Investigating the cognitive mechanisms by which sleep supports emotion regulation and mental health

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Abstract

Sleep plays an important role in how we process and deal with our emotions on a daily basis. As emotion regulation difficulties are a key predictor of poorer mental health, understanding the mechanisms by which sleep supports emotion regulation and mental health is of the upmost importance to further our understanding of psychiatric vulnerability. This thesis aims to investigate the cognitive mechanisms by which sleep supports emotion regulation and mental health. Specifically, three components of emotion regulation are examined: cognitive emotion regulation (CER), emotional reactivity, and emotional inertia. The first empirical chapter (Chapter 2) investigates whether the benefits of adaptive CER strategies (to lower depression and anxiety) are contingent on high sleep quality. The second empirical chapter (Chapter 3) examines whether sleep deprivation (versus a night of sleep) influences the evolution of arousal responses during exposure to ambiguous threat, as well as the reciprocal influence of slow wave activity (SWA) on affect regulation. The third empirical chapter (Chapter 4) explores whether the benefits of adaptive CER strategy use (to lower emotional inertia) are contingent on high sleep quality. Our findings suggest that: 1) greater use of adaptive CER strategies and high sleep quality independently promote resilience to depression, 2) a night of sleep (versus sleep deprivation) promotes the regulation of affect in response to prolonged ambiguous threat; however, SWA is not associated with this regulation, and 3) greater use of adaptive CER strategies and high sleep quality independently reduce the persistence of negative emotions over time. In light of these findings, cognitive control is proposed as one critical mechanism underlying the association between sleep and emotion regulation. Altogether, this thesis provides important insights into the cognitive mechanisms by which sleep supports emotion regulation, and mental health, and points towards modifiable mechanisms that may buffer against psychiatric vulnerability.

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Author's declarations

I, Emma Sullivan, declare that this thesis is a presentation of original work and I am the sole author, under the supervision of Dr Scott Cairney (Primary Supervisor), Dr Cade McCall and Professor Lisa-Marie Henderson. This work has not previously been presented for a degree or other qualification at this University or elsewhere. All sources are acknowledged as references. The data presented in Chapter 2 was a secondary analysis of data collected by Cunningham, Fields, and Kensinger, (2021) and has been made publicly available on the Open Science Framework.

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Chapter 2

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Chapter 1: Introduction

1.1 Overview

Sleep problems are a common co-occurrence in nearly all psychiatric conditions and are a strong risk factor for both initial and recurrent episodes (Baglioni, Spiegelhalder, et al., 2010; Bi & Chen, 2022; Chellappa & Aeschbach, 2022; Freeman et al., 2017; Harvey, 2001). Reciprocally, improving sleep quality leads to greater improvements in mental health outcomes such as depression, anxiety, and stress (Kudrnáčová & Kudrnáč, 2023; A. J. Scott et al., 2021). A growing body of research suggests that sleep plays an important role in emotion processing in both clinical and non-clinical populations (Tempesta et al., 2018). Since emotion dysregulation is a key predictor of poorer mental health (Gross, 2014; Kring, 2010), understanding the mechanisms by which sleep supports emotion processing is of the upmost importance for learning more about not only clinical-level psychiatric vulnerability but also daily fluctuations in emotion states in non-clinical populations.

Thus, the overarching aim of this thesis is to address this gap in understanding. To do this, I take an integrated approach by examining the cognitive mechanisms through which sleep contributes to various aspects of emotion processing (see Figure 1.1). To isolate and examine the basic mechanisms underlying this association, whilst minimising other confounding variables (e.g. interventions, medication, symptom severity), I primarily focus on individuals without any current psychiatric disorders.

1.1.1 Emotion regulation

When we encounter affective experiences, we modulate our emotional responses through emotion regulation. Emotion regulation involves processes that influence which emotions we have, when we have them, and how we experience and express them (Gross, 1998; Gross & Feldman Barrett, 2011). Emotion regulation distinguishes between voluntary and involuntary regulation as well as between adaptive and maladaptive regulation (Kohn et al., 2014). This thesis examines three components of emotion regulation: cognitive emotion regulation (CER; i.e. the thought strategies that individuals employ to deal with negative events), emotional reactivity (i.e. the quality and/or intensity of an initial response to an event), and emotional inertia (i.e. the persistence of emotion states from one moment to the next).

1.1.2 Cognitive emotion regulation

The preponderance of research on emotion regulation focuses on the strategies that individuals employ to modify their emotion states (Gross, 2015). CER strategies are the cognitive thought processes that an individual engages in after being exposed to an emotional experience that attempt to modify an individual's response to the event (Aldao & Nolen-Hoeksema, 2010; Garnefski et al., 2001). Specific CER strategies have been categorised as either adaptive or maladaptive (Aldao et al., 2010). Adaptive CER strategies have been conceptualised as more 'positive-focused', whereas maladaptive strategies have been conceptualised as more 'negative-focused' (Garnefski et al., 2001). Greater use of adaptive CER strategies have been associated with lower levels of depression and anxiety in both clinical and non-clinical samples (Domaradzka & Fajkowska, 2018; Kirschbaum-Lesch et al., 2021; Min et al., 2013). Therefore, greater use of these positive focused strategies may be an important safeguard against the development of psychiatric disturbance when enduring unpleasant and stressful experiences in everyday life. Reciprocally, psychological well-being may promote the use of adaptive CER strategies. Nonetheless, most studies have focused on how people deploy adaptive CER strategies in response to laboratory-induced stimuli. In these situations, artificial stressors are briefly presented and individuals may be explicitly taught or encouraged to use different strategies. As a result, we know little about how adaptive CER strategies are used spontaneously in the context of real-world, chronic stressors. Unsurprisingly, poor sleep impairs people's ability to effectively deploy adaptive CER strategies (Mauss et al., 2013; Parsons et al., 2021; Tamm et al., 2019; Zhang et al., 2019). Given that the brain mechanisms underlying the successful use of adaptive CER strategies are contingent on good sleep (R. Gruber & Cassoff, 2014; Palmer & Alfano, 2017), sleep may moderate the effectiveness of adaptive CER strategies. However, whether sleep moderates the effectiveness of adaptive CER strategies following sustained stress remains unknown.

1.1.3 Emotional reactivity

Emotional reactivity can be defined as one's initial affective response to an event (Koval, Brose, et al., 2015). It is the starting point of an emotional experience and is causally related to the ability to regulate emotions as the experience unfolds (Becerra & Campitelli, 2013). Greater emotional reactivity, particularly in response to potential threats, has been associated with exacerbated anxiety (Goldin et al., 2009; Grillon, 2002; Nock et al., 2008). Inadequate sleep is a potentiating factor in emotional reactivity and threat perception (Baglioni, Lombardo, et al., 2010; Franzen et al., 2009; Tempesta et al., 2018). Conversely, certain properties of sleep, namely slow wave activity (SWA), have been associated with the restoration of brain mechanisms that are critical for affect regulation (Bishop, 2007; Bishop et al., 2004; M. J. Kim et al., 2011; Simmons et al., 2008). However, previous studies have assessed emotional reactivity at only single moments in time in response to short, static threats (e.g. images or film clips). Real-world threatening environments often evolve over time and include uncertainty regarding the presence of threat, the nature of the threat, and how to best respond to the threat (i.e. ambiguity; McCall et al., 2022). We know little about how sleep deprivation (versus sleep) influences the evolution of emotional reactivity during exposure to ambiguous threat.

1.1.4 Emotional inertia

Emotional inertia is another aspect of emotional experience. Emotional inertia refers to the persistence of an emotion state over time (Koval et al., 2016; Kuppens, Allen, et al., 2010). Inflexibility in emotional responding (i.e. high emotional inertia) is considered a hallmark of many psychiatric disorders (Kuppens, Allen, et al., 2010). Less frequent use of adaptive CER strategies and greater use of maladaptive CER strategies have also been associated with higher emotional inertia (Bean et al., 2021; Blanke et al., 2022; Koval, Butler, et al., 2015; Koval et al., 2012; Kuppens, Oravecz, et al., 2010). Unlike the other by-products of emotion regulation, few studies have examined how sleep influences emotional inertia. However, given that sleep promotes the effectiveness of adaptive CER strategies and appropriately modulates emotional reactivity, it is likely that sleep affects the persistence of emotion states over time. Current research on sleep and emotional inertia is in its infancy and prior studies have produced mixed findings (Frérart et al., 2023; Minaeva et al., 2021; X. Wen et al., 2020). Therefore, more research is needed to elucidate the association between sleep and emotional inertia.

1.1.5 Thesis chapters

This thesis addresses these gaps in understanding across three chapters, each of which presents an empirical study (see Box 1 for an overview of each research question). Each chapter examines the cognitive mechanisms by which sleep supports emotion regulation (CER, emotional reactivity, and emotional inertia) and mental health. This introductory chapter (Chapter 1) reviews the role of sleep in emotion regulation. Synthesised evidence for the role of sleep in CER, emotional reactivity, and emotional inertia from behavioural, physiological, and functional neuroimaging (fMRI) studies will be examined. The first empirical chapter (Chapter 2) examines whether the positive benefits of adaptive CER strategies (for reducing depression and anxiety) are contingent on good sleep quality during a real-world chronic stressor, the COVID-19 pandemic. Given that the COVID-19 pandemic was a prolonged and unique source of stress for people across the world, it offered a unique context in which to study the effects of adaptive CER strategy use and sleep on mental health. Chapter 3 investigates how sleep deprivation (versus a night of sleep) influences the evolution of emotional reactivity during ambiguous threat exposure. This study built on previous work that assessed emotional reactivity in response to predictable threats at only single moments in time. In a complementary manner, I also examined whether specific properties of sleep (namely SWA) restore affect regulation processes during exposure to ambiguous threat. Chapter 4 examines the associations between adaptive CER strategies, sleep quality, and emotional inertia. Only a handful of studies have investigated the association between sleep and emotional inertia and have produced conflicting findings. However, given the influence of sleep on other components of emotion regulation, I wanted to further explore this association. Notably, in each chapter, I consider how emotion regulation unfolds over time (i.e. in response to a chronic stressor, during exposure to prolonged ambiguous threat, and how emotion states persist over time). Together, these chapters offer new insights into the role of sleep in emotion regulation and mental health. Ultimately, the work presented will help us better understand the mechanisms contributing to poorer mental health in individuals with inadequate sleep.

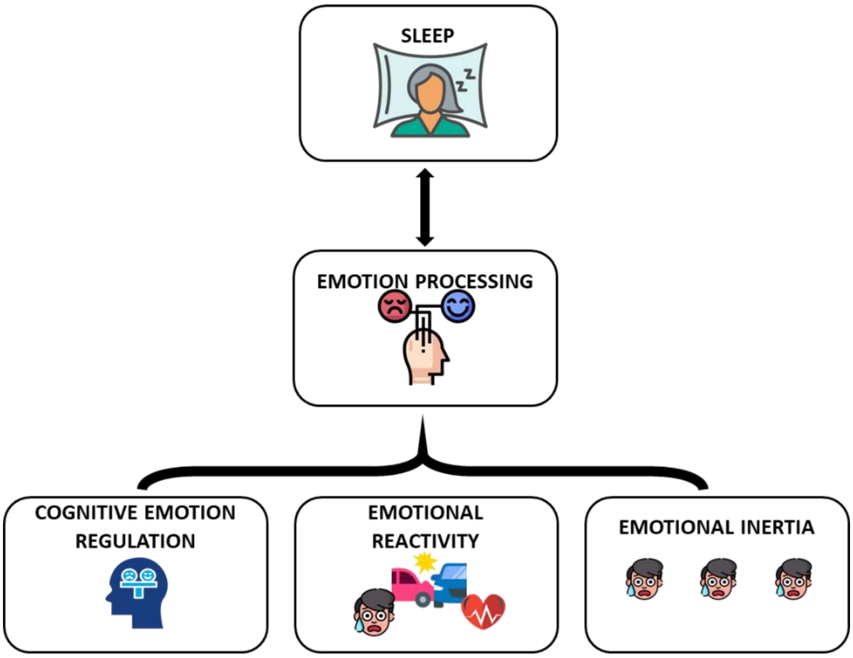

Figure 1.1. Overview of the cognitive mechanisms linking sleep and emotion processing. Cognitive emotion regulation refers to the thought processes that an individual voluntarily engages in after exposure to an emotional experience. Chapter 2 addresses how sleep supports cognitive emotion regulation with regard to its influence on depression and anxiety outcomes.

