) to identify "patterns of thought" (x-axis = component number and y-axis = % variance explained by each component). In total, 137 participants (pre-COVID = 78, during-COVID = 59) and 3252 observations (pre-COVID = 1995; during-COVID = 1257) were included in this analysis.

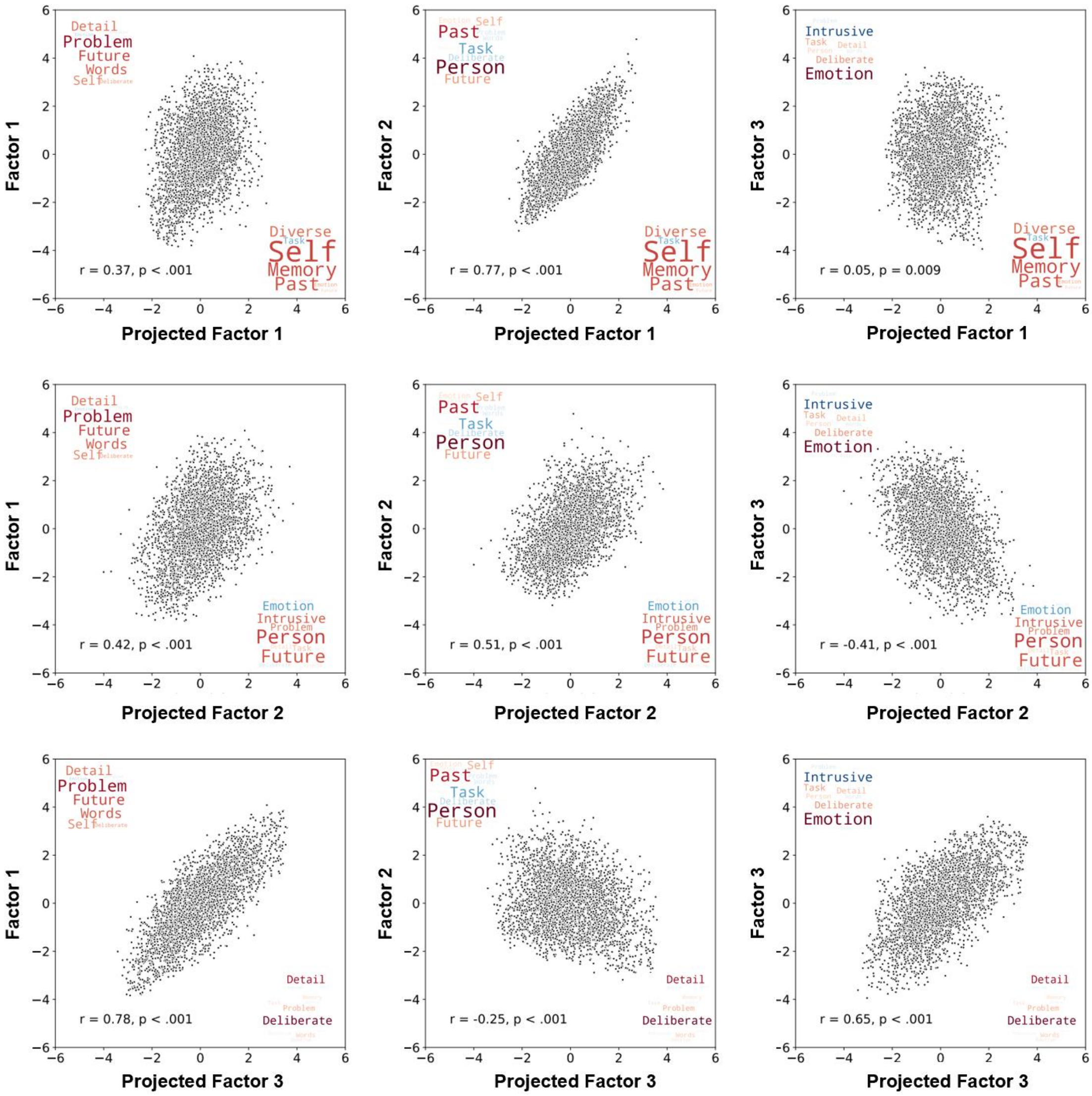

Fig P. Scatterplots and correlations demonstrating the correspondence between PCA components (varimax rotated) derived from 1) combined daily life thought datasets (pre- and during-COVID; specified three components for extraction) and 2) projecting the PCA solutions derived from the combined laboratory thought datasets on to the combined daily life thought datasets. Top panel shows the correspondence between the first projected component (x-axis) and the three components derived directly from the daily life combined data (y-axis). Second panel shows the correspondence between the second projected component (x-axis) and the three components derived directly from the daily life combined data (y-axis). Third panel shows the correspondence between the third projected component (x-axis) and the three components derived directly from the daily life combined data (y-axis). Pearson correlation R and p-values were calculated using the ‘pearsonr’ function from the ‘scipy’ library (Virtanen et al., 2020). In each plot, the word clouds representing the PCA components on the y-axis are in the top left corner and the word clouds representing the PCA components on the x-axis are in the bottom right corner. In total, 137 participants (pre-COVID = 78, during-COVID = 59) and 3252 observations (pre-COVID = 1995, during-COVID = 1257) were included in this analysis.

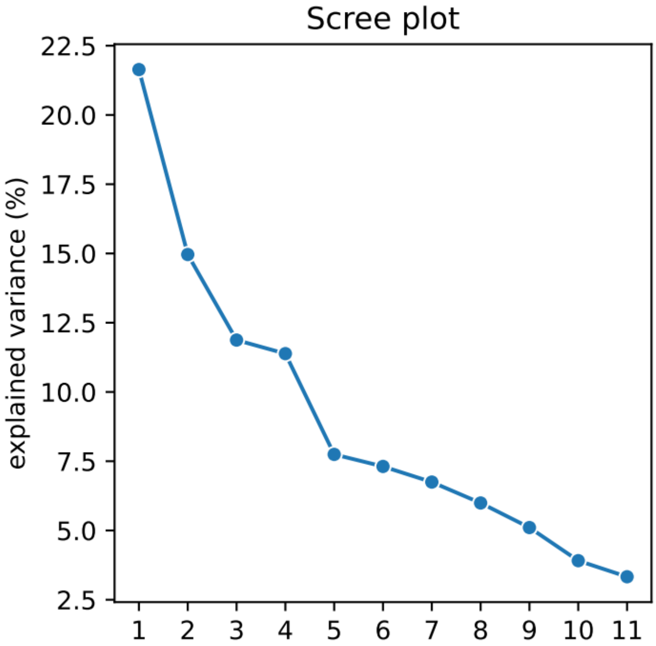

Fig Q. Scree plot from the PCA applied to the thought data from the pre-COVID daily life sample to identify "patterns of thought" (x-axis = component number and y-axis = % variance explained by each component). In total, 78 participants and 1995 observations were included in this analysis.

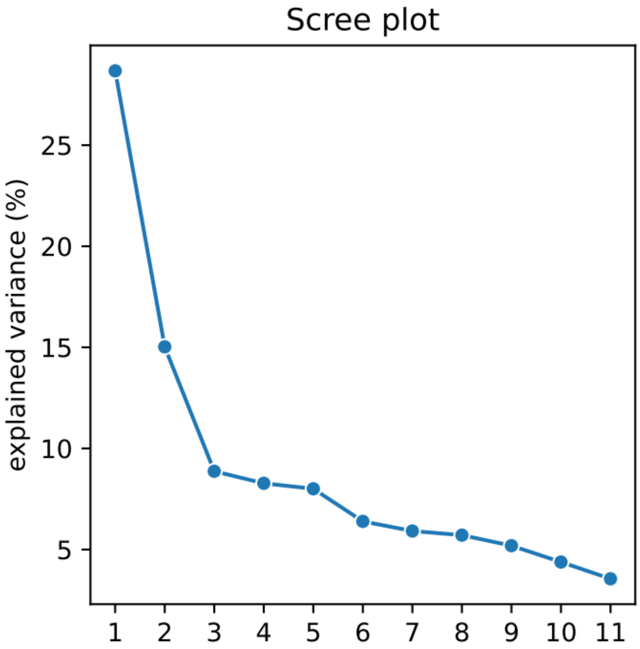

Fig R. Scree plot from the PCA applied to the thought data from the COVID daily life sample to identify "patterns of thought" (x-axis = component number and y-axis = % variance explained by each component). In total, 59 participants and 1257 observations were included in this analysis.