Emotional reactivity is an individual’s initial affective response to an emotional event. Chapter 3 examines the impact of sleep deprivation (versus a night of sleep) on the evolution of emotional reactivity during ambiguous threat exposure. Emotional inertia is the persistence of an emotion state over time. Chapter 4 investigates the influence of sleep on emotional inertia.

Box 1. Research questions addressed in this thesis:

1. **Chapter 2:** Investigating the influence of cognitive emotion regulation strategy use and sleep quality on changes in mental health (i.e. depression and anxiety) in the context of a unique and protracted stressor, the COVID-19 pandemic.
2. **Chapter 3:** Using virtual reality to investigate the influence of sleep deprivation (versus a night of sleep) on the evolution of emotional reactivity during exposure to prolonged ambiguous threat.
3. **Chapter 4:** Investigating the influence of cognitive emotion regulation strategy use and sleep quality on emotional inertia.

1.2 Cognitive emotion regulation

CER involves the conscious use of strategies that attempt to modify responses to an emotion-eliciting experience (Aldao & Nolen-Hoeksema, 2010; Gross, 2015). The employment of CER strategies can influence the intensity, duration, and/or quality of emotional responses (Gross, 2013). Most commonly, CER strategies are employed to decrease negative emotions, including sadness and anxiety (Gross et al., 2006), or enhance positive emotions, such as happiness (Quoidbach et al., 2010). Less frequently, individuals try to increase negative emotions (Sutton, 1991) or decrease positive ones (J. Gruber et al., 2011).

Depending on an individual’s goals, CER strategies can be differentiated based on their ability to foster adaptive or maladaptive emotional outcomes (Aldao & Nolen-Hoeksema, 2010). Garnefski et al. (2001) proposed nine CER strategies (see Table 1.1): positive reappraisal, refocus on planning, positive refocusing, putting into perspective, acceptance, rumination, self-blame, other-blame and catastrophising. The first five strategies have been conceptualised as adaptive, and the latter four have been conceptualised as maladaptive (Domínguez-Sánchez et al., 2013; Garnefski & Kraaij, 2006; Garnefski et al., 2001). However, Martin and Dahlen (2005) argue that acceptance is a maladaptive CER strategy, as it has been positively associated with depression, stress, and maladaptive anger suppression, and may therefore reflect a degree of hopelessness. Expression suppression is another CER strategy thought to foster maladaptive emotional outcomes (Dryman & Heimberg, 2018).

Table 1.1. Definitions of cognitive emotion regulation strategies.

Strategy	**Definition**
Adaptive CER strategies	
Positive reappraisal	Re-evaluating an event as either more positive or less negative.
Refocus on planning	Thinking about the next steps and how to handle an event.
Positive refocusing	Turning thoughts towards joyful and pleasant matters following an event.
Putting into perspective	Downregulating the seriousness of an event and comparing it to other events.
Acceptance	Resigning to what happened following an event.
Maladaptive CER strategies	
Rumination	Tendency to dwell on the negative feelings or thoughts associated with an event.
Self-blame	Blaming oneself for what they have experienced following an event.
Other-blame	Blaming others for what they have experienced following an event.
Catastrophising	Overemphasising the negative parts of an event.
Expressive suppression	Suppression of outward emotional expressions.

Greater use of adaptive CER strategies has been negatively associated with psychopathology (Aldao & Nolen-Hoeksema, 2012a; Aldao et al., 2010) and is thought to promote psychological well-being in the long-term (Kirschbaum-Lesch et al., 2021). The most common adaptive CER strategy examined in the literature is positive reappraisal. Positive reappraisal is defined as re-evaluating an event as more positive (or less negative) to decrease negative emotions and increase positive ones (Aldao & Nolen-Hoeksema, 2010). For example, an individual might get made redundant. To reduce the negative emotions associated with this, they may appraise the situation positively by seeing it as an opportunity to complete various side projects that they have not yet managed to do. The implementation of positive reappraisal has been associated with adaptive outcomes, such as reduced negative affect (NA) and decreased amygdala and insula responses when exposed to negative film clips (Goldin et al., 2008; McRae, 2016). Conversely, less frequent use of positive reappraisal has been associated with higher levels of both depression and anxiety symptoms (Aldao & Nolen-Hoeksema, 2010; Domaradzka & Fajkowska, 2018; Garnefski et al., 2002; Martin & Dahlen, 2005). Previous studies have predominantly focused on how individual adaptive CER strategies such as positive reappraisal are associated with mental health outcomes. However, more recently, Domaradzka and Fajkowska (2018) demonstrated that higher scores on a composite measure of adaptive CER strategy use was associated with lower depression and anxiety. Promoting the use of adaptive CER strategies is also an important theme in traditional Cognitive Behavioural Therapy (CBT) for depression and anxiety (Hayes, 2008; S. G. Hofmann & Asmundson, 2008; Moser et al., 2014). Collectively, these studies suggest a role for adaptive CER strategies in buffering against the development of psychopathology and promoting psychological well-being.

Given the positive benefits of adaptive CER strategy use, it is important to uncover the cognitive mechanisms that govern their success. Adaptive CER strategies enlist a number of executive functions. Executive functions are higher-order cognitive processes that are necessary for the cognitive control of behaviour (Schmeichel & Tang, 2015). Three related but separable executive functions have been proposed (Friedman & Miyake, 2017; Miyake & Friedman, 2012). These include a) inhibition (i.e. resisting inappropriate behaviours), b) updating (i.e. holding information in mind in order to act on the basis of it), and c) shifting (i.e. quickly and flexibly adapting to changing situations). Engaging in adaptive CER strategy use involves inhibition of prepotent responses, memory updating, and flexible task switching (Joormann & Tanovic, 2015; McRae et al., 2012; Ochsner & Gross, 2005). Therefore, it is likely that executive functions are necessary for successful adaptive CER strategy use.

On a neurobiological level, adaptive CER strategy use involves interactions between regions of the prefrontal cortex (PFC) that implement control processes, and subcortical and posterior cortical regions that encode and represent emotional information (R. Gruber &

Cassoff, 2014; Kohn et al., 2014). It is thought that prefrontal regions enable individuals to selectively use executive functions that allow them to successfully utilise adaptive CER strategies (Etkin et al., 2015; R. Gruber & Cassoff, 2014; Ochsner et al., 2012). In support of this view, the use of positive reappraisal (both instructed positive reappraisal and habitual positive reappraisal in daily life) has been associated with greater prefrontal activity and reduced amygdala activation when viewing emotion-eliciting stimuli (Drabant et al., 2009; S. H. Kim & Hamann, 2007; Ochsner et al., 2002, 2004; Phan et al., 2005; van Reekum et al., 2007). Taken together, these findings suggest that the effectiveness of adaptive CER strategies relies on prefrontal functioning.

Conversely, greater use of maladaptive CER strategies has been associated with the aetiology and maintenance of psychopathology (Aldao & Nolen-Hoeksema, 2012a; Aldao et al., 2010). Maladaptive CER strategies provide only short-term respite (Campbell-Sills & Barlow, 2007) and can even amplify affective disturbances in the long term (Aldao et al., 2010; Garnefski et al., 2001; Nolen-Hoeksema et al., 2008). One of the most common maladaptive CER strategies investigated in previous studies is rumination. Rumination is defined as the tendency to dwell on negative feelings or thoughts associated with an event (McRae et al., 2012). Returning to the example of an individual being made redundant, rumination would involve the individual excessively thinking about why they got made redundant and how they might never get another job as a result of this. Greater use of rumination has been associated with psychological maladjustment, including increased negative affect, as well as diminished autonomic flexibility (Blanke et al., 2022; Carnevali et al., 2018; McRae et al., 2012; Radstaak et al., 2011). Furthermore, greater use of rumination has been positively associated with depression and anxiety (Aldao & Nolen-Hoeksema, 2010; Domaradzka & Fajkowska, 2018; Garnefski et al., 2002; Martin & Dahlen, 2005). Higher scores on a composite measure of maladaptive CER strategy use have also been associated with greater depression and anxiety severity (Domaradzka & Fajkowska, 2018; Garnefski et al., 2001). Together, these studies support an association between maladaptive CER strategy use and the development and maintenance of psychopathology.

Most research on adaptive and maladaptive CER strategy use focuses on the frequency with which individuals use different strategies in response to naturally occurring emotional events. This is typically assessed using standardised self-report questionnaires, such as the Cognitive Emotion Regulation Questionnaire- Short version (CERQ-short; Garnefski & Kraaij, 2006) and the Emotion Regulation Questionnaire (ERQ; Gross & John, 2003). Both the CERQ-short and ERQ have demonstrated good psychometric properties (Ioannidis & Siegling, 2015; Ireland et al., 2017). The use of CER strategies has also been experimentally examined. In these studies, participants are often explicitly instructed or encouraged to use a specific strategy in response to artificially induced stressors. The success of each CER strategy is then assessed by measuring the degree to which the strategy modifies an individual's subjective and/or physiological emotional responses (McRae, 2016). Therefore, CER strategies can be deployed and measured implicitly (i.e. in response to an event) but can also be modified through explicit instruction, implying that they can be used flexibly and are amenable to intervention.

1.2.1 Sleep and cognitive emotion regulation

Sleep difficulties have a detrimental impact on people's ability to effectively use adaptive CER strategies (Mauss et al., 2013; Stenson et al., 2021; Tamm et al., 2019; Zhang et al., 2019). Poor sleep quality diminishes the ability to reduce self-reported sadness when participants are instructed to reinterpret the context of a negative picture to feel emotionally neutral (Mauss et al., 2013). Another study examining daily fluctuations in self-reported sleep quality found that poor sleep quality was associated with decreased next-day use of adaptive CER strategies (Parsons et al., 2021). Furthermore, the deleterious effect of sleep deprivation on the use of positive reappraisal has been evidenced through the impairment of an electroencephalography (EEG) marker of emotion regulation, the late positive potential (LPP). Emotionally valanced stimuli tend to elicit larger LPPs than neutral stimuli, and prior studies have demonstrated a reduction in LPP amplitude following positive reappraisal (Foti & Hajcak, 2008; Hajcak et al., 2006; Hajcak & Nieuwenhuis, 2006; MacNamara et al., 2011). Therefore, reappraisal-related reductions in LPP are thought to reflect a shift in interpretation (Foti & Hajcak, 2008; Lazarus, 1991). Zhang et al. (2019) found that sleep deprivation, compared to a night of sleep, disrupted the attenuation of LPP amplitudes when participants were instructed to think about the situation in a more positive light following the presentation of sad film clips. This suggests that sleep deprivation impairs the reinterpretation of negative events. Together, these findings point to a potential mechanism linking inadequate sleep and psychopathology, whereby the utility of adaptive CER strategies (i.e. for decreasing negative affect and promoting psychological well-being) is contingent on good sleep.

Findings from neuroimaging studies help elucidate the mechanisms by which sleep loss impairs adaptive CER strategy use. Sleep loss decreases the connectivity between prefrontal and subcortical regions, such as the amygdala, when participants are exposed to negative emotional stimuli (Gujar, McDonald, et al., 2011; Simon et al., 2015; Yoo et al., 2007). Along with these findings, poor sleep quality has been associated with hypoactivation in the PFC during reappraisal implementation (Minkel et al., 2012). Therefore, inadequate sleep is thought to compromise the top-down inhibitory control of the PFC over amygdala driven emotional responses (Gujar, Yoo, et al., 2011; Yoo et al., 2007), resulting in global deficits in executive functioning and regulatory control (Palmer & Alfano, 2017). As the executive functions required for successful adaptive CER strategy use, such as inhibition, working memory, and attention, are depleted by sleep loss (Drummond et al., 1999; Mograss et al., 2009; Nilsson et al., 2005; Qi et al., 2010; Skurvydas et al., 2020), this suggests that poor sleep may undercut the positive benefits that adaptive CER strategies typically provide.

Poor sleep quality has also been associated with increased use of maladaptive CER strategies (Boon et al., 2023; Latif et al., 2019). Boon et al. (2023) found that participants reported higher use of rumination following a night of sleep fragmentation (as assessed by frequent awakenings throughout the night), compared to a normal night of sleep. This finding suggests that disrupted sleep makes it difficult to disengage attention from negative thoughts. One explanation for this is a lack of motivation. Poor sleep impairs motivation (Fairholme & Manber, 2015; Palmer & Alfano, 2017), meaning that individuals may be willing to exert less cognitive effort to modify their emotional response. As adaptive CER strategies are more cognitively demanding in the long term than maladaptive CER strategies (Sheppes & Levin, 2013), they may alternatively resort to maladaptive CER strategies. Together, these findings imply that sleep loss results in greater use of maladaptive CER strategies in response to negative events.

Importantly, most research on sleep and CER strategy use is limited to the laboratory. In the real world, individuals spontaneously deploy (or fail to deploy) CER strategies in response to aversive experiences in the absence of explicit instruction. Relatedly, experimentally induced stressors in these laboratory contexts often take the form of aversive images or film clips, which lack the enduring quality of stressful life changes. Real-world stressors often arise unexpectedly and are chronic in nature. Consequently, they generally require continuous input from CER strategies to modify frequent emotional responses. Recent work in adolescents demonstrated that higher emotion regulation ability attenuates the association between stressful real-life events and depressive symptoms (Liu et al., 2023), suggesting that high emotion regulation ability may buffer against the development of mental health problems when encountering real-world stressful life events. Nevertheless, little is known about how individuals deploy adaptive CER strategies spontaneously in a real-world context. As such, Chapter 2 examines the influence of adaptive CER strategy use and sleep quality on changes in mental health (i.e. depression and anxiety) in the context of a unique and protracted stressor, the COVID-19 pandemic.

1.2.2 Interim conclusion

To summarise, CER refers to the use of strategies to modify an individual's response to an emotional experience. These strategies have been characterised as adaptive or maladaptive, with higher use of the former safeguarding against the development of mental health problems in the long term. Sleep loss has been associated with a reduced ability to effectively use adaptive CER strategies. Additionally, some studies have shown that poor sleep results in increased maladaptive CER strategy use. Together, these findings suggest a potential mechanistic link between sleep and mental health, whereby the benefits of adaptive CER strategy use are contingent on obtaining high quality sleep. However, our current understanding of the role of sleep in CER strategy use is confined to laboratory contexts, where participants are often explicitly instructed to use one type of CER strategy and/or images or film clips are used as experimental stressors. Therefore, Chapter 2 addresses the relationship between adaptive CER strategy use, sleep quality, and mental health outcomes in response to a real-world chronic stressor.

1.3 Emotional reactivity

Emotional reactivity refers to a person's initial affective response to an event (Koval, Brose, et al., 2015). These emotional responses prepare individuals for action, allowing them to discriminate between pleasant and unpleasant stimuli and produce appropriate behavioural responses (Becerra & Campitelli, 2013). Emotional reactivity has been theorised to consist of three components. These include the magnitude of the stimulus required to trigger an emotional response, how strongly the emotional response manifests, and how long the emotional response persists before returning to baseline (R. J. Davidson, 1998; Nock et al., 2008). Conceptually, these have been termed activation, intensity, and duration, respectively (Becerra & Campitelli, 2013). Emotional reactivity appears to be a multifaceted phenomenon that leads to changes in subjective experience, psychophysiology, and behavioural responses.

Emotional reactivity has been associated with CER strategy use (Aldao et al., 2010). For example, it has been suggested that individuals who ruminate more frequently experience heightened emotional reactivity to affective events, which may persist for longer periods of time compared to those who ruminate less frequently (Nolen-Hoeksema et al., 2008).

Additionally, rumination has been associated with impaired cardiovascular recovery (e.g. heart rate) following an evocative event, leading to sustained physiological arousal (Brosschot et al., 2006). In contrast, greater use of positive reappraisal has been shown to reduce physiological arousal measures, including skin conductance response (SCR; Feeser et al., 2014) and facial corrugator electromyographic (EMG) responses (S. H. Kim & Hamann, 2012). These findings suggest that maladaptive CER strategy use increases emotional reactivity, and that adaptive CER strategy use decreases emotional reactivity in response to an affective event.

Several theoretical models have highlighted an association between heightened emotional reactivity and the development and maintenance of psychopathology (R. J. Davidson, 2003; Gross, 2002; Porges et al., 1994). Emotional hyperactivity is a salient feature of clinical anxiety (Cisler et al., 2010; Grillon, 2002). Although heightened emotional reactivity can be adaptive in unfamiliar and uncertain environments, symptoms of anxiety result from inappropriate activation of normally adaptive defensive responses (Grillon, 2002; Robinson et al., 2013).

Prior studies have explored the neural underpinnings of emotional reactivity. These findings reveal an important role for ventral emotion detection/generation-related limbic regions, including the amygdala, insula, and anterior cingulate cortex (ACC; Goldin et al., 2009). Moreover, PFC regions (e.g. ventromedial cortex and dorsomedial PFC) have also been implicated in the processing of valence and emotional intensity (Goldin et al., 2009). It is important to note that the involvement of emotion-related limbic regions and the PFC in the appropriate modulation of emotional reactivity overlaps with the brain regions involved in adaptive CER strategy use.

Emotional reactivity can be measured by assessing arousal (calm-excited) and valence (unpleasant-pleasant) responses to affective stimuli (Bradley & Lang, 2007; LaBar & Cabeza, 2006) using subjective or objective measures. Subjective ratings of emotional reactivity are commonly captured using the Self-Assessment Manikin (SAM), a Likert scale that asks participants to rate how excited (arousal) and pleasant (valence) they feel in response to a stimulus (Bradley & Lang, 1994). Objective measures of emotional reactivity include physiological indices, such as skin conductance, heart rate (HR), EMG, and pupillometry. These measures specifically focus on capturing state levels of emotional reactivity. However, convergent changes in subjective and objective measures of emotional reactivity in response to an emotional event are not always observed (Tempesta et al., 2018), alluding to the possibility that these measures might tap into different constructs and/or have different levels of sensitivity, as discussed in further detail below.

1.3.1 Sleep and emotional reactivity

A wealth of evidence demonstrates that emotional reactivity is influenced by sleep (Tempesta et al., 2018). Inadequate sleep amplifies negative emotions and blunts positive ones (Kahn et al., 2013; Zohar et al., 2005). Sleep loss has also been shown to promote negative bias. For example, sleep deprived individuals judge neutral stimuli to be more negative than sleep rested individuals (Pilcher et al., 2015; Tempesta et al., 2010; van der Helm et al., 2010). This negative bias effect was also observed when examining sleep quality. Tempesta et al. (2015) found that poor sleepers rated positive and neutral images as more negative compared to good sleepers. The potentiating effects of sleep loss on emotional reactivity have also been measured physiologically. Sleep-deprived participants showed greater pupillary reactivity in response to negative emotional stimuli compared to those who had a normal night of sleep (Franzen et al., 2008, 2009). However, Franzen et al. (2009) reported equivalent subjective arousal ratings in those who were sleep-deprived and those who had slept in response to these negative stimuli. One reason for this discrepancy is that physiological measures capture fine-grained implicit emotional responses whereas subjective measures are often coarse and require cognitive introspection (Bradley & Lang, 2007; Cunningham et al., 2014; Franzen et al., 2009; Tempesta et al., 2020). Therefore, physiological measures may be more appropriate for measuring emotional reactivity. Nonetheless, these findings support the idea that sleep loss promotes negative bias in the categorisation of positive and neutral stimuli and increases physiological reactivity to negative stimuli.

A lack of sleep also enhances the perception and generalisation of threats (Barber & Budnick, 2015; Goldstein-Piekarski et al., 2015; Zenses et al., 2020). Goldstein-Piekarski et al. (2015) found that participants judged significantly more stimuli as threatening, and less stimuli as non-threatening, when sleep deprived compared to sleep rested. Moreover, sleep deprivation impaired the autonomic-cardiac discrimination (as indexed by changes in HR) of non-threatening and threatening stimuli (Goldstein-Piekarski et al., 2015). Therefore, sleep deprivation may impose a negative bias on threat discrimination, resulting in heightened threat sensitivity.

Evidence from functional imaging provides important insights into the mechanisms by which sleep loss amplifies emotional reactivity. Sleep deprivation results in heightened activity in emotion-related limbic brain regions, such as the amygdala and ACC, each of which has been associated with greater reactivity to negative and neutral emotional stimuli (Ben Simon et al., 2020; Goldstein et al., 2013; Simon et al., 2015; van der Helm & Walker, 2012; Yoo et al., 2007). Sleep loss is also associated with decreased activity in the medial prefrontal cortex (mPFC), as well as decreased connectivity between the amygdala and mPFC when viewing negative images (Yoo et al., 2007). This neural composition reflects a complementary mechanism to that underlying adaptive CER strategy use, whereby sleep loss leads to a breakdown of top-down inhibitory control of emotional responses, resulting in amplified emotional reactivity (Ben Simon et al., 2020; van der Helm & Walker, 2012; Yoo et al., 2007). Moreover, another study demonstrated that impaired discrimination of threat and safety following sleep loss was associated with a generalised anticipatory response in the amygdala and insula (Goldstein et al., 2013). Taken together, it appears that sleep loss impairs the brain pathways thought to underlie adaptive threat responding (Grillon, 2002).

Despite evidence of heightened threat sensitivity in the absence of sleep, prior research has assessed emotional reactivity using one-shot ratings of aversive stimuli, such as images and film clips. There are two key drawbacks to this approach. First, emotional experiences often fluctuate in their intensity over a long period (Hildebrandt et al., 2016). However, previous studies have only focused on how sleep loss influences emotional reactivity during initial exposure to short, static threats. Consequently, there is a need to examine how sleep loss not only influences initial reactivity in response to a threatening experience but also the ability to return to calm over time and between disturbing events. Second, when an individual encounters a negative emotional experience, the exact nature of the threat is not always clear (McCall et al., 2022). For example, if we went to the theatre then had to walk through a dark alleyway on our way home, we might anticipate someone jumping out and mugging us. Temporal unpredictability (i.e. when will a threat occur) is a feature of most ambiguously threatening experiences and shapes our emotional responses (McCall et al., 2022). Heightened emotional reactivity to ambiguously threatening stimuli, including difficulty disengaging from those stimuli, may result in pathological anxiety (Grillon, 2008; McCall et al., 2022). Despite the threats and uncertainties we face in our day-to-day lives, we know very little about how sleep loss influences emotional reactivity in response to ambiguous threat. To address this, Chapter 3 investigates whether sleep deprivation amplifies emotional reactivity when participants are exposed to an unfolding emotional experience designed to elicit ambiguous threat.