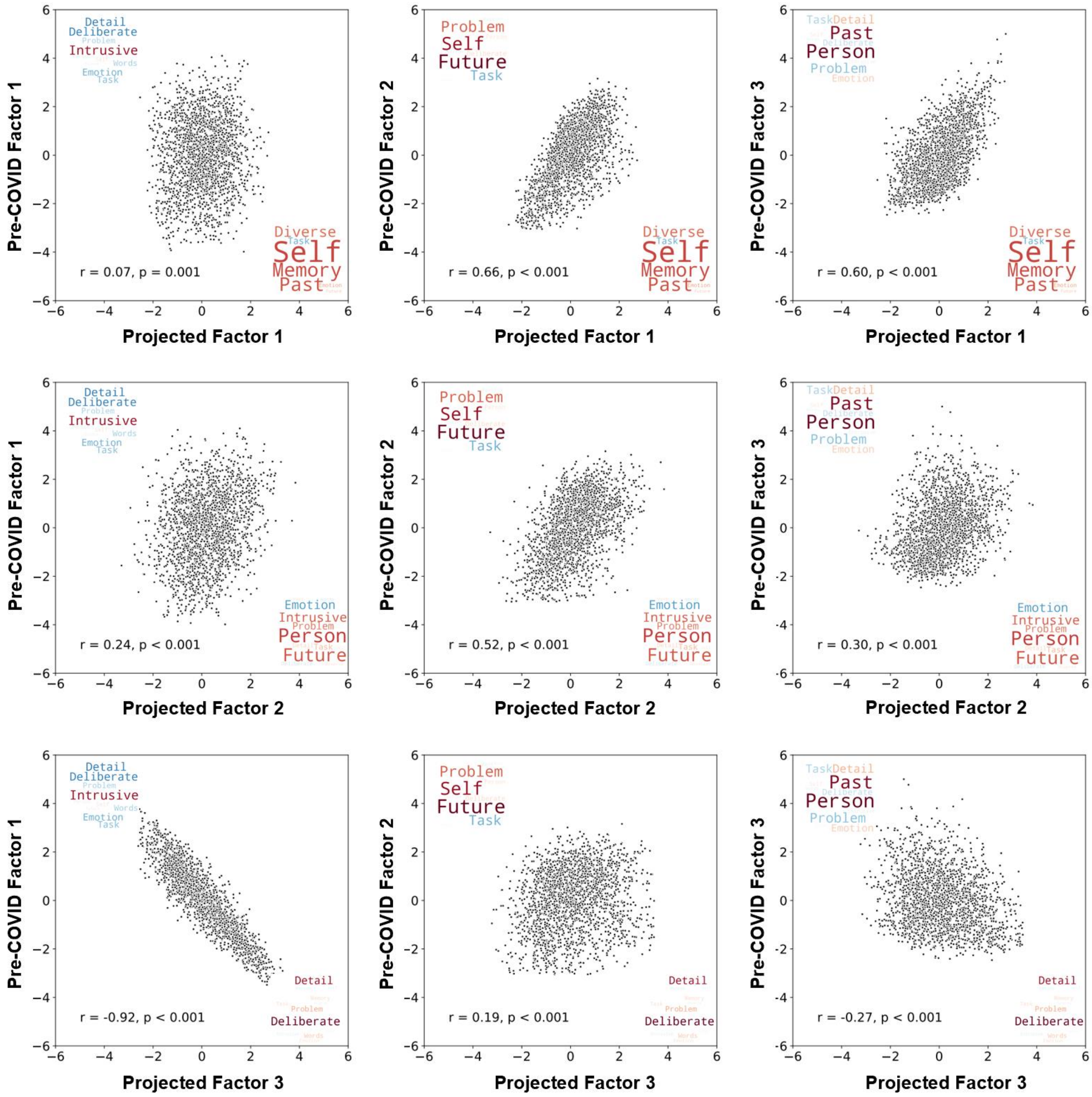

Fig S. Scatterplots and correlations demonstrating the correspondence between PCA components (varimax rotated) derived from 1) the pre-COVID daily life sample directly (specified three components for extraction) and 2) projecting the PCA solutions derived from the combined laboratory thought datasets on to the pre-COVID daily life sample. Top panel shows the correspondence between the first projected component (x-axis) and the three components derived directly from the pre-COVID daily life data (y-axis). Second panel shows the correspondence between the second projected component (x-axis) and the three components derived directly from the pre-COVID daily life data (y-axis). Third panel shows the correspondence between the third projected component (x-axis) and the three components derived directly from the pre-COVID daily life data (y-axis). Pearson correlation R and p-values were calculated using the 'pearsonr' function from the 'scipy' library (Virtanen et al., 2020). In each plot, the word clouds representing the PCA components on the y-axis are in the top left corner and the word clouds representing the PCA components on the x-axis are in the bottom right corner. In total, 78 participants and 1995 observations were included in this analysis.

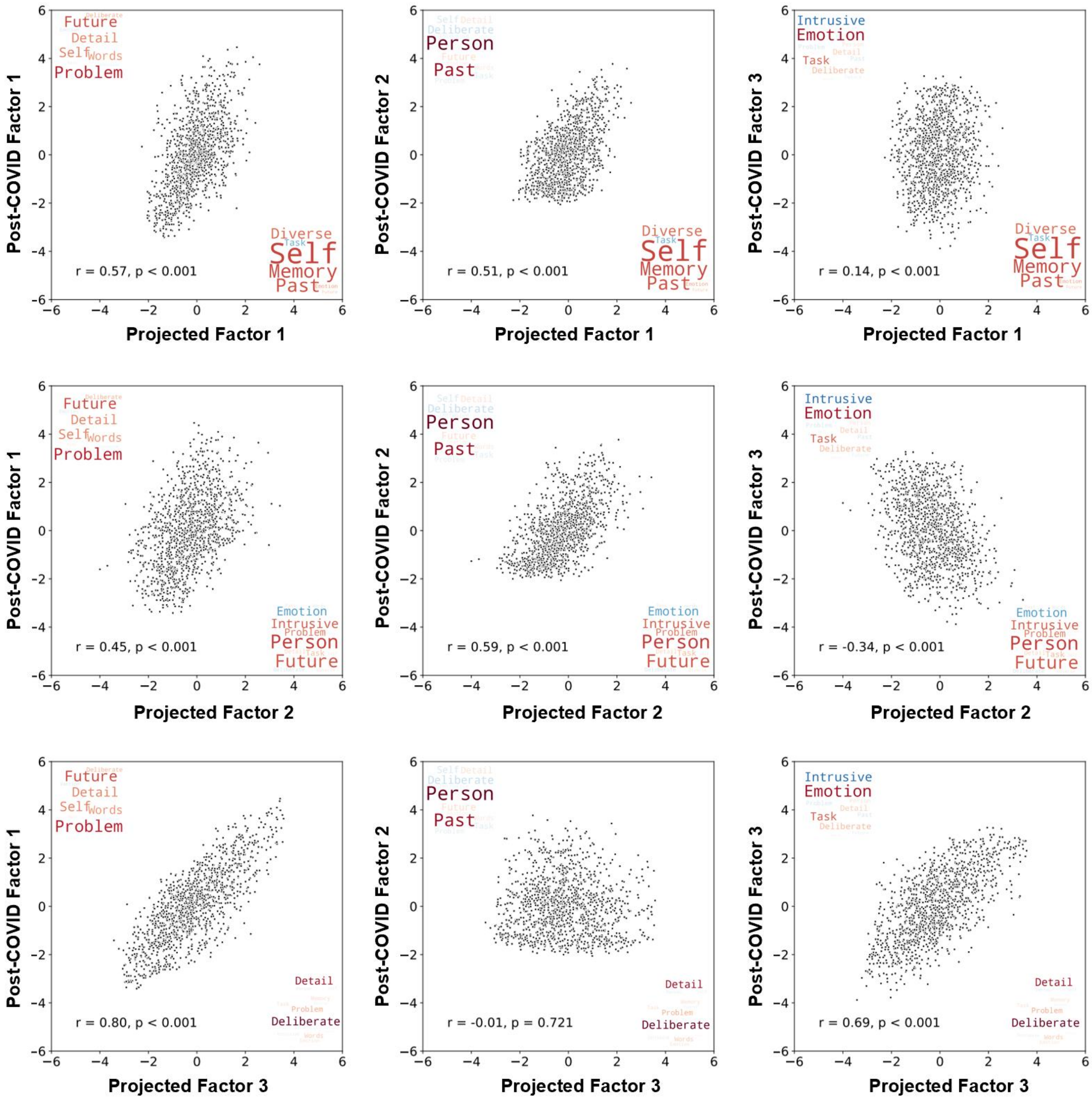

Fig T. Scatterplots and correlations demonstrating the correspondence between PCA components (varimax rotated) derived from 1) the COVID daily life sample directly (specified three components for extraction) and 2) projecting the PCA solutions derived from the combined laboratory thought datasets on to the COVID daily life sample. Top panel shows the correspondence between the first projected component (x-axis) and the three components derived directly from the COVID daily life data (y-axis). Second panel shows the correspondence between the second projected component (x-axis) and the three components derived directly from the COVID daily life data (y-axis). Third panel shows the correspondence between the third projected component (x-axis) and the three components derived directly from the COVID daily life data (y-axis). Pearson correlation R and p-values were calculated using the ‘pearsonr’ function from the ‘scipy’ library (Virtanen et al., 2020). In each plot, the word clouds representing the PCA components on the y-axis are in the top left corner and the word clouds representing the PCA components on the x-axis are in the bottom right corner. In total, 59 participants and 1257 observations were included in this analysis.

S2 Text

Supplementary Analysis

ANOVAs Comparing Mean Arousal and Mean Uncertainty Ratings between Video Conditions in the Combined Laboratory Samples (n = 119)

Since the residual plots from the Linear Mixed Models (LMMs) comparing arousal and uncertainty ratings between video conditions indicated non-randomness of the residuals (see Fig A), we performed two one-way repeated measures ANOVAs using the mean ratings for arousal and uncertainty for each video condition as outcome variables and 'video condition' as the predictor variable with three levels ('control', 'action', and 'suspense'). To perform these analyses, we used the anova_test function as part of the rstatix package (Kassambara, 2021). We used the get_anova_table function to extract the anova table and automatically apply the Greenhouse-Geisser sphericity correction if the sphericity assumption is violated.

We found that mean arousal ratings ($F(1.31, 155.14) = 219.44$, $p < .001$, eta2[g] = 0.42) and mean uncertainty ratings ($F(1.55, 183.18) = 371.63$, $p < .001$, eta2[g] = 0.57) were significantly different between video conditions. Post-hoc pairwise *t*-tests with a Bonferroni adjustment (3 tests) revealed that arousal was significantly higher in the 'action' condition compared to the 'suspense' ('action' – 'suspense': $b = 0.28$, 95% CI (0.08, 0.49), $t(118) = 2.70$, $p < .001$) and 'control' ('action' – 'control': $b = 3.70$, 95% CI (3.24, 4.17), $t(118) = 15.7$, $p = .024$) conditions. In addition, uncertainty was significantly higher in the 'suspense' condition compared to the 'action' ('suspense' – 'action': $b = 0.61$, 95% CI (0.37, 0.86), $t(118) = 5.00$, $p < .001$) and 'control' condition ('suspense' – 'control': $b = 4.54$, 95% CI (4.14, 4.94), $t(118) = 22.30$, $p < .001$). The results from these ANOVAs are summarized in Fig B.

However, the Shapiro-Wilk test and QQ plots both suggested the data violated the assumption of normality (see Fig E for QQ plots). Therefore, we repeated these analyses using the Friedman test (non-parametric equivalent of ANOVA). Importantly, the Friedman tests revealed consistent results with the repeated measures ANOVAs (see Fig C). Finally, since outliers (arousal: 15 observations, uncertainty: 14 observations) were also identified using the identify_outliers function as part of the rstatix package, we re-ran the Friedman tests with the outliers removed (arousal: n = 109 & uncertainty: n = 106). Importantly, there were no substantial differences between these results and the results including outliers (see Fig D).

Supplementary Tables

Table A. Summary of the consistency of ANOVA results across all LMMs assessing whether each thought pattern varied significantly by 1) video condition (3 levels: ‘control’, ‘action’, and ‘suspense’), 2) subjective arousal, and 3) subjective uncertainty using thought components derived either by 1) applying PCA to combined laboratory samples, 2) applying PCA to each sample separately or 3) projecting patterns from one laboratory sample to the other.

		Factor 1						Factor 2						Factor 3					
N	Analysis	Cond	Arou	Uncert	Cond * Arou	Cond * Uncert	Arou* Uncert	Cond	Arou	Uncert	Cond * Arou	Cond * Uncert	Arou* Uncert	Cond	Arou	Uncert	Cond * Arou	Cond * Uncert	Arou* Uncert
119	Combined	**.001**	**<.001**	**<.001**	.576	**.003**	.081	**.001**	**<.001**	**<.001**	.180	.054	.443	.561	.288	.536	.059	.067	.309
70	Combined	**.025**	**<.001**	**.001**	.910	.553	.212	**.003**	**<.001**	**<.001**	**.048**	**.034**	.918	.986	.310	.358	.246	**.009**	.664
70	Separate	**.011**	**<.001**	**<.001**	.975	.402	.289	**.021**	**<.001**	**<.001**	**.040**	**.007**	.927	.568	.662	**.037**	.637	.058	.399
70	Projected	.082	**<.001**	**.014**	.707	.625	.203	**<.001**	**<.001**	**<.001**	**.032**	.078	.568	.899	.129	.936	.132	**.004**	.713
49	Combined	**.007**	**<.001**	**.016**	.501	**.001**	.136	**.001**	.081	**<.001**	.271	.137	.429	.297	.534	.967	.196	.940	.581
49	Separate	.053	**<.001**	.146	.423	**.002**	.146	**<.001**	**.025**	**<.001**	.063	.197	.385	.209	.416	.604	.292	.893	.773
49	Projected	**.002**	**<.001**	**.005**	.529	**.001**	.110	**.009**	.153	**<.001**	.579	.115	.411	.429	.476	.210	.230	.945	.510

Note. N = number of participants included in the LMM analysis. Analysis = which thought components were used in analysis (combined = PCA applied to both laboratory samples; Separate = PCA applied to that sample only; Projected = PCA applied to other sample and projected onto that sample). ‘Cond’ = Video condition predictor. ‘Arou’ = Subjective arousal predictor. ‘Uncert’ = Subjective uncertainty predictor. P-values shown are for F-tests returned by the package ‘lmerTest’ (Kuznetsova et al., 2017) and P-values <.05 highlighted in bold. Main effects that are consistently significant across all model combinations are highlighted in yellow.

Table B. Type 3 Sum of Squares ANOVA table for LMMs assessing whether subjective arousal and subjective uncertainty varied significantly by video condition (three levels: control, action, suspense) in the combined laboratory samples (n = 119).

	Arousal				Uncertainty			
Fixed effects	*SS*	*DF*	*F*	*p*	*SS*	*DF*	*F*	*p*
Video condition	149.38	2, 12	189.91	**<.001**	313.09	2, 14	402.87	**<.001**

Note. SS = Sum of Squares. DF = numerator and denominator degrees of freedom. P-values < .05 are in bold. Information in this table obtained using anova function as part of the lmerTest package (Kuznetsova et al., 2017).

Table C. Standardized parameter estimates for LMMs assessing whether subjective arousal and subjective uncertainty varied significantly by video condition (three levels: control, action, suspense) in the combined laboratory samples (n = 119).

	Arousal				Uncertainty			
Predictors	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	***p***
(Intercept)	-0.03	-0.14 – 0.09	-0.46	.643	-0.04	-0.13 – 0.05	-0.91	.364
Control condition	-0.82	-0.90 – -0.74	-19.46	**<.001**	-0.94	-1.00 – -0.87	-28.22	**<.001**
Action condition	0.46	0.36 – 0.56	9.34	**<.001**	0.37	0.29 – 0.44	10.00	**<.001**

Note. Summed contrasts were used meaning that the intercept reflects the grand mean of all conditions for each model. Therefore, for different video conditions, each estimate (*b*) reflects the difference between the factor level and the intercept. P-values < .05 are in bold. P-values and confidence intervals calculated using Satterthwaite approximation. Information in this table obtained using tab_model function as part of the sjPlot package (Lüdecke, 2021a). All dependent variables were z-scored prior to analysis.

Table D. A summary of the variance explained by random effects for LMMs assessing whether subjective arousal and subjective uncertainty varied significantly by video condition (three levels: control, action, suspense) in the combined laboratory samples (n = 119).

	Arousal	**Uncertainty**
σ^2	0.39	0.39
τ_{00}	0.25 $_{\text{Participant}}$	0.18 $_{\text{Participant}}$
	0.01 $_{\text{Video}}$	0.01 $_{\text{Video}}$
N	119 $_{\text{Participant}}$	119 $_{\text{Participant}}$
	21 $_{\text{Video}}$	21 $_{\text{Video}}$
Observations	1338	1338

Note. σ2 = population variance, τ00 = random intercept variance. Video = video name. Information in this table obtained using tab_model function as part of the sjPlot package (Lüdecke, 2021a).

Table E. Type 3 Sum of Squares ANOVA table for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) video condition, 2) subjective arousal, and 3) subjective uncertainty in the combined laboratory samples (n = 119).

	Factor 1				**Factor 2**				**Factor 3**			
Fixed effects	*SS*	*DF*	*F*	*p*	*SS*	*DF*	*F*	*p*	*SS*	*DF*	*F*	*p*
Condition	9.50	2, 16	10.10	**.001**	10.23	2, 17	12.14	**.001**	0.83	2, 19	0.60	.561
Arousal	39.31	1, 1308	83.58	**<.001**	8.48	1, 1310	20.13	**<.001**	0.79	1, 1284	1.13	.288
Uncertainty	6.96	1, 1323	14.79	**<.001**	31.38	1, 1322	74.52	**<.001**	0.27	1, 1326	0.38	.536
Arousal * Uncertainty	1.44	1, 1314	3.05	.081	0.25	1, 1314	0.59	.443	0.72	1, 1322	1.04	.309
Condition * Arousal	0.52	2, 1245	0.55	.576	1.44	2, 1245	1.72	.180	3.97	2, 1243	2.84	.059
Condition * Uncertainty	5.48	2, 1252	5.82	**.003**	2.46	2, 1253	2.92	.054	3.79	2, 1263	2.71	.067

Note. SS = Sum of Squares. DF = numerator and denominator degrees of freedom. P-values < .05 are in bold. Information in this table obtained using anova function as part of the lmerTest package (Kuznetsova et al., 2017).

Table F. Standardized parameter estimates for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) video condition, 2) subjective arousal, and 3) subjective uncertainty in the combined laboratory samples (n = 119).

	Factor 1				**Factor 2**				**Factor 3**			
Predictors	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*
(Intercept)	0.08	-0.05 – 0.21	1.18	.243	0.03	-0.10 – 0.16	0.45	.652	0.06	-0.08 – 0.20	0.89	.375
Control condition	0.34	0.18 – 0.49	4.41	**<.001**	-0.36	-0.50 – -0.21	-4.92	**<.001**	-0.08	-0.24 – 0.08	-0.95	.341
Action condition	-0.12	-0.27 – 0.02	-1.79	.093	0.16	0.02 – 0.30	2.48	**.025**	0.06	-0.06 – 0.19	1.03	.314
Arousal	-0.29	-0.36 – -0.23	-9.14	**<.001**	0.14	0.08 – 0.20	4.49	**<.001**	0.04	-0.03 – 0.12	1.06	.288
Uncertainty	-0.13	-0.20 – -0.07	-3.85	**<.001**	0.28	0.22 – 0.35	8.63	**<.001**	-0.03	-0.11 – 0.06	-0.62	.536
Arousal * Uncertainty	-0.06	-0.12 – 0.01	-1.75	.081	-0.02	-0.08 – 0.04	-0.77	.443	-0.04	-0.12 – 0.04	-1.02	.309
Control condition * Arousal	-0.05	-0.14 – 0.04	-1.05	.294	-0.08	-0.16 – 0.01	-1.73	.084	-0.02	-0.13 – 0.09	-0.42	.675
Action condition * Arousal	0.02	-0.05 – 0.09	0.56	.575	0.02	-0.05 – 0.08	0.44	.661	-0.08	-0.16 – 0.01	-1.70	.089
Control condition * Uncertainty	0.13	0.01 – 0.24	2.13	**.034**	0.11	0.00 – 0.22	1.99	**.047**	0.10	-0.04 – 0.24	1.35	.178
Action condition * Uncertainty	-0.14	-0.22 – -0.06	-3.38	**.001**	-0.02	-0.09 – 0.06	-0.47	.641	0.02	-0.08 – 0.12	0.36	.716

Note. Summed contrasts were used meaning that the intercept reflects the grand mean of all conditions for each model. Therefore, for different video conditions, each estimate (*b*) reflects the difference between the factor level and the intercept. P-values < .05 are in bold. P-values and confidence intervals calculated using Satterthwaite approximation. Information in this table obtained using tab_model function as part of the sjPlot package (Lüdecke, 2021a). All dependent and continuous independent variables were z-scored prior to analysis.