Given the potentiating effects of sleep deprivation on emotional reactivity, a reciprocal question concerns the components of sleep that modulate emotional reactivity. Rapid eye movement (REM) sleep is one property of sleep thought to be important for reducing the affective tone of emotional memories. The "Sleep to remember, sleep to forget" hypothesis supports the role of REM sleep in reducing mnemonic arousal (Greenberg et al., 1972; Gujar, McDonald, et al., 2011; Hutchison et al., 2021; Rosales-Lagarde et al., 2012; van der Helm et al., 2011). Further work suggests that REM sleep provides a mechanism by which emotion-related limbic and prefrontal regions can reset to restore affective responding (Goldstein & Walker, 2014). Simon et al. (2015) demonstrated that sleep deprivation, compared to a night of sleep, resulted in enhanced activity in the right dorsolateral PFC and left amygdala to neutral distractor information during a working memory task. This was coupled with a significant decrease in connectivity between the amygdala and prefrontal regions, suggesting a generic reduction in the threshold for emotional activation following sleep loss. Importantly, decreased prefrontal connectivity was associated with lower amounts of overnight REM sleep (Simon et al., 2015), highlighting an important role for REM sleep in the discrimination of emotional and neutral stimuli. Previous models have suggested that the recalibration of noradrenergic tone during REM sleep promotes the appropriate modulation of both amygdala and PFC activations to salient emotional events, resulting in appropriate next-day reactivity (Goldstein & Walker, 2014; Simon et al., 2015). Thus, REM sleep helps promote the accurate discrimination of emotional and non-emotional stimuli.

Other properties of sleep also play a critical role in affect regulation, which may enable individuals to respond adaptively to threat. Individuals with anxiety disorders often demonstrate reductions in non-rapid eye movement (NREM) sleep including slow wave sleep (SWS) and slow wave activity (SWA; EEG power density 0.5–4 Hz), with the latter being one of the hallmarks of SWS (Arriaga & Paiva, 1990; Baglioni et al., 2016; Forbes et al., 2008; Fuller et al., 1997). In contrast, greater amounts of SWA has been associated with the overnight reduction of state anxiety (Ben Simon et al., 2020; Chellappa & Aeschbach, 2022). Moreover, SWA enhancement has been associated with improved executive functions including working memory and reasoning (Wilckens et al., 2016, 2018). The amount of SWA an individual obtains is the best-characterised marker of sleep intensity (Borbély et al., 2016). Research suggests that increased sleep intensity may facilitate cortical plasticity in brain regions that support executive functioning (Huber et al., 2008; Tononi, 2009). In support of this view, greater NREM SWA has been associated with greater next-day restoration of prefrontal mechanisms (Ben Simon et al., 2020; Campbell-Sills et al., 2011) that are critical for affect regulation during threat-related information processing (Bishop, 2007; Bishop et al., 2004; M. J. Kim et al., 2011; Simmons et al., 2008). Taken together, these findings imply that SWA may promote regulatory control when adaptively responding to threat. To substantiate this argument, Chapter 3 also examines whether SWA supports the regulation of emotional reactivity in response to ambiguous threat.

The evolution of emotional reactivity can be mapped using virtual reality (VR) methodology. VR is a tool that provides a powerful means of eliciting emotions as it accounts for the surrounding context and allows exposure to multisensory information (Barrett et al., 2011; Gendron & Feldman Barrett, 2009; S. M. Hofmann et al., 2021; Marcolin et al., 2021; Marín-Morales et al., 2020; McCall et al., 2016). Critically, VR allows for the creation of an enduring and unfolding emotional experience, during which real-time physiological measurements can be recorded to capture emotional reactivity. As a result, Chapter 3 uses VR to investigate the aforementioned research questions. As the VR environment transitions between two ambiguously threatening and two non-threatening environments, this enabled me to examine how sleep deprivation (compared to a night of sleep) influences physiological arousal during exposure to ambiguous threat.

1.3.2 Interim conclusion

In summary, sleep loss enhances negative bias and promotes heightened threat sensitivity, likely as a result of impaired top-down inhibitory control of emotional responses. Furthermore, the specific properties of NREM sleep (namely SWA) may help protect the integrity of this top-down control. Previous work often adopts sleep deprivation designs which help determine the mechanisms underlying the association between sleep and emotional reactivity. However, the use of static and predictable threatening stimuli limits our understanding of how sleep deprivation (versus a night of sleep) influences emotional reactivity beyond initial reactivity to threat. Moreover, in our day-to-day lives, we often face uncertainties regarding the nature of threat. As a result, very little is known about how sleep deprivation (versus a night of sleep) influences the evolution of emotional reactivity during exposure to ambiguous threat. Chapter 3 addresses this research question and reciprocally examines the influence of SWA on affect regulation.

1.4 Emotional inertia

Emotional inertia is defined as the autocorrelation between an individual's current emotion state and their previous emotion state (Koval et al., 2016; Kuppens, Allen, et al., 2010). In other words, emotional inertia reflects the persistence of emotion states over time. Emotional inertia is typically operationalised using a first-order autoregressive [AR(1)] model, in which a person's emotion state at each occasion (t) is regressed on to their emotion state at the previous occasion ($t - 1$). Therefore, the AR slope captures the degree to which emotions are self-predictable or persist across time, with more positive AR slopes indicating greater persistence of emotion states over time (Koval et al., 2021).

Emotional inertia is measured on a continuum, from high to low. In individuals with higher emotion inertia, emotion states are highly predictable from one moment to the next. Moreover, these individuals are relatively resistant to both internal (e.g. regulatory efforts) and external (e.g. environmental events) influences, reflecting emotional rigidity. In contrast, among individuals with lower emotion inertia, emotion states are far less predictable from one moment to the next. These individuals are more malleable to both internal and environmental influences, reflecting emotional flexibility (Koval et al., 2016; Kuppens, Allen, et al., 2010). Theoretically, high emotional inertia is thought to capture both dampened emotional reactivity, reflecting disengagement from psychological and environmental demands, and impaired emotion regulation skills, reflecting a diminished ability to recover following negative events (Kuppens, Allen, et al., 2010). Some studies have attempted to determine the extent to which each of these processes are involved in emotional inertia. For instance, Koval, Brose, et al. (2015) found that impaired recovery from negative events, but not blunted reactivity to events, was associated with higher inertia of negative emotions, suggesting that emotional inertia is driven primarily by impaired recovery following negative events.

Emotional inertia has also been associated with the use of CER strategies. With regard to maladaptive CER strategy use, greater use of rumination has been associated with higher NA inertia (Blanke et al., 2022; Koval et al., 2012). Few studies have examined the association between the use of adaptive CER strategies and emotional inertia. Kuppens, Oravecz et al. (2010) found that greater use of positive reappraisal was associated with a steeper decline back to baseline following an emotional event, which is considered inversely associated with emotional inertia. However, other studies have found no association between positive reappraisal and NA inertia (Bean et al., 2021; Koval, Butler, et al., 2015). Nonetheless, no studies have yet examined how composite measures of adaptive and maladaptive CER strategy use are associated with emotional inertia.

The ability to flexibly adapt to both internal and external influences has been shown to be an important indicator of psychological well-being. Studies have demonstrated higher inertia (and thus rigidity of emotional responding) may be characteristic of psychopathology. This is particularly true for the inertia of negative emotions (e.g. depression, sadness; Houben et al., 2015) and may result from failures in the emotion regulation process aimed at altering negative emotion states (Kuppens, Allen, et al., 2010). Heightened emotional inertia has been positively associated with depression (Kuppens, Allen, et al., 2010; Kuppens et al., 2012; Minaeva et al., 2021), anxiety (Bosley et al., 2019; Gilbert et al., 2019; Seidl et al., 2023), psychosis (Westermann et al., 2017), borderline personality disorder (Ebner-Priemer et al., 2015), post-traumatic stress disorder (Simons et al., 2021), and eating disorders (Williams-Kerver et al., 2020).

At the sub-clinical level, higher emotion inertia has also been positively correlated with neuroticism (Koval et al., 2016; Suls et al., 1998; Waugh et al., 2017), depressive symptoms (Brose et al., 2015; Koval & Kuppens, 2012; Koval et al., 2012, 2013), rumination (Koval et al., 2016; Waugh et al., 2017), and NA (Koval & Kuppens, 2012; Koval et al., 2016). Conversely, heightened emotional inertia has been negatively correlated with self-esteem (Houben et al., 2015; Koval & Kuppens, 2012; Koval et al., 2016; Kuppens, Allen, et al., 2010) and positive affect (PA; Houben et al., 2015). Furthermore, the association between higher emotional inertia and lower psychological well-being is stronger for the inertia of negative emotions than for positive ones (e.g. happiness, excitement; Houben et al., 2015). This finding implies that the rigidity of negative and not positive emotions results in a higher likelihood of psychological maladjustment. Taken together, higher levels of negative emotional inertia may be a transdiagnostic risk factor for poor mental health.

Two fMRI studies have attempted to uncover the neural mechanisms underlying emotional inertia. First, Waugh et al. (2017) investigated whether changes in cerebral blood flow before and after an emotional task were associated with emotional inertia in response to daily events the following week. During the emotional task, participants viewed and rated the intensity of emotions elicited by self-relevant statements. This task has previously been shown to induce mood changes (Velten, 1968). They found that individuals who showed increased activation in the lateral prefrontal cortex (lPFC) during the emotional task (suggesting greater recruitment of emotion-regulatory neural systems) showed lower emotional inertia in daily life.

Thus, it was suggested that increased lPFC activity from before to after the emotional task enabled participants to inhibit the persistence of emotional intensity from one self-relevant statement to the next. Similarly, these participants may also recruit the lPFC in daily life to inhibit emotional responses to a prior event and prevent them from carrying over to the next event (Waugh et al., 2017). Building on these findings, Provenzano et al. (2018) examined how changes in neural activation in response to a socio-emotional laboratory task are associated with emotional inertia in daily life over the course of two weeks. They found that greater activity in the right parahippocampal gyrus (PHG) and right lateral orbitofrontal cortex (lOFC) in response to negative feedback in the socio-emotional laboratory task was associated with higher inertia of negative emotions (Provenzano et al., 2018). Taken together, these studies do not provide converging evidence regarding the specific brain regions involved in emotional inertia. Nonetheless, it seems that the PFC plays an important role in emotional inertia, potentially by preventing emotional responses spilling over from one event to the next.

Many studies investigating emotional inertia have used experience sampling methodology (ESM; Csikszentmihalyi & Larson, 2014). ESM involves asking participants several times a day, over a period of time (e.g. days, week), to report their current emotion states, and how intensely they feel these emotion states (Kuppens, Allen, et al., 2010). From these ratings, AR modelling is used to calculate emotional inertia (Kuppens, Allen, et al., 2010). Recent studies have also used observational paradigms (e.g. family interactions) or have exposed participants to emotional stimuli in the laboratory to assess emotional inertia. Using a dual-method approach, some studies have combined ESM and laboratory paradigms to capitalise on high ecological validity and control for the emotional events that participants experience. For example, one study used ESM to examine emotional inertia in daily life before and after experimentally manipulating anticipatory social stress (Koval & Kuppens, 2012). They found that higher emotional inertia in daily life was associated with higher depression, higher fear of negative evaluation, and lower self-esteem. However, when anticipating a socially stressful situation, emotional inertia was reduced, highlighting the importance of context when studying emotional functioning. Although the majority of studies use self-report ratings of emotion states to calculate emotional inertia, others have used observational paradigms to assess second-by-second affective behaviours during emotional episodes or physiological indices, such as heart rate variability (HRV). For example, De Longis et al. (2020) found that higher persistence of negative emotions at work (i.e. higher emotional inertia) was associated with lower HRV, suggesting that HRV may be a physiological indicator of emotional flexibility.