Table G. A summary of the variance explained by random effects for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) video condition, 2) subjective arousal, and 3) subjective uncertainty in the combined laboratory samples (n = 119).

	Factor 1	**Factor 2**	**Factor 3**
σ^2	0.47	0.42	0.70
τ_{00}	0.23 $_{\text{Participant}}$	0.21 $_{\text{Participant}}$	0.28 $_{\text{Participant}}$
	0.02 $_{\text{Video}}$	0.02 $_{\text{Video}}$	0.01 $_{\text{Video}}$
N	119 $_{\text{Participant}}$	119 $_{\text{Participant}}$	119 $_{\text{Participant}}$
	21 $_{\text{Video}}$	21 $_{\text{Video}}$	21 $_{\text{Video}}$
Observations	1338	1338	1338

Note. σ2 = population variance, τ00 = random intercept variance. Video = video name. Information in this table obtained using tab_model function as part of the sjPlot package (Lüdecke, 2021a).

Table H. Type 3 Sum of Squares ANOVA table for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) video condition, 2) subjective arousal, 3) subjective uncertainty, and 4) trait anxiety in laboratory Sample 1 (n = 70).

	Factor 1				**Factor 2**				**Factor 3**			
Fixed effects	*SS*	*DF*	*F*	*p*	*SS*	*DF*	*F*	*p*	*SS*	*DF*	*F*	*p*
Arousal	15.49	1, 736	36.25	**<.001**	10.39	1, 727	26.77	**<.001**	0.92	1, 722	1.36	.245
Uncertainty	5.01	1, 739	11.72	**.001**	12.37	1, 728	31.84	**<.001**	0.71	1, 737	1.05	.306
Trait anxiety	1.47	1, 72	3.44	.068	1.33	1, 72	3.42	.069	0.40	1, 71	0.59	.446
Condition	4.16	2, 15	4.87	**.023**	5.86	2, 20	7.55	**.004**	0.02	2, 15	0.02	.985
Arousal * Uncertainty	0.48	1, 718	1.13	.289	0.01	1, 718	0.02	.882	0.00	1, 732	0.00	.990
Arousal * Trait anxiety	0.12	1, 728	0.27	.604	0.16	1, 744	0.42	.518	3.49	1, 705	5.15	**.024**
Uncertainty * Trait anxiety	0.02	1, 725	0.04	.845	2.86	1, 725	7.38	**.007**	1.79	1, 741	2.64	.104
Arousal * Condition	0.04	2, 701	0.05	.956	2.69	2, 700	3.46	.032	1.41	2, 696	1.04	.354
Uncertainty * Condition	0.43	2, 692	0.50	.607	2.65	2, 693	3.42	**.033**	5.68	2, 701	4.18	**.016**
Trait anxiety * Condition	1.18	2, 698	1.38	.251	0.10	2, 702	0.13	.878	0.84	2, 704	0.62	.539

Note. SS = Sum of Squares. DF = numerator and denominator degrees of freedom. P-values < .05 are in bold. Information in this table obtained using anova function as part of the lmerTest package (Kuznetsova et al., 2017).

Table I. Standardized parameter estimates for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) video condition, 2) subjective arousal, 3) subjective uncertainty, and 4) trait anxiety in laboratory Sample 1 (n = 70).

	Factor 1				**Factor 2**				**Factor 3**			
Predictors	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*
(Intercept)	0.06	-0.12 – 0.24	0.64	.525	-0.04	-0.20 – 0.13	-0.45	.652	0.05	-0.13 – 0.23	0.59	.559
Arousal	-0.28	-0.37 – -0.19	-6.02	**<.001**	0.23	0.14 – 0.31	5.17	**<.001**	0.07	-0.05 – 0.18	1.16	.245
Uncertainty	-0.15	-0.24 – -0.07	-3.42	**.001**	0.24	0.16 – 0.32	5.64	**<.001**	-0.06	-0.16 – 0.05	-1.02	.306
Trait anxiety	0.12	-0.01 – 0.26	1.85	.068	0.13	-0.01 – 0.28	1.85	.069	-0.06	-0.21 – 0.09	-0.77	.446
Control condition	0.32	0.11 – 0.52	3.06	**.003**	-0.32	-0.49 – -0.16	-3.81	**<.001**	-0.02	-0.23 – 0.20	-0.16	.869
Action condition	-0.12	-0.30 – 0.07	-1.31	.211	0.13	0.01 – 0.25	2.19	**.036**	0.01	-0.14 – 0.16	0.16	.877
Arousal * Uncertainty	-0.05	-0.14 – 0.04	-1.06	.289	-0.01	-0.10 – 0.08	-0.15	.882	0.00	-0.11 – 0.12	0.01	.990
Arousal * Trait anxiety	-0.02	-0.09 – 0.05	-0.52	.604	0.02	-0.05 – 0.09	0.65	.518	-0.10	-0.19 – -0.01	-2.27	**.024**
Uncertainty * Trait anxiety	-0.01	-0.08 – 0.07	-0.20	.845	-0.10	-0.17 – -0.03	-2.72	**.007**	0.08	-0.02 – 0.17	1.63	.104
Arousal * Control condition	0.00	-0.12 – 0.12	0.02	.981	-0.14	-0.25 – -0.02	-2.39	**.017**	-0.00	-0.15 – 0.14	-0.04	.968
Arousal * Action condition	-0.01	-0.12 – 0.09	-0.27	.787	0.01	-0.09 – 0.11	0.23	.822	-0.08	-0.21 – 0.05	-1.23	.218
Uncertainty * Control condition	0.02	-0.14 – 0.17	0.21	.830	0.08	-0.07 – 0.22	1.01	.313	0.14	-0.06 – 0.33	1.40	.161
Uncertainty * Action condition	-0.04	-0.15 – 0.06	-0.82	.413	0.05	-0.05 – 0.15	0.90	.370	0.05	-0.08 – 0.18	0.70	.486
Trait anxiety * Control condition	0.06	-0.05 – 0.17	1.14	.255	-0.03	-0.13 – 0.08	-0.51	.611	0.08	-0.06 – 0.21	1.10	.270
Trait anxiety * Action condition	-0.07	-0.14 – 0.01	-1.66	.097	0.01	-0.06 – 0.09	0.34	.731	-0.03	-0.13 – 0.07	-0.63	.526

Note. Summed contrasts were used meaning that the intercept reflects the grand mean of all conditions for each model. Therefore, for different video conditions, each estimate (*b*) reflects the difference between the factor level and the intercept. P-values < .05 are in bold. P-values and confidence intervals calculated using Satterthwaite approximation. Information in this table obtained using tab_model function as part of the sjPlot package (Lüdecke, 2021a). All dependent and continuous independent variables were z-scored prior to analysis.

Table J. A summary of the variance explained by random effects for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) video condition, 2) subjective arousal, 3) subjective uncertainty, and 4) trait anxiety in laboratory Sample 1 (n = 70).

	Factor 1	**Factor 2**	**Factor 3**
σ^2	0.43	0.39	0.68
τ_{00}	0.26 $_{\text{Participant}}$	0.31 $_{\text{Participant}}$	0.31 $_{\text{Participant}}$
	0.03 $_{\text{Video}}$	0.01 $_{\text{Video}}$	0.00 $_{\text{Video}}$
N	70 $_{\text{Participant}}$	70 $_{\text{Participant}}$	70 $_{\text{Participant}}$
	17 $_{\text{Video}}$	17 $_{\text{Video}}$	17 $_{\text{Video}}$
Observations	763	763	763

Note. σ2 = population variance, τ00 = random intercept variance. Video = video name. Information in this table obtained using tab_model function as part of the sjPlot package (Lüdecke, 2021a).

Table K. Type 3 Sum of Squares ANOVA table for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) sample (pre- vs during-COVID) and 2) trait anxiety in the combined daily life samples (n = 129).

	Factor 1				**Factor 2**				**Factor 3**			
Fixed effects	*SS*	*DF*	*F*	*p*	*SS*	*DF*	*F*	*p*	*SS*	*DF*	*F*	*p*
Sample	0.01	1, 127	0.02	.894	10.61	1, 125	15.39	**< .001**	3.69	1, 126	5.02	**.027**
Trait anxiety	0.20	1, 124	0.27	.603	2.54	1, 122	3.69	.057	0.91	1, 123	1.23	.269
Age	1.64	1, 124	2.23	.138	0	1, 122	0.00	.986	0.93	1, 124	1.26	.264
Trait anxiety * Sample	0.38	1, 124	0.52	.472	1.32	1, 122	1.92	.169	0.1	1, 123	0.13	.720

Note. SS = Sum of Squares. DF = numerator and denominator degrees of freedom. P-values < .05 are in bold. Information in this table obtained using anova function as part of the lmerTest package (Kuznetsova et al., 2017).