1.4.1 Sleep and emotional inertia

Given that sleep loss impairs the effectiveness of adaptive CER strategies (Mauss et al., 2013; Parsons et al., 2021; Tamm et al., 2019; Zhang et al., 2019) and potentiates emotional reactivity (Franzen et al., 2008, 2009), there is clear motivation to understand how a lack of sleep influences emotional inertia. This area of research is in its infancy, with only three studies to date investigating the association between sleep and emotional inertia. The findings of these studies are mixed. The first study used ESM to assess negative and positive affect over a 7-day period and used actigraphy to record total sleep duration from night to night. They found that shorter sleep duration was associated with higher inertia of a depressive mood state over this 7-day period (X. Wen et al., 2020). However, the two other studies found no significant associations between either subjective sleep duration or sleep quality and the persistence of negative emotion states both overnight (i.e. from evening to morning) and during the day (i.e. from morning to evening; Frérart et al., 2023; Minaeva et al., 2021).

These contrasting findings may be due to methodological differences between these studies. X. Wen et al. (2020) measured sleep duration objectively, whereas Minaeva et al. (2021) and Frérart et al. (2023) subjectively assessed sleep duration and sleep quality using single-item daily questionnaires. Moreover, Minaeva et al. (2021) and Frérart et al. (2023) focused primarily on the change in affect from evening to morning (i.e. overnight emotional inertia), which may be affected by circadian influences. For instance, prior work has demonstrated that evening-type individuals reported later peaks in PA and lower PA overall compared to morning-type individuals on work versus non-work days (M. A. Miller et al., 2015). Therefore, evening types may experience higher overnight inertia than morning types because they experience lower PA in the morning.

The studies investigating sleep and emotional inertia have used ESM to track emotion states over time outside of a laboratory context (Houben et al., 2015; Koval et al., 2016). Although ESM allows for a naturalistic assessment of emotional responding in daily life, it does not account for the context within which the emotional reaction takes place (Koval et al., 2013; Kuppens et al., 2022). Previous studies have found an association between NA inertia and the self-reported intensity of emotional events experienced in daily life. For instance, Koval, Brose, et al. (2015) found that individuals who encounter more intense negative events (but not more frequent negative events) in daily life display higher levels of negative emotional inertia. This association can be problematic as it prevents us from determining whether individual differences in emotional inertia are a result of environment differences (e.g. encountered events) or internal differences in emotional reactivity and regulation (Koole, 2009; Koval et al., 2013). To help rule out exogenous influences on emotional inertia, individuals need to be exposed to the same emotional experiences

To address this limitation, prior studies have used a standardised mood induction procedure (MIP) to expose participants to a fixed order sequence of emotional events in the laboratory. This paradigm controls for the events participants experience and allows the assessment of emotional inertia over shorter timescales (e.g. seconds and minutes) than ESM (e.g. hours and days). In this task, participants are asked to rate how they feel on several emotion dimensions after the presentation of film clips and again after a subsequent rest period following each of the film clips (Koval et al., 2013, 2016). These studies found that higher negative emotional inertia was associated with higher depressive symptoms, greater use of rumination, and greater NA, thus replicating studies using ESM paradigms (Koval, Brose, et al., 2015; Koval et al., 2013, 2016). Nonetheless, it has been argued that using staged film clips reduces the ability to accept the events depicted in the film as real (Rottenberg et al., 2007; Samson et al., 2016). This can be difficult when attempting to elicit strong emotional responses. In light of this, in Chapter 4, the approach of Koval et al. (2016) was adopted to examine the influence of CER strategy use and sleep quality on emotional inertia. This helped to control for the events that the participants encountered. Furthermore, amateur film clips depicting real-life events were used to produce emotional responses akin to those experienced in daily life.

Although previous work has demonstrated that both adaptive CER strategy use and sleep independently contribute to emotional inertia, no studies have yet examined their synergistic association. Greater use of adaptive CER strategies has been shown to decrease emotional inertia (Kuppens, Oravecz, et al., 2010). However, a lack of sleep reduces the effectiveness of adaptive CER strategies (Mauss et al., 2013; Zhang et al., 2019). Together, these findings suggest a potential mechanistic link between adaptive CER strategy use and emotional inertia, whereby the successful implementation of adaptive CER strategies (to reduce the persistence of negative emotion states) is contingent on high quality sleep. However, empirical studies examining whether lower emotional inertia results from the association between adaptive CER strategy use and sleep quality have not yet been conducted. Therefore, Chapter 4 also investigates the extent to which the association between adaptive CER strategies and emotional inertia is influenced by sleep quality.

1.4.2 Interim conclusion

In summary, emotional inertia refers to the persistence of an emotion state from one moment to the next. Higher levels of (mainly negative) emotional inertia have been associated with vulnerability to and the development of psychopathology. Moreover, higher emotional inertia is thought to reflect impaired recovery following negative events. Emotional inertia has also been associated with CER strategies such as rumination and positive reappraisal. With regard to the neural mechanisms, increased prefrontal activity in response to emotional laboratory tasks has been shown to play an important role in emotional inertia in daily life, potentially through the inhibition of emotional responses. To date, only a handful of studies have investigated the relationship between sleep and emotional inertia with mixed findings. One study found that decreased sleep duration was associated with the maintenance of a depressed state over time. The other two studies found no associations between subjective measures of sleep and the inertia of negative emotions during the day, or night. As these latter studies assessed emotional inertia overnight, they may have been confounded by circadian factors. Moreover, prior work has used ESM paradigms to examine the association between sleep and emotional inertia, which cannot control for contextual factors (i.e. differential exposure to daily events across participants). Given the association between adaptive CER strategies and sleep, a potential mechanistic link is proposed, whereby the use of adaptive CER strategies (to reduce the persistence of negative emotion states) is contingent on high quality sleep. To help control for contextual factors and examine this mechanistic association, Chapter 4 adopts a controlled laboratory paradigm to investigate whether the association between adaptive CER strategy use and emotional inertia is influenced by sleep quality.

1.5 Conclusion

In summary, the overarching aim of this thesis is to examine the cognitive mechanisms by which sleep supports emotion regulation and mental health. First, I examine whether the positive benefits of adaptive CER strategies (to reduce depression and anxiety) are contingent on high quality sleep (Chapter 2). I address the limitations of previous work by examining how individuals deploy adaptive CER strategies in the context of a protracted real-world stressor. Second, I investigate whether sleep deprivation (versus a night of sleep) influences emotional reactivity during exposure to prolonged ambiguous threat (Chapter 3). Reciprocally, I examine whether SWA influences the regulation of emotional reactivity during this exposure. Importantly, I focus on how sleep deprivation influences emotional reactivity as it unfolds over time, rather than in response to short, static threats. Finally, I explore whether the positive benefits of adaptive CER strategy use (to lower emotional inertia) are contingent on high quality sleep. To do this, I adopt a task which helps controls for the emotional events participants encounter whilst exposing participants to stimuli depicting real-world events. Across these three research questions, I consider the temporal aspect of emotion regulation and utilise a range of methodological approaches (i.e. large-scale individual differences and sleep deprivation designs). To uncover the basic mechanisms by which sleep supports emotion regulation, I predominantly focus on non-clinical samples. Together, the findings from each of these studies provide important insights into the mechanisms by which poor sleep contributes to emotion dysregulation and poorer mental health and conversely, how good sleep contributes to emotion regulation and psychological well-being.

1.6 Reproducibility statement

Reproducibility and open science are the mainstays of the work presented in this thesis. In each of the thesis chapters, analysis plans were pre-registered and power analyses were conducted. All of the data and analysis code used in Chapter 2 has been made publicly available (on the Open Science Framework), and data and analysis code pertaining to Chapters 3 and 4 will also be made publicly available following the completion of the thesis.

Chapter 2: The Influence of Emotion Regulation Strategies and Sleep Quality on Depression and Anxiety

This chapter is adapted from a published article:

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Abstract

Chronic stress is a major risk factor for a number of mental health disorders, including depression and pathological anxiety. Adaptive cognitive emotion regulation (CER) strategies (i.e. positively-focused thought processes) can help to prevent psychiatric disturbance when enduring unpleasant and stressful experiences, but little is known about the inter-individual factors that govern their success. Sleep plays an important role in mental health, and may moderate the effectiveness of adaptive CER strategies by maintaining the executive functions on which they rely. In this study, we carried out a secondary analysis of self-reported mental health and sleep data acquired during a protracted and naturally-occurring stressor – the COVID-19 pandemic – to firstly test the hypothesis that adaptive CER strategy use is associated with positive mental health outcomes and secondly, that the benefits of adaptive CER strategy use for mental health are contingent on high-quality sleep. Using established self-report tools, participants estimated their depression (N = 551) and anxiety (N = 590)[1] levels, sleep quality and tendency to engage in adaptive and maladaptive CER strategies during the Spring and Autumn of 2020. Using a linear mixed modelling approach, we found that greater use of adaptive CER strategies and higher sleep quality were independently associated with lower self-reported depression and anxiety. However, adaptive CER strategy use was not a significant predictor of self-reported anxiety when accounting for sleep quality in our final model. The positive influence of adaptive CER strategy use on depression was observed at different levels of sleep quality. These findings highlight the importance of adaptive CER strategy use and good sleep quality in promoting resilience to depression and anxiety when experiencing chronic stress.

2.1 Introduction

Chronic stress is a well-known risk factor for mental illness. However, not all individuals who experience chronic stress go on to experience psychological disturbance. These divergent effects of chronic stress are thought to arise from pre-existing vulnerabilities, which vary between individuals (Marin et al., 2011). Understanding the factors that contribute

[1] Due to a minor coding error that resulted in an incorrectly computed predictor measure, we have more missing data than was originally reported in our Stage 1 Registered Report. Our total sample size therefore differs from that reported in our Stage 1 Registered Report for both the pilot study (from n = 118 to n = 117 for the depression sample and from n = 123 to n = 122 for the anxiety sample) and the main study (from n = 562 to n = 551 for the depression sample and from n = 604 to n = 590 for the anxiety sample). These corrections received editorial approval on 30th November 2022.

to the onset of mental health problems when undergoing stressful life events is thus an important step towards reducing the global burden of mental illness.

Psychological responses to stress are influenced by cognitive emotion regulation (CER) strategies, which are thought processes that an individual voluntarily engages in to regulate emotional experiences (Garnefski & Kraaij, 2006; Garnefski et al., 2001). CER strategies can be categorised as adaptive (e.g. positive reappraisal) or maladaptive (e.g. rumination; Aldao & Nolen-Hoeksema, 2010) and these subtypes are associated with distinct mental health outcomes. Whereas adaptive CER strategies tend to improve psychological well-being in the long term (Kirschbaum-Lesch et al., 2021), maladaptive CER strategies provide only short-term respite (Campbell-Sills & Barlow, 2007) and can even amplify affective disturbances (Aldao et al., 2010; Garnefski et al., 2001; Nolen-Hoeksema et al., 2008). Indeed, among clinical populations, more frequent use of self-blame, rumination and catastrophising (maladaptive CER strategies) and less frequent use of positive reappraisal (an adaptive CER strategy) have all been shown to significantly predict higher levels of both depression and anxiety (Aldao & Nolen-Hoeksema, 2010; Domaradzka & Fajkowska, 2018; Garnefski et al., 2002; Martin & Dahlen, 2005). Adaptive CER strategy use thus appears to be an important safeguard against the development of mental health problems when undergoing chronic stress.