Table L. Standardized parameter estimates for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) sample (pre- vs during-COVID) and 2) trait anxiety in the combined daily life samples (n = 129).

	Factor 1				**Factor 2**				**Factor 3**			
Predictors	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*
(Intercept)	0.03	-0.06 – 0.12	0.62	.538	-0.05	-0.15 – 0.04	-1.10	.274	-0.02	-0.11 – 0.07	-0.45	.654
Pre-COVID	0.01	-0.11 – 0.12	0.13	.894	0.23	0.12 – 0.35	3.92	**<.001**	0.13	0.02 – 0.24	2.24	**.027**
Trait anxiety	-0.02	-0.11 – 0.07	-0.52	.603	0.09	-0.00 – 0.18	1.92	.057	-0.05	-0.14 – 0.04	-1.11	.269
Age	-0.09	-0.20 – 0.03	-1.49	.138	0.00	-0.12 – 0.12	0.02	.986	0.07	-0.05 – 0.18	1.12	.264
Trait anxiety * Pre-COVID	0.03	-0.06 – 0.12	0.72	.472	-0.06	-0.16 – 0.03	-1.38	.169	0.02	-0.07 – 0.11	0.36	.720

Note. Summed contrasts were used meaning that the intercept reflects the grand mean of all conditions for each model. P-values < .05 are in bold. P-values and confidence intervals calculated using Satterthwaite approximation. Information in this table obtained using tab_model function as part of the sjPlot package (Lüdecke, 2021a). All dependent and continuous independent variables were z-scored prior to analysis.

Table M. A summary of the variance explained by random effects for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) sample (pre- vs during-COVID) and 2) trait anxiety in the combined daily life samples (n = 129).

	Factor 1	**Factor 2**	**Factor 3**
σ^2	0.74	0.69	0.74
τ_{00}	0.05 $_{\text{Day : Participant}}$	0.03 $_{\text{Day : Participant}}$	0.06 $_{\text{Day : Participant}}$
	0.21 $_{\text{Participant}}$	0.22 $_{\text{Participant}}$	0.20 $_{\text{Participant}}$
N	7 $_{\text{Day}}$	7 $_{\text{Day}}$	7 $_{\text{Day}}$
	129 $_{\text{Participant}}$	129 $_{\text{Participant}}$	129 $_{\text{Participant}}$
Observations	3100	3100	3100

Note. σ2 = population variance, τ00 = random intercept variance. Day = Day number. Participant = Participant identifier. Information in this table obtained using tab_model function as part of the sjPlot package (Lüdecke, 2021a).

Table N. Type 3 Sum of Squares ANOVA table for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) subjective uncertainty and 2) trait anxiety in the COVID daily life sample (n = 59).

	Factor 1				**Factor 2**				**Factor 3**			
Fixed effects	*SS*	*DF*	*F*	*p*	*SS*	*DF*	*F*	*p*	*SS*	*DF*	*F*	*p*
Uncertainty	5.39	1, 1231	8.93	**.003**	82.08	1, 1208	141.42	**<.001**	0.11	1, 1207	0.16	.690
Trait anxiety	0.89	1, 56	1.47	.231	0.32	1, 56	0.55	.461	0.38	1, 58	0.57	.452
Age	1.04	1, 53	1.73	.194	0.03	1, 52	0.05	.821	0.56	1, 54	0.85	.359
Uncertainty * Trait anxiety	3.06	1, 1132	5.07	**.025**	1.96	1, 1078	3.37	.066	2.16	1, 1115	3.27	.071

Note. SS = Sum of Squares. DF = numerator and denominator degrees of freedom. P-values < .05 are in bold. Information in this table obtained using anova function as part of the lmerTest package (Kuznetsova et al., 2017).

Table O. Standardized parameter estimates for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) subjective uncertainty and 2) trait anxiety in the COVID daily life sample (n = 59).

	Factor 1				**Factor 2**				**Factor 3**			
Predictors	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*
(Intercept)	0.07	-0.09 – 0.23	0.85	.401	0.02	-0.12 – 0.16	0.30	.767	0.03	-0.12 – 0.19	0.41	.684
Uncertainty	0.10	0.03 – 0.16	2.99	**.003**	0.37	0.31 – 0.43	11.89	**<.001**	-0.01	-0.08 – 0.05	-0.40	.690
Trait anxiety	-0.10	-0.26 – 0.06	-1.21	.231	0.05	-0.09 – 0.20	0.74	.461	-0.06	-0.22 – 0.10	-0.76	.452
Age	-0.11	-0.27 – 0.06	-1.31	.194	-0.02	-0.16 – 0.13	-0.23	.821	0.07	-0.09 – 0.24	0.92	.359
Uncertainty * Trait anxiety	-0.07	-0.13 – -0.01	-2.25	**.025**	-0.05	-0.11 – 0.00	-1.84	.066	-0.06	-0.12 – 0.00	-1.81	.071

Note. Summed contrasts were used meaning that the intercept reflects the grand mean of all conditions for each model. P-values < .05 are in bold. P-values and confidence intervals calculated using Satterthwaite approximation. Information in this table obtained using tab_model function as part of the sjPlot package (Lüdecke, 2021a). All dependent and continuous independent variables were z-scored prior to analysis.

Table P. A summary of the variance explained by random effects for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) subjective uncertainty and 2) trait anxiety in the COVID daily life sample (n = 59).

	Factor 1	**Factor 2**	**Factor 3**
σ^2	0.60	0.58	0.66
τ_{00}	0.08 $_{\text{Day : Participant}}$	0.06 $_{\text{Day : Participant}}$	0.04 $_{\text{Day : Participant}}$
	0.29 $_{\text{Participant}}$	0.23 $_{\text{Participant}}$	0.29 $_{\text{Participant}}$
N	7 $_{\text{Day}}$	7 $_{\text{Day}}$	7 $_{\text{Day}}$
	59 $_{\text{Participant}}$	59 $_{\text{Participant}}$	59 $_{\text{Participant}}$
Observations	1257	1257	1257

Note. σ2 = population variance, τ00 = random intercept variance. Day = Day number. Participant = Participant identifier. Information in this table obtained using tab_model function as part of the sjPlot package (Lüdecke, 2021a).

Table Q. Type 3 Sum of Squares ANOVA table for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) COVID uncertainty, 2) COVID threat, and 3) trait anxiety in the COVID daily life sample (n = 59).

	Factor 1				**Factor 2**				**Factor 3**			
Fixed effects	*SS*	*DF*	*F*	*p*	*SS*	*DF*	*F*	*p*	*SS*	*DF*	*F*	*p*
COVID threat	0.78	1, 867	1.28	.259	0.83	1, 832	1.29	.256	4.06	1, 786	6.15	**.013**
COVID uncertainty	0.50	1, 1017	0.82	.367	4.17	1, 991	6.50	**.011**	0.72	1, 945	1.08	.298
Trait anxiety	1.22	1, 58	2.00	.163	1.17	1, 59	1.83	.182	1.20	1, 60	1.82	.182
Age	1.00	1, 51	1.64	.206	0.14	1, 52	0.22	.641	0.81	1, 53	1.22	.274
COVID threat * COVID uncertainty	0.16	1, 1030	0.26	.608	0.00	1, 985	0.00	.967	0.06	1, 940	0.08	.773
COVID threat * Trait anxiety	1.06	1, 728	1.74	.188	1.68	1, 707	2.62	.106	0.22	1, 673	0.34	.562
COVID uncertainty * Trait anxiety	0.03	1, 1028	0.04	.840	0.25	1, 999	0.39	.532	0.14	1, 952	0.21	.646

Note. SS = Sum of Squares. DF = numerator and denominator degrees of freedom. P-values < .05 are in bold. Information in this table obtained using anova function as part of the lmerTest package (Kuznetsova et al., 2017).

Table R. Standardized parameter estimates for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) COVID uncertainty, 2) COVID threat, and 3) trait anxiety in the COVID daily life sample (n = 59).

	Factor 1				**Factor 2**				**Factor 3**			
Predictors	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*	*b*	*95% CI*	*t*	*p*
(Intercept)	0.04	-0.13 – 0.21	0.44	.662	0.04	-0.13 – 0.21	0.46	.645	-0.02	-0.18 – 0.14	-0.25	.805
COVID threat	0.06	-0.05 – 0.17	1.13	.259	0.06	-0.04 – 0.17	1.14	.256	0.13	0.03 – 0.24	2.48	**.013**
COVID uncertainty	0.05	-0.06 – 0.15	0.90	.367	0.14	0.03 – 0.24	2.55	**.011**	-0.06	-0.16 – 0.05	-1.04	.298
Trait anxiety	-0.12	-0.29 – 0.05	-1.41	.163	0.11	-0.05 – 0.28	1.35	.182	-0.11	-0.27 – 0.05	-1.35	.182
Age	-0.11	-0.28 – 0.06	-1.28	.206	-0.04	-0.20 – 0.13	-0.47	.641	0.09	-0.07 – 0.24	1.10	.274
COVID threat * COVID uncertainty	-0.02	-0.11 – 0.06	-0.51	.608	0.00	-0.08 – 0.09	0.04	.967	0.01	-0.07 – 0.10	0.29	.773
COVID threat * Trait anxiety	0.07	-0.03 – 0.17	1.32	.188	-0.08	-0.19 – 0.02	-1.62	.106	0.03	-0.07 – 0.13	0.58	.562
COVID uncertainty * Trait anxiety	-0.01	-0.11 – 0.09	-0.20	.840	0.03	-0.07 – 0.14	0.62	.532	0.02	-0.08 – 0.13	0.46	.646

Note. Summed contrasts were used meaning that the intercept reflects the grand mean of all conditions for each model. P-values < .05 are in bold. P-values and confidence intervals calculated using Satterthwaite approximation. Information in this table obtained using tab_model function as part of the sjPlot package (Lüdecke, 2021a). All dependent and continuous independent variables were z-scored prior to analysis.

Table S. A summary of the variance explained by random effects for LMMs 1-3 assessing whether each thought pattern varied significantly by 1) COVID uncertainty, 2) COVID threat, and 3) trait anxiety in the daily life sample (n = 59).

	Factor 1	**Factor 2**	**Factor 3**
σ^2	0.61	0.64	0.66
τ_{00}	0.08 $_{\text{Day : Participant}}$	0.05 $_{\text{Day : Participant}}$	0.04 $_{\text{Day : Participant}}$
	0.31 $_{\text{Participant}}$	0.30 $_{\text{Participant}}$	0.27 $_{\text{Participant}}$
N	7 $_{\text{Day}}$	7 $_{\text{Day}}$	7 $_{\text{Day}}$
	59 $_{\text{Participant}}$	59 $_{\text{Participant}}$	59 $_{\text{Participant}}$
Observations	1256	1256	1256

Note. σ2 = population variance, τ00 = random intercept variance. Day = Day number. Participant = Participant identifier. Information in this table obtained using tab_model function as part of the sjPlot package (Lüdecke, 2021a).

Supplementary Figures

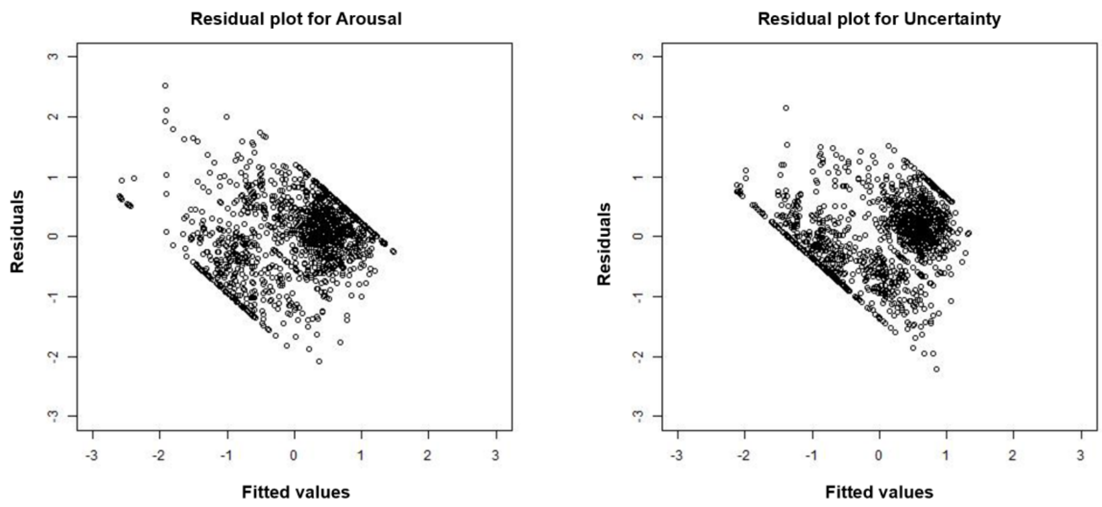

Fig A. Residual plots for Linear Mixed Models assessing whether arousal and uncertainty ratings significantly varied between video conditions in the combined laboratory samples (n =119; n observations = 1338), demonstrating non-randomness of the residuals.

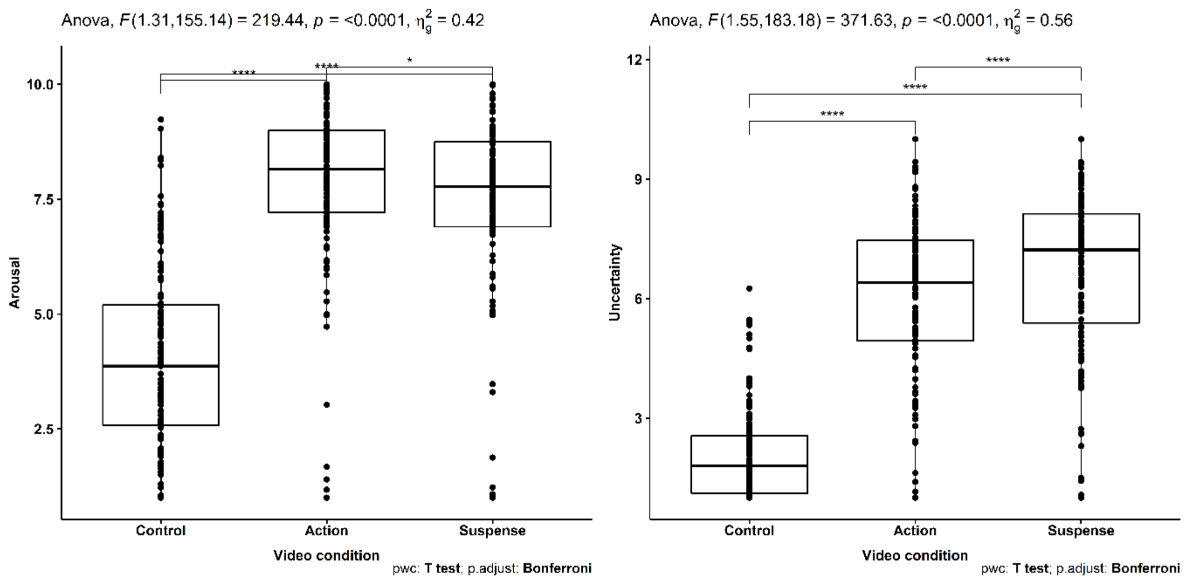

Fig B. Results from the one-way repeated measures ANOVAs comparing mean arousal and mean uncertainty ratings between video conditions in the laboratory samples (n = 119). On the left-hand side is the boxplot for mean arousal ratings (y-axis) by video condition (x-axis) with the ANOVA results at the top and the significance of the pairwise comparisons (t-test; Bonferroni adjustment) are displayed using asterisks (* = p < .05, ** = p <.01, *** = p <.001). On the right-hand side is the boxplot for mean uncertainty ratings (y-axis) by video condition (x-axis) with the ANOVA results at the top and the significance of the pairwise comparisons (t-test; Bonferroni adjustment) are displayed using asterisks (* = p < .05, ** = p <.01, *** = p <.001). However, these results should be interpreted with caution since the Shapiro-Wilk test and QQ plots (see Fig E) indicated non-normality of the data.

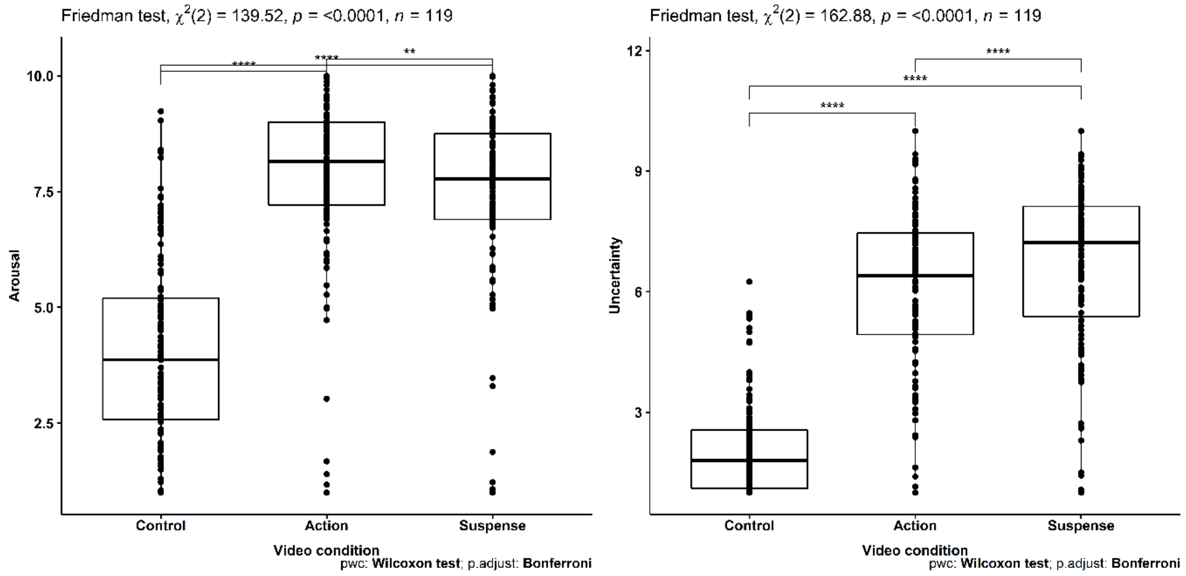

Fig C. Results from the non-parametric Friedman's test comparing mean arousal and mean uncertainty ratings between video conditions in the laboratory samples (n = 119). On the left-hand side is the boxplot for mean arousal ratings (y-axis) by video condition (x-axis) with the Friedman test results at the top and the significance of the pairwise comparisons (Wilcoxon test; Bonferroni adjustment) are displayed using asterisks (* = p < .05, ** = p <.01, *** = p <.001). On the right-hand side is the boxplot for mean uncertainty ratings (y-axis) by video condition (x-axis) with the Friedman test results at the top and the significance of the pairwise comparisons Wilcoxon test; Bonferroni adjustment) are displayed using asterisks (* = p < .05, ** = p <.01, *** = p <.001).