Adaptive CER strategy use enlists a number of executive functions such as memory updating, flexible task switching and inhibition of prepotent responses (Joormann & Tanovic, 2015; McRae et al., 2012; Ochsner & Gross, 2005). It is therefore likely that factors influencing executive control also impact on our ability to deploy adaptive CER strategies effectively. Consistent with this view, previous work has shown that executive control deficits are associated with less frequent and unsuccessful use of adaptive CER strategies (Joormann, 2010; Joormann & Gotlib, 2010; Malooly et al., 2013; Pe et al., 2013; Schmeichel & Tang, 2015; Schmeichel et al., 2008), potentially undercutting the positive mental health outcomes that they typically afford.

Poor sleep quality is widely associated with executive control deficits (Drummond et al., 1999; Mograss et al., 2009; Nilsson et al., 2005; Qi et al., 2010; Skurvydas et al., 2020) and emotion dysregulation (Ben Simon et al., 2020; Harrington, Ashton, Sankarasubramanian, et al., 2021; Harrington & Cairney, 2021; Yoo et al., 2007). Moreover, empirical findings suggest that sleep disturbances are causally related to mental health problems (Baglioni, Spiegelhalder, et al., 2010; Bi & Chen, 2022; Freeman et al., 2017), with a recent meta-analysis showing that improving sleep quality leads to a reduction in self-reported symptoms of depression and anxiety (A. J. Scott et al., 2021). Unsurprisingly, sleep difficulties also have a negative impact on people's ability to deploy adaptive CER strategies effectively (Mauss et al., 2013; Parsons et al., 2021; Tamm et al., 2019; Zhang et al., 2019). These findings point to a potential mechanistic link between disordered sleep and psychological disturbance, wherein the benefits of adaptive CER strategies (i.e. for downregulating negative emotions and thus preserving mental well-being) are contingent on ample and good quality sleep (Mauss et al., 2013; Parsons et al., 2021; Tamm et al., 2019; Zhang et al., 2019). Whether mental health outcomes following a sustained period of stress can be attributed to the relationship between sleep and adaptive CER strategy use, however, has yet to be established.

Stressful experiences often arise unexpectedly and evolve over long periods of time. Yet, research on sleep and adaptive CER strategy use is typically limited to the laboratory, where artificial stressors (e.g. aversive images or videos) are presented very briefly. Participants in laboratory experiments are also trained on how to deploy an array of CER strategies, whereas people in the real world must respond to aversive experiences in the absence of any explicit instruction. Hence, although findings from the laboratory have laid an important foundation for understanding the relationship between sleep, adaptive CER strategy use and mental health outcomes, a crucial next step is to address this question in the context of a naturally-occurring and chronic stressor.

The COVID-19 pandemic has been a prolonged and unique source of stress for people across the entire world. Although many studies have reported significant increases in mental health problems during the pandemic (Morin et al., 2021), others have shown no change or even improvements in psychological well-being (Bottary et al., 2021; Cunningham, Fields, Garcia, et al., 2021; Cunningham, Fields, & Kensinger, 2021; Fields et al., 2021; Rezaei & Grandner, 2021; Robbins et al., 2021; Tyson & Wild, 2021), highlighting the divergent impacts of sustained emotional hardship. Given the unexpected and protracted nature of COVID-19, it offers a unique context with which to study the influence of adaptive CER strategy use on mental health outcomes when enduring a naturally-occurring and chronic stressor, as well as the moderating role of sleep.

In this study, we capitalised on a longitudinal dataset acquired during the first nine months of the COVID-19 pandemic (Cunningham, Fields, Garcia, et al., 2021; Cunningham, Fields, & Kensinger, 2021) to investigate the influence of adaptive CER strategy use and sleep quality on changes in self-reported depression and anxiety.

A sample of $N = 1600$ healthy adults provided self-reported scores of depression, anxiety, sleep quality and CER strategy use at multiple time points between March and November of 2020. Our planned analyses of this data allowed us to address two research questions.

1) Is adaptive CER strategy use associated with positive mental health outcomes?
2) Are the mental health benefits of adaptive CER strategy use contingent on good quality sleep?

We tested the following hypotheses using a null hypothesis significance testing framework:

(1) Greater use of adaptive CER strategies will be associated with:

  (a) Decreased self-reported depression.

  (b) Decreased self-reported anxiety.

(2) Higher sleep quality will be associated with:

  (a) Decreased self-reported depression.

  (b) Decreased self-reported anxiety.

(3) Use of adaptive CER strategies will be moderated by sleep quality such that:

  (a) The relationship between greater use of adaptive CER strategies and decreased self-reported depression will be stronger at higher levels of sleep quality.

  (b) The relationship between greater use of adaptive CER strategies and decreased self-reported anxiety will be stronger at higher levels of sleep quality.

2.2 Methods

We report how we determined our sample size, all data exclusions, all inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all manipulations, and all measures in the study.

2.2.1 Measures and design

The accepted Stage 1 manuscript of this Registered Report was registered on the Open Science Framework (OSF). This study was a secondary analysis of data collected by Cunningham, Fields, and Kensinger, (2021). The cited data descriptor contains additional information on the data collection process (beyond that described below), should it be required.

See Table 2.1 for our study design table and Figure 2.1 for an overview of the data collection periods for each of the measures included in our analysis.

Table 2.1. Hypotheses, sampling plan, analysis plan, and interpretations for each of our primary research questions.

Aim	Hypothesis	Sampling plan	Analysis plan	Interpretation given different outcomes
1. Is adaptive CER strategy use associated with positive mental health outcomes?	**1a.** Greater use of adaptive CER strategies will be associated with decreased self-reported depression.	Power analyses have been computed to calculate the minimum effect sizes which can be detected at 90% power and 0.02 alpha level for each fixed effect and interaction effect in Model 2, addressing hypotheses 1a (Table 2.2).	We will perform a linear mixed effects analysis of the relationship between adaptive CER strategy use and depression over time, as indexed by the change from baseline to follow-up. As fixed effects, we will enter: 1) time as a categorical predictor and 2) adaptive CER strategy use as a continuous predictor (grand-mean centred). We will also include a random intercept for participants. Age, biological sex and mental health diagnosis will be included as covariates along with the interactions between covariates and the predictors. *Depression ~ 1 + time*age + time*biological sex + time*mental health diagnosis + adaptive CER strategy use*age + adaptive CER strategy use*biological sex + adaptive CER strategy use*mental health diagnosis + time*adaptive CER strategy use + (1 | participant).*	**Significant**: If there is a main effect of time it can be concluded that depression changes from baseline to follow-up. If there is a main effect of adaptive CER strategy use it can be concluded that adaptive CER strategy use influences depression. If there is an interaction between time and adaptive CER strategy use it can be concluded that adaptive CER strategy use leads to a change in depression from baseline to follow-up. If there is a main effect of age it can be concluded that age influences depression. If there is a main effect of sex it can be concluded that sex (female/male) influences depression. If there is a main effect of mental health diagnosis it can be concluded that mental health diagnosis (yes/no) influences depression.
1. Is adaptive CER strategy use associated with positive mental health outcomes?	**1b.** Greater use of adaptive CER strategies will be associated with decreased self-reported anxiety.	Power analyses have been computed to calculate the minimum effect sizes which can be detected at 90% power and 0.02 alpha level for each fixed effect and interaction effect in Model 2, addressing hypotheses 1b (Table 2.2).	We will perform a linear mixed effects analysis of the relationship between adaptive CER strategy use and anxiety over time, as indexed by the change from baseline to follow-up. As fixed effects, we will enter: 1) time as a categorical predictor and 2) adaptive CER strategy use as a continuous predictor (grand-mean centred). We will also include a random intercept for participants. Age, biological sex and mental health diagnosis will be included as covariates along with the interactions between covariates and the predictors. *Anxiety ~ 1 + time*age + time*biological sex + time*mental health diagnosis + adaptive CER strategy*	**Significant**: If there is a main effect of time it can be concluded that anxiety changes from baseline to follow-up. If there is a main effect of adaptive CER strategy use it can be concluded that adaptive CER strategy use influences anxiety. If there is an interaction between time and adaptive CER strategy use it can be concluded that adaptive CER strategy use leads to a change in anxiety from baseline to follow-up. If there is a main effect of age it can be concluded that age influences anxiety. If there is a main effect of sex it can be concluded that sex (female/male) influences anxiety. If there is a main effect of mental

			*use*age + adaptive CER strategy use*biological sex + adaptive CER strategy use*mental health diagnosis + time*adaptive CER strategy use + (1 | participant).*	health diagnosis it can be concluded that mental health diagnosis (yes/no) influences anxiety.
2. Are the mental health benefits of adaptive CER strategy use contingent on good quality sleep?	**2a.** Higher sleep quality will be associated with decreased self-reported depression. **3a.** Use of adaptive CER strategies will be moderated by sleep quality such that the relationship between greater use of adaptive CER strategies and decreased self-reported depression will be stronger at higher levels of sleep quality.	Power analyses have been computed to calculate the minimum effect sizes which can be detected at 90% power and 0.02 alpha level for each fixed effect and interaction effect in Model 3i, addressing hypothesis 2a and 3a (Table 2.2).	We will perform a linear mixed effects analysis of the moderating role of sleep quality on the relationship between adaptive CER strategy use and depression over time, as indexed by the change from baseline to follow-up. As fixed effects, we will enter: 1) time as a categorical predictor and 2) adaptive CER strategy use and 3) sleep quality as continuous predictors (grand-mean centred). We will also include a random intercept for participants. Age, biological sex and mental health diagnosis will be included as covariates along with the interactions between covariates and the predictors. *Depression ~ 1 + time*adaptive CER strategy use*age + time*adaptive CER strategy use*biological sex + time*adaptive CER strategy use*mental health diagnosis + time*sleep quality*age + time*sleep quality*biological sex + time*sleep quality*mental health diagnosis + adaptive CER strategy use*sleep quality*age + adaptive CER strategy use*sleep quality*biological sex + adaptive CER strategy use*sleep quality*mental health diagnosis + time*adaptive CER strategy use*sleep quality + (1 | participant).*	**Significant:** If there is a main effect of sleep quality it can be concluded that sleep quality influences depression. If there is an interaction between time and sleep quality it can be concluded that sleep quality leads to a change in depression from baseline to follow-up. If there is an interaction between adaptive CER strategy use and sleep quality it can be concluded that sleep quality influences the relationship between adaptive CER strategy use and depression. If there is an interaction between adaptive CER strategy use, sleep quality and time it can be concluded that sleep quality influences the relationship between adaptive CER strategy use and the change in depression from baseline to follow-up.
2. Are the mental health benefits of adaptive CER strategy use contingent on good quality sleep?	**2b.** Higher sleep quality will be associated with decreased self-reported anxiety. **3b.** Use of adaptive CER strategies will be moderated by sleep quality such that the relationship	Power analyses have been computed to calculate the minimum effect sizes which can be detected at 90% power and 0.02 alpha level for each fixed effect and interaction effect in Model 3ii, addressing hypothesis 2b and 3b (Table 2.2).	We will perform a linear mixed effects analysis of the moderating role of sleep quality on the relationship between adaptive CER strategy use and anxiety over time, as indexed by the change from baseline to follow-up. As fixed effects, we will enter: 1) time as a categorical predictor and 2) adaptive CER strategy use and 3) sleep quality as continuous predictors (grand-mean centred). We will also include a random intercept for participants. Age, biological sex and mental health diagnosis will be included	**Significant:** If there is a main effect of sleep quality it can be concluded that sleep quality influences anxiety. If there is an interaction between time and sleep quality it can be concluded that sleep quality leads to a change in anxiety from baseline to follow-up. If there is an interaction between adaptive CER strategy use and sleep quality it can be concluded that sleep quality influences the

	between greater use of adaptive CER strategies and decreased self-reported anxiety will be stronger at higher levels of sleep quality.		as covariates along with the interactions between covariates and the predictors. *Anxiety ~ 1 + time*adaptive CER strategy use*age + time*adaptive CER strategy use*biological sex + time*adaptive CER strategy use*mental health diagnosis + time*sleep quality*age + time*sleep quality*biological sex + time*sleep quality*mental health diagnosis + adaptive CER strategy use*sleep quality*age + adaptive CER strategy use*sleep quality*biological sex + adaptive CER strategy use*sleep quality*mental health diagnosis + time*adaptive CER strategy use*sleep quality + (1 | participant).*	relationship between adaptive CER strategy use and anxiety. If there is an interaction between adaptive CER strategy use, sleep quality and time it can be concluded that sleep quality influences the relationship between adaptive CER strategy use and the change in anxiety from baseline to follow up.