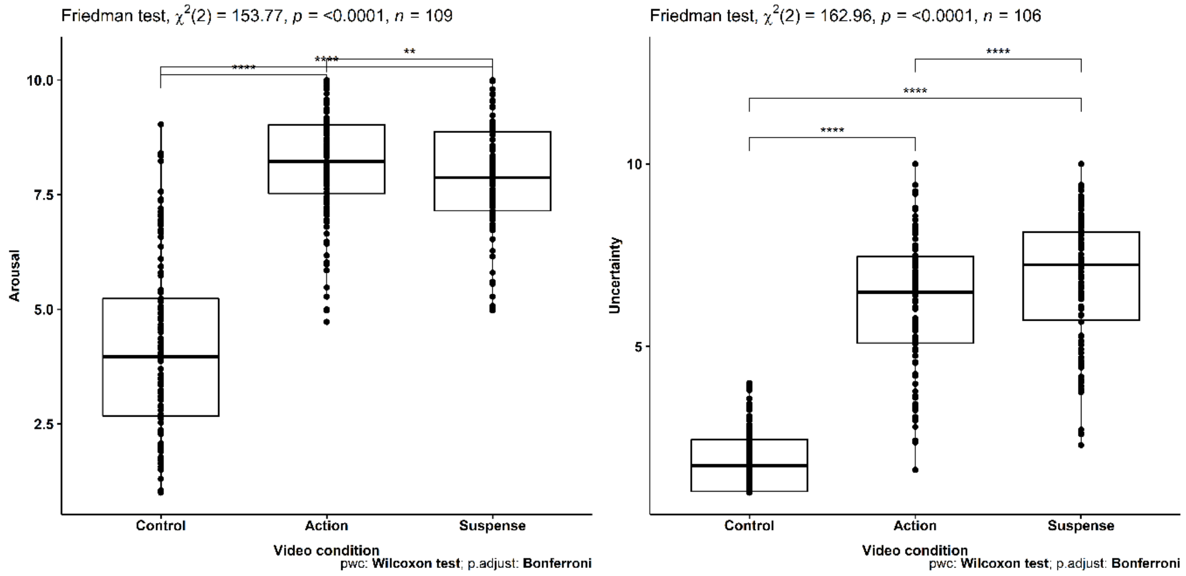

Fig D. Results from the non-parametric Friedman's test comparing mean arousal (n = 109) and mean uncertainty (n = 106) ratings between video conditions in the laboratory samples with outliers removed. On the left-hand side is the boxplot for mean arousal ratings (y-axis) by video condition (x-axis) with the Friedman test results at the top and the significance of the pairwise comparisons (Wilcoxon test; Bonferroni adjustment) are displayed using asterisks (* = p < .05, ** = p <.01, *** = p <.001). On the right-hand side is the boxplot for mean uncertainty ratings (y-axis) by video condition (x-axis) with the Friedman test results at the top and the significance of the pairwise comparisons Wilcoxon test; Bonferroni adjustment) are displayed using asterisks (* = p < .05, ** = p <.01, *** = p <.001).

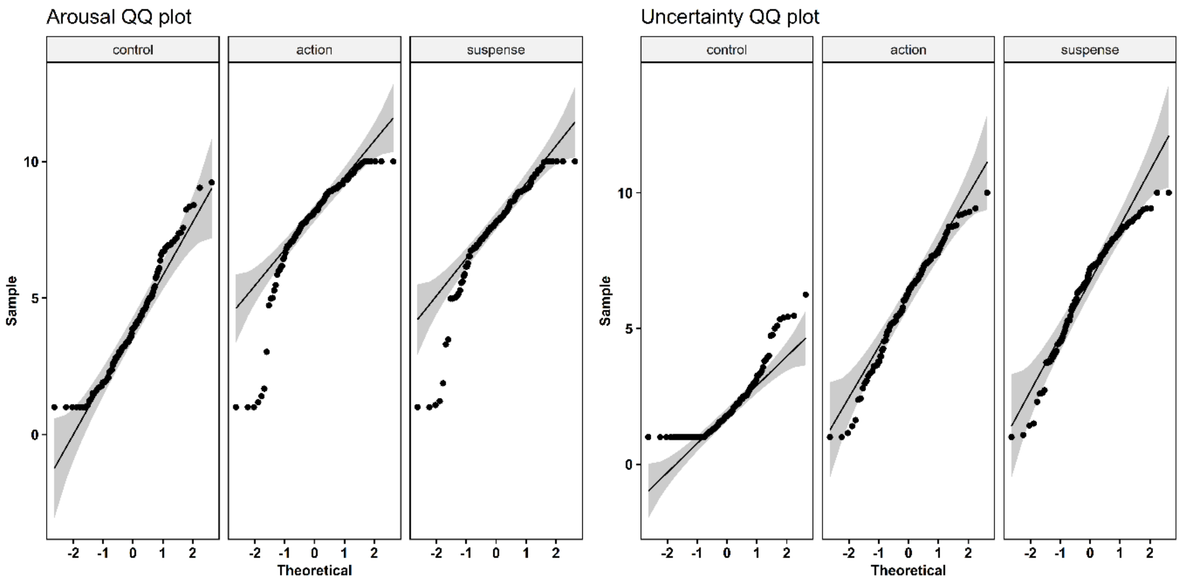

Fig E. QQ-plots for mean arousal and mean uncertainty ratings by video condition in the laboratory samples (n = 119) demonstrating non-normality.

Fig F. Scatterplots showing the correlation between trait anxiety and mean scores for each thought pattern split by video condition in laboratory Sample 1 (n = 70; n observations = 210). The top panel shows the correlations between trait anxiety and mean self-relevant and past-focused off-task thought, the middle panel shows the correlations between trait anxiety and mean emotional, social future-directed problem-solving, and the bottom panel shows the correlations between trait anxiety and mean detailed deliberate thought. Each thought pattern is represented here as word clouds where the size of the word reflects the importance of the item, and the colour reflects the polarity (warmer colours = positive, cooler colours = negative). Red corresponds to the control condition, green corresponds to the action condition, and blue corresponds to the suspense condition. Pearson correlation R and p-values were calculated using the ‘stat_cor’ function from the ‘ggpubr’ library in R (Kassambara, 2020).

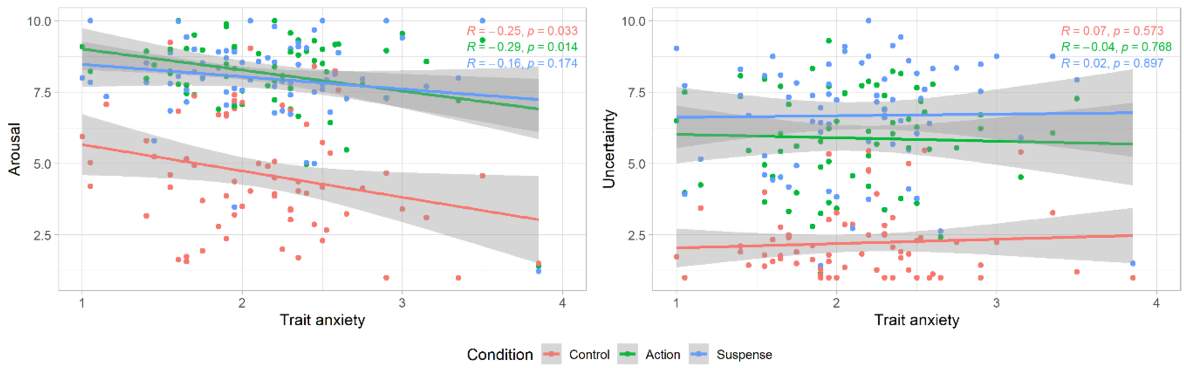

Fig G. Scatterplots showing the correlation between trait anxiety and emotional states by video condition in laboratory Sample 1 (n = 70, n observations = 210). The left-hand side shows the correlation between mean arousal by video condition and trait anxiety, while the right-hand side shows the correlation between mean uncertainty by video condition and trait anxiety. Red corresponds to the control condition, green corresponds to the action condition, and blue corresponds to the suspense condition. Pearson correlation R and p-values were calculated using the 'stat_cor' function from the 'ggpubr' library in R (Kassambara, 2020).

Fig H. Scatterplots showing the correlation between trait anxiety and mean scores for each projected thought pattern split by sample (pre- vs during-COVID) in daily life (n = 129). The top panel shows the correlations between trait anxiety and mean self-relevant and past-focussed off-task thought, the middle panel shows the correlations between trait anxiety and mean emotional, social future-directed problem-solving, and the bottom panel shows the correlations between trait anxiety and mean detailed deliberate thought. Each thought pattern is represented here as word clouds where the size of the word reflects the importance of the item, and the colour reflects the polarity (warmer colours = positive, cooler colours = negative). Pearson correlation R and p-values were calculated using the ‘stat_cor’ function from the ‘ggpubr’ library in R (Kassambara, 2020).

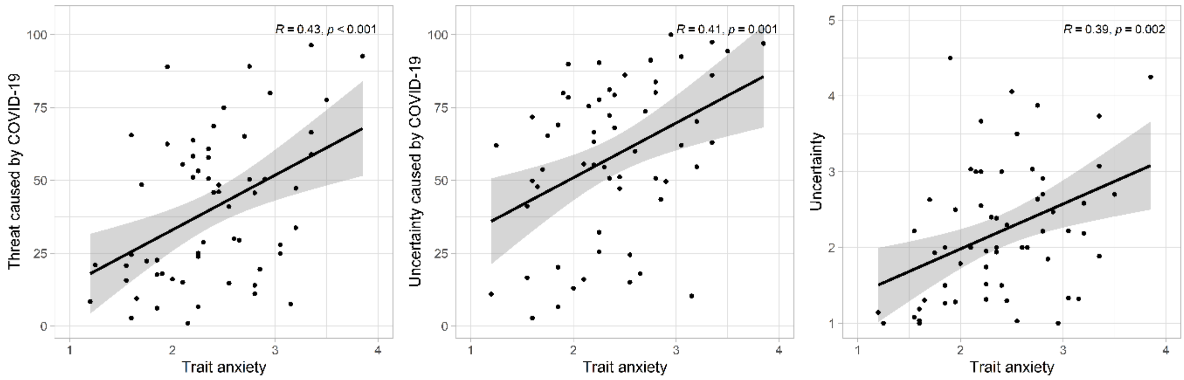

Fig I. Scatterplots showing the correlation between trait anxiety, mean threat caused by COVID-19, mean uncertainty caused by COVID-19, and mean uncertainty generally in the daily life COVID sample (n = 59). Pearson correlation R and p-values were calculated using the ‘stat_cor’ function from the ‘ggpubr’ library in R (Kassambara, 2020).

A.3 Supplementary Materials: Chapter 4

This section contains the supplementary materials for Chapter 4 including:

- Figures S1 to S3
- Tables S1 to S2

Supplementary Figures

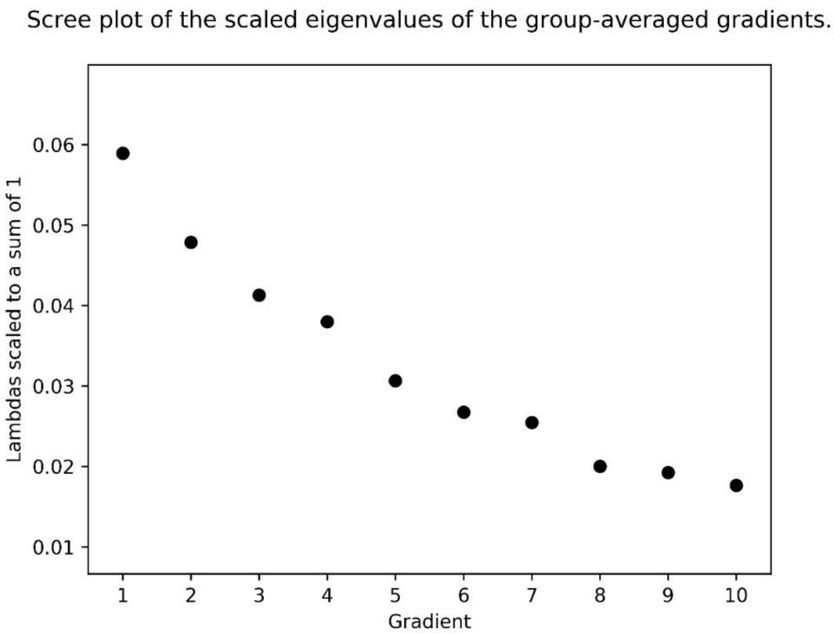

Figure S1. Scree plot showing the proportion of variance explained by each of the group-level whole-brain connectivity gradients one to ten. Y-axis shows the eigenvalues scaled to a sum of 1. X-axis shows the gradient number. The first three gradients were retained for further multivariate analyses as these gradients have the clearest mapping to cognitive function (e.g., Murphy et al., 2018; Murphy et al., 2019; Turnbull et al., 2020b).

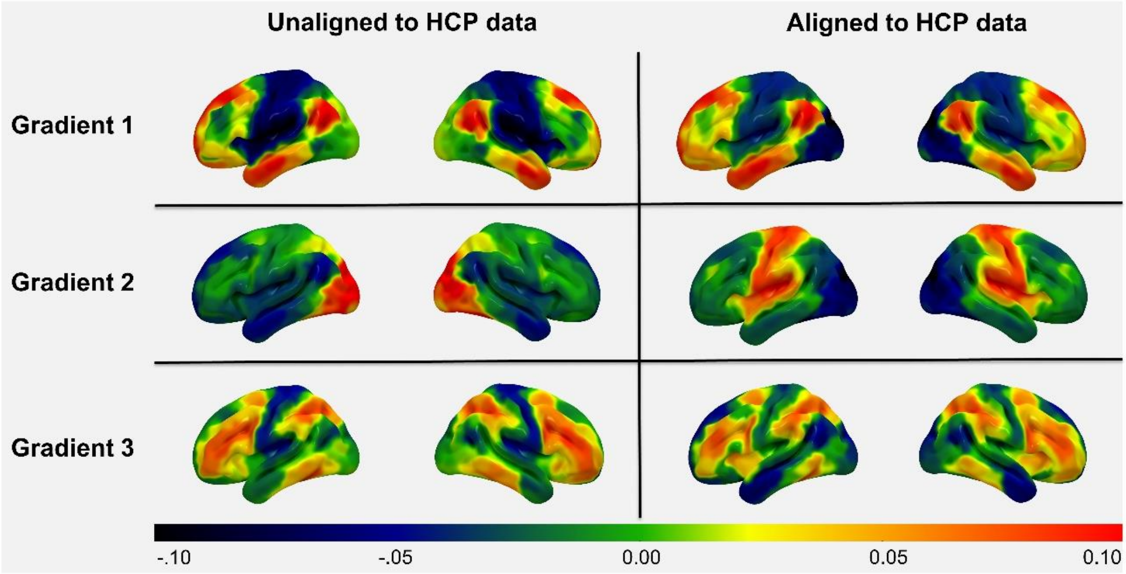

Figure S2. Demonstration of how aligning the group-level gradients to a subsample of the HCP dataset using Procrustes rotation changes the first three group-level gradients. Regions that share similar connectivity profiles fall together along each gradient (similar colours) and regions that have more distinct connectivity profiles fall further apart (different colours). It is important to note that the positive and negative loading is arbitrary and can flip each time the diffusion embedding is applied to the data. For example, in this figure, the visual cortex along gradient two has a positive loading in the unaligned map but has a negative loading in the aligned map. Thus, differences in loadings are not meaningful and occur randomly.

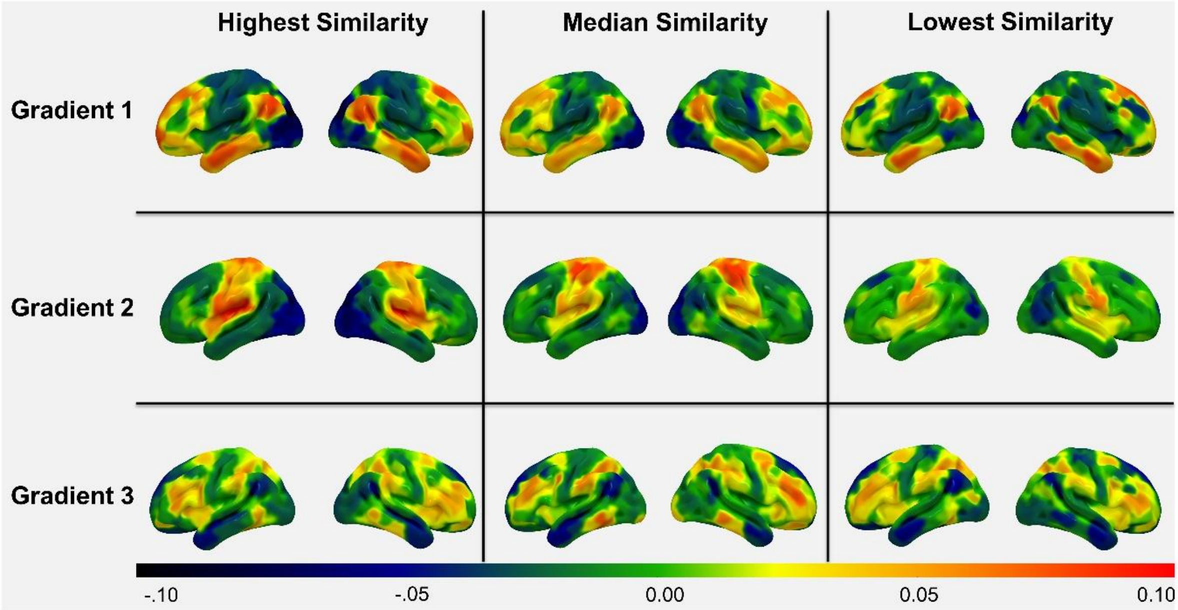

Figure S3. Individual-level connectivity gradients one to three which have the highest (left), median (middle) and lowest (right) similarity with the respective group-level gradients to demonstrate the variability of gradients across participants in the current sample. Regions that share similar connectivity profiles fall together along each gradient (similar colours) and regions that have more distinct connectivity profiles fall further apart (different colours). The positive and negative loading is arbitrary.

Supplementary Tables

Table S1. Improvement in the degree of fit (or similarity) between individual-level and group-level gradients when extracting ten gradients compared to only extracting three gradients. Mean similarity was calculated by averaging all participant's R-to-Z transformed Spearman Rank correlation coefficients for each respective gradient.

N gradients extracted	Gradient	Minimum	Maximum	Mean	Std. Deviation
3	1	0.31	1.31	0.84	0.21
10	1	0.70	1.76	1.36	0.16
3	2	0.28	1.48	0.84	0.25
10	2	0.90	1.85	1.37	0.16
3	3	-0.07	1.04	0.57	0.19
10	3	0.58	1.38	1.12	0.12

Table S2. Spearman rank correlation values for the first five aligned and unaligned group-level gradients with the first five group-level gradients reported in Margulies et al. (2016). This demonstrates that aligning the group-level gradients to the subsample of HCP data improves correspondence between the gradients calculated in the current study and previous literature.

Gradient	Aligned to HCP	Unaligned to HCP
1	0.62	0.40
2	-0.47	0.23
3	-0.45	-0.38
4	-0.20	0.07
5	-0.18	-0.03

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