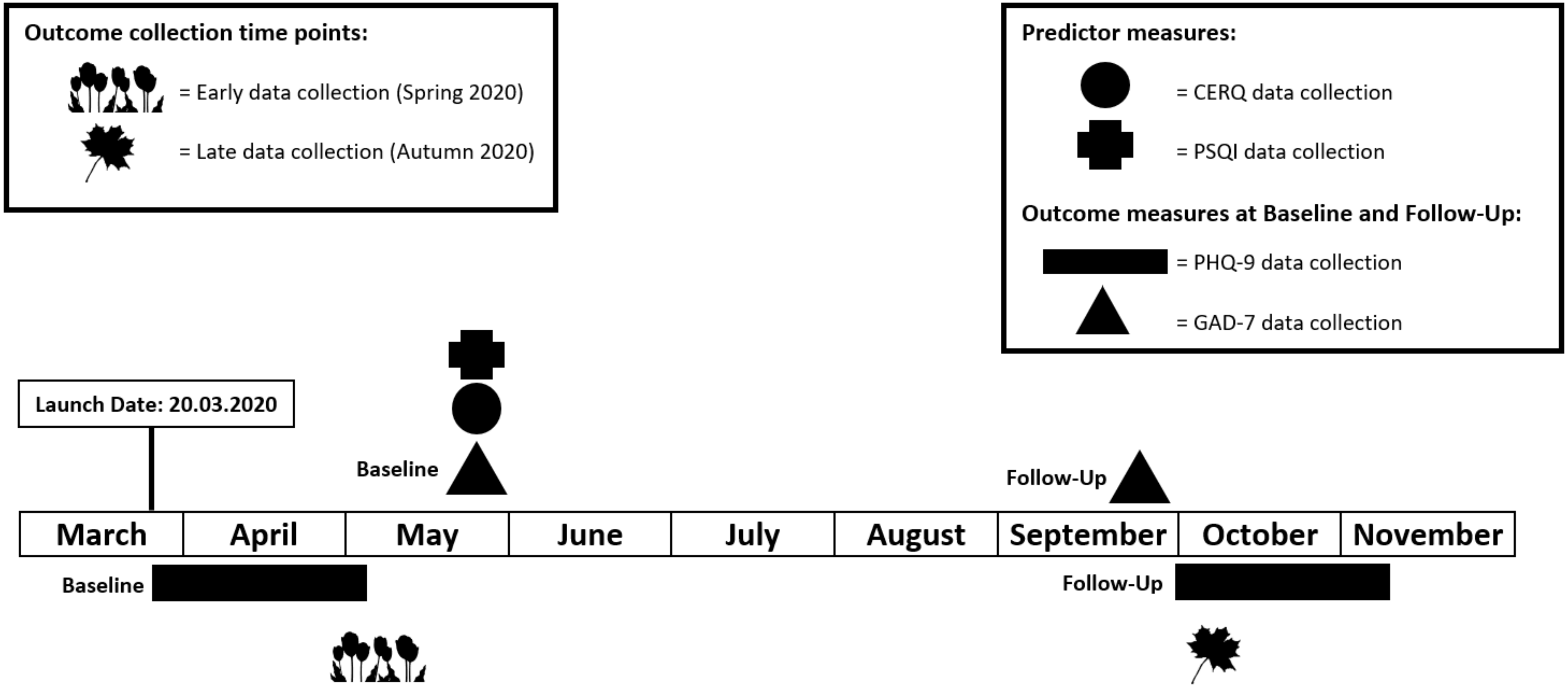

Figure 2.1. Schematic of the study timeline. The PSQI and CERQ were administered once between May and August 2020. PHQ-9 responses were collected between March and May 2020 (Baseline) and again between October and November 2020 (Follow-Up). GAD-7 responses were collected between May and June 2020 (Baseline) and again between September and November 2020 (Follow-Up). For the purpose of our analyses, March to June 2020 is referred to as the early data collection period (Spring 2020) and September to November 2020 is referred to as the late data collection period (Autumn 2020).

All participants provided consent via an online form and were invited to complete the following.

2.2.1.1 Demographic survey

The demographic survey included the following items: age, biological sex, gender identity, ethnicity, race, current residence and previous diagnoses of mental health disorders.

2.2.1.2 Cognitive emotion regulation

The Cognitive Emotion Regulation Questionnaire- Short version (CERQ-short; Garnefski & Kraaij, 2006) is an eighteen-item, self-report questionnaire designed to identify the emotion regulation strategies that individuals use after experiencing a negative event or situation. Participants are asked to rate how often they use nine conceptually different CER strategies (two questionnaire items per strategy) on a scale ranging from 1 (*almost never*) to 5 (*almost always*). Individual scores for each CER strategy are obtained by summing the two questionnaire items associated with each strategy to form an overall score (ranging from 2 to 10). The higher the overall score, the more a CER strategy is used. CER strategies can be dichotomised as adaptive and maladaptive (Aldao et al., 2010; Garnefski et al., 2001). Adaptive CER strategies include *refocus on planning* (i.e. thinking about the next steps and how to handle the negative event), *positive refocusing* (i.e. turning thoughts towards joyful and pleasant matters), *positive reappraisal* (i.e. attaching a positive meaning to an event) and *putting into perspective* (i.e. downregulating the seriousness of the event and comparing it to other events). Although *acceptance* (i.e. coming to terms with the situation that has occurred) has been previously classified as an adaptive CER strategy, there are concerns that it may only be adaptive under certain circumstances (Martin & Dahlen, 2005). Consequently, it is not considered as either an adaptive or maladaptive CER strategy in the current study. Maladaptive CER strategies include *self-blame* (i.e. blaming oneself for what they have experienced), *other-blame* (i.e. blaming others for what they have experienced), *rumination* (i.e. dwelling on the negative feelings or thoughts associated with an event) and *catastrophising* (i.e. overemphasising the negative parts of an experience). Overall, the CERQ-short has demonstrated good validity and reliability in the general population (Araujo et al., 2020; Garnefski & Kraaij, 2006). In the current dataset, the CERQ-short was administered once in Spring 2020, between 19th May and 26th August.

To assess adaptive CER strategy use, we created a composite score by summing the scores for all adaptive items on the CERQ-short (*positive refocusing, refocus on planning,* *positive reappraisal*, *putting into perspective*). Scores ranged from 8 to 40 (two questionnaire items per adaptive CER strategy), with higher scores indicating more frequent use of adaptive CER strategies. Higher scores on this composite measure of adaptive CER strategy use have been associated with positive mental health outcomes in previous work (e.g. lower prevalence of depression and anxiety; Domaradzka & Fajkowska, 2018; Garnefski et al., 2001).

We also assessed maladaptive CER strategy use (for inclusion in exploratory analyses). To do so, we created a composite score by summing the scores for all maladaptive items on the CERQ-short (*self-blame*, *other-blame, rumination*, *catastrophising*). Scores ranged from 8 to 40 (two questionnaire items per maladaptive CER strategy), with higher scores indicating more frequent use of maladaptive CER strategies. Higher scores on this composite measure of maladaptive CER strategy use have been associated with negative mental health outcomes in previous work (e.g. higher prevalence of depression and anxiety; Domaradzka & Fajkowska, 2018; Garnefski et al., 2001).

2.2.1.3 Sleep quality

The Pittsburgh Sleep Quality Index (PSQI; Buysse et al., 1989) is a self-report questionnaire designed to assess sleep quality over the preceding month. The questionnaire consists of nineteen items, which are grouped to form seven sub-scores: (1) subjective sleep quality, (2) sleep latency, (3) sleep duration, (4) sleep efficiency, (5) sleep disturbance, (6) use of sleep medication and (7) daytime dysfunction. Each sub-score ranges from 0 to 3, with 3 reflecting the poorest sleep quality. Sub-scores are then summed to produce a global score, which ranges from 0 to 21. Higher global scores indicate poorer sleep quality. The PSQI has demonstrated strong reliability and validity in both clinical and non-clinical samples (Buysse et al., 1989; Mollayeva et al., 2016). In the current dataset, the PSQI was administered once in Spring 2020, between 19th May and 26th August.

2.2.1.4 Depression

The Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001) is a nine-item self-report questionnaire designed to measure depression severity. Participants report how often they have been bothered by nine core symptoms of depression over the preceding fortnight. Each item is rated on a Likert scale from 0 (*not at all*) to 3 (*nearly every day*). Usually, all nine items are summed to create a total score ranging from 0 to 27. However, the suicidality item was omitted during data collection, and so we summed the remaining eight items to create a modified score ranging from 0 to 24. A higher modified score indicates higher depression severity. Prior evidence indicates that the PHQ-9 has excellent internal reliability in both clinical (Cronbach's α = .89) and non-clinical (Cronbach's α = .87) samples (Kocalevent et al., 2013; Kroenke et al., 2001).

The PHQ-9 was assessed across two time periods: Spring and Autumn 2020 (both five weeks in duration). For the Spring 2020 data collection period, depression data was collected between 21st March and 1st May, and for the Autumn 2020 data collection period, depression data was collected between 1st October and 14th November. Participants were invited to complete the PHQ-9 on two days of each assessment week. The PHQ-9 was administered pseudorandomly such that the randomly selected days in the first week were then eliminated from choice in the following week until the PHQ-9 had been assessed on each day of the week before starting over. This ensured that the days of the week were sampled evenly. There were some weeks where the PHQ-9 was administered more than twice a week. Firstly, in the first week of the Spring period, when the study launched, participants were invited to complete the PHQ-9 on all seven days of the assessment week (21/03/2020-27/03/2020) before this was dropped down to two times a week to reduce participant burden. Secondly, the PHQ-9 was administered four times a week instead of two times a week during the fortnight around the US election (31/10/2020-14/11/2020). The PHQ-9 was therefore administered more frequently than the PSQI, CERQ, and the GAD-7, with the PSQI and CERQ being administered only once in Spring, and the GAD-7 being administered once in Spring and once again in Autumn (see below). All PHQ-9 scores (modified total score of 0–24) collected in the Spring period were averaged to create a mean baseline depression index. Similarly, all PHQ-9 scores collected in the Autumn period were averaged to create a mean follow-up depression index.

2.2.1.5 Anxiety

The Generalised Anxiety Disorder Questionnaire (GAD-7; Spitzer et al., 2006) is a seven-item self-report questionnaire designed to measure anxiety severity. Participants report how often they have been bothered by seven core symptoms of generalised anxiety disorder over the preceding fortnight. Items are scored from 0 (*not at all*) to 3 (*nearly every day*) and a total score is obtained by summing across all individual items. The total score ranges from 0 to 21, with higher scores indicating a higher severity of generalised anxiety. The GAD-7 has excellent internal reliability in both clinical (Cronbach's α = 0.92) and non-clinical (Cronbach's α = 0.89) samples (Löwe et al., 2008; Spitzer et al., 2006).

The GAD-7 was assessed in Spring and Autumn 2020 (once at each time point). For the Spring 2020 data collection period, anxiety data was collected between 19th May and 30th June, and for the Autumn 2020 data collection period, anxiety data was collected between 28th September and 9th November. The Spring data collection period was therefore slightly later for the anxiety data than the depression data, whereas the Autumn data collection period was highly overlapping for the anxiety and depression data. The GAD-7 score collected in the Spring formed a baseline anxiety index, whereas the GAD-7 score collected in the Autumn formed a follow-up anxiety index.

2.2.2 Participants

$N = 1600$ participants (77.0% females, age $M = 35.05$ years, $SD = 15.03$ years) completed the initial demographic survey. Our final samples (for depression and anxiety) were obtained after applying the exclusion procedures described below (see *Exclusion Criteria*). Because the PHQ-9 and GAD-7 were collected at different times in the Spring and Autumn of 2020, the final sample sizes differ for each measure (depression $N = 551$: 457 female, age $M = 39.12$, $SD = 17.07$ years; anxiety $N = 590$: 489 female, age $M = 38.49$, $SD = 16.89$). Of the depression sample, 98.7% of participants were also included in the anxiety sample. Likewise, of the anxiety sample, 92.2% of participants were also included in the depression sample[2]. See the Supplementary Material (Table A.1) for a detailed overview of demographics in our depression and anxiety samples.

Participants were entered into raffles to receive gift cards. Ethical approval for the original study was obtained by the Institutional Review Board at Boston College, United States (US), and the current study has been approved by the Research Ethics Committee of the Department of Psychology at the University of York, UK.

2.2.3 Exclusion criteria

Because COVID-19 restrictions (e.g. nationwide lockdowns) varied according to country, we excluded participants who were not residing in the US at the time of data collection. Non-US participants were used instead in our pilot analyses (see *Statistical Analysis*). Participants with missing item data on the CERQ or PSQI (predictor measures) were excluded from all analyses. Participants with missing item data on the PHQ-9 and/or GAD-7 (outcome measures) during both assessment periods (Spring and Autumn) were excluded from the

[2] Due to a minor coding error, our total sample size has changed. See footnote 1 for further details.

analysis of depression and/or anxiety, respectively. Participants who fully completed the PHQ-9 and/or GAD-7 at one of the two assessment periods (Spring or Autumn) were, however, included in the respective analysis of depression and/or anxiety. For the depression sample, *N* = 226 completed time point one only, *N* = 44 completed time point two only, and *N* = 281 completed both time points. For the anxiety sample, *N* = 239 completed time point one only, *N* = 16 completed time point two only and *N* = 335 completed both time points[3]. A full breakdown on how we reached our final sample sizes, for both the depression and anxiety outcomes, can be found in the Supplementary Material (Figures A.1 and A.2).

2.2.4 Statistical analysis

Our predictor measures were the CERQ (adaptive CER strategies composite score) and PSQI (total score). Our outcome measures were the PHQ-9 (mean modified total score) and the GAD-7 (total score) at baseline (Spring) and follow-up (Autumn).

To formulate our analysis pipeline and conduct a power analysis, we created a pilot dataset using the non-US participants (excluded from our main analysis). Sample sizes for our pilot analyses of depression and anxiety were *N* = 117 and *N* = 122, respectively[4].

2.2.4.1 Self-certification of data blindness

All authors remained blind to the data from the US participants that was used in our planned analyses prior to in principal acceptance of the manuscript.

2.2.4.2 Planned analyses

All hypotheses were tested using linear mixed effects models with a random intercept for participants. We carried out two models per hypothesis (corresponding to the two outcome measures of depression and anxiety) with an alpha threshold of 0.05 (corrected for the false discovery rate). To quantify the evidence in support of the experimental (H_1) or null hypotheses (H_0), we calculated Bayes Factors for each effect of interest (Wetzels & Wagenmakers, 2012) using Jeffreys (1961) conventional cut-offs to determine the strength of the evidence.

We included age and biological sex as covariates in all models because they have been found to influence both emotion regulation (Costa Martins et al., 2016; Ford, DiBiase, & Kensinger, 2018; Ford, DiBiase, Ryu, et al., 2018) and sleep quality in previous work (Buysse et al., 1991; Madrid-Valero et al., 2017; Middelkoop et al., 1996). Specifically, older age has

[3] For reasons noted in footnote 1, our total sample size has changed.
[4] Our pilot sample size has also changed.

been associated with an increased focus on the positive aspects of emotional events (Ford, DiBiase, & Kensinger, 2018; Ford, DiBiase, Ryu, et al., 2018), lower depression symptomatology over the initial course of the COVID-19 pandemic (Cunningham, Fields, Garcia, et al., 2021; Cunningham, Fields, & Kensinger, 2021; Fields et al., 2021) and poorer sleep quality (Buysse et al., 1991; Madrid-Valero et al., 2017), suggesting that the link between sleep quality and adaptive CER strategy use might be tempered in older relative to younger adults. Along similar lines, females report less frequent use of adaptive CER strategies (Costa Martins et al., 2016; Kelly et al., 2008) and poorer sleep quality than males (Buysse et al., 1991; Middelkoop et al., 1996), meaning that the link between sleep quality and adaptive CER use may be stronger in females than males. We also included the interactions between these covariates and our variables of interest [Time, PSQI, CERQ] in each of our models. See Table 2.1 for an overview of each model.

Standard assumptions of linear mixed models (i.e. linearity, homogeneity of variance, multicollinearity, normality of residuals, and influential data points) were checked throughout the modelling process. We used a decision tree to check model assumptions and carry out appropriate transformations of the data in the event that any assumptions were violated (see Figure A.3 in the Supplementary Material). Because linear models are relatively robust to violations of distributional assumptions (such as normality of residuals; Schielzeth et al., 2020), any model issues that were not satisfactorily resolved are reported and the results interpreted with necessary caution. All continuous predictors and covariates in the linear mixed models were grand mean-centred to enhance the interpretability of model intercepts (Enders & Tofighi, 2007). We used simple slopes analysis with Johnson-Neyman intervals to probe any significant two-way and three-way interactions in Model 2 and Model 3, respectively (Carden et al., 2017; Lin, 2020). In case non-convergence issues arose in our final dataset, we produced a workflow outlining the steps we would take to address such matters. This is illustrated in the Supplementary Material (Figure A.4).

All analyses were conducted using R (v.4.0.2) with the R packages *lme4* (Bates et al., 2014), *lmerTest* (Kuznetsova et al., 2017) and *afex* (Singmann et al., 2021). These packages were used to model regressions and calculate p-values using Satterthwaite approximations. Plots were created with the R package *ggplot2* (Wickham, 2016). The code for our linear mixed effects models has been adapted from Rodriguez-Seijas et al. (2020) and can be found on the OSF.

Model 1, baseline model investigating the effect of time on self-reported depression and anxiety. Model 1 was used as a baseline model to investigate the effect of time on depression (PHQ-9 mean modified total score) and anxiety (GAD-7 total score), as indexed by the change from baseline to follow-up. From this model, we were able to determine whether depression and/or anxiety change from Spring to Autumn 2020 in the absence of any predictor variables. Accordingly, the only fixed effect was time, which was added as a categorical predictor alongside the covariates. Time-bin was simple coded (early = −0.5, late = 0.5). Previous studies using the same dataset as ours (and similar models) have shown a significant effect of time on depression during the early to later months of the pandemic (i.e. a reduction in PHQ-9 scores; Fields et al., 2021; Rodriguez-Seijas et al., 2020). The effect of time on anxiety has yet to be investigated in this dataset, but findings from other COVID-19 datasets have indicated that anxiety has followed a similar trajectory to depression (Carr et al., 2022; Fancourt et al., 2020; Kujawa et al., 2020; O'Connor et al., 2020; van der Velden et al., 2021).

Model 2, testing hypotheses 1a and 1b: greater use of adaptive CER strategies will be associated with decreased self-reported depression and anxiety over time. Model 2 addressed the effect of adaptive CER strategy use on depression and anxiety. The adaptive CER strategies (composite) score was added as a continuous fixed effect, alongside the interaction between the adaptive CER strategies score and time. Support for our hypotheses will be indicated by a significant interaction between the adaptive CER strategies score and time on self-reported depression and/or anxiety ($p < .05$), such that greater use of adaptive CER strategies will be associated with a decrease in depression and/or anxiety from baseline.

Model 3 (i), testing hypotheses 2a and 2b: higher sleep quality will be associated with decreased self-reported depression and anxiety over time. Model 3 addressed the effect of sleep quality on depression and anxiety. The sleep quality (PSQI) score was added to the baseline model as a continuous fixed effect, alongside the interaction between the sleep quality score and time. Support for our hypotheses will be indicated by a significant interaction between time and the sleep quality score on self-reported depression and/or anxiety ($p < .05$), such that higher sleep quality will be associated with a decrease in depression and/or anxiety from baseline.

Model 3 (ii), testing hypotheses 3a and 3b: the relationship between greater use of adaptive CER strategies and decreased self-reported depression and anxiety will be stronger at higher levels of sleep quality. The three-way interaction between sleep quality score, adaptive CER strategies score and time was added to Model 3 to investigate whether sleep quality moderates the relationship between adaptive CER strategy use and either depression or anxiety. Support for our hypotheses will be indicated by a significant three-way interaction between time, adaptive CER strategies score and sleep quality score on depression and/or anxiety ($p < .05$), such that the relationships described for Model 2 will be stronger at higher (above average) levels of sleep quality.

2.2.4.3 Missing data

Maximum likelihood was used to handle missing outcome data (e.g. when PHQ-9 and/or GAD-7 data is only available for the early or late time point). Consistent with ordinary least squares regression, maximum likelihood uses all of the available outcome data – complete and incomplete – to identify parameter values that maximise the fit of the model with the observed data (Baraldi & Enders, 2010; Brown, 2021). Note that the PHQ-9 was administered numerous times within each assessment period (with a mean score calculated across all scores within that period), meaning that participants must have fully completed the PHQ-9 at least once during the Spring or Autumn to be included in the analysis of depression.

2.2.5 Power analysis

The sample size for this study was already determined by the secondary data available. However, it is important to determine whether the data available can provide a sufficiently powered test of our key hypotheses. We used a data simulation approach to calculate the minimum effect sizes that we were able to detect with 90% power, an alpha threshold of 0.02 and the sample available for each analysis (depression $N = 551$; anxiety $N = 590$)[5]. If these minimum effect sizes are comparable to or smaller than those expected in the context of the current literature, we can be reassured that the data provide a suitable means of addressing of our research questions. Please note that the 90% power and alpha threshold of 0.02 were selected in accordance with Cortex's Registered Report guidelines for power analyses. We chose an alpha threshold of 0.05 for our main analyses to protect against overly conservative p-values when controlling for the false discovery rate.

Simulated datasets were generated from the model parameters extracted from the pilot analyses (depression $N = 117$; anxiety $N = 122$; see Table A.2 in the Supplementary Material)[6]. For each hypothesis, we varied the size of the associated model coefficient that generated the simulated data, ranging from 0 (i.e. a null effect) to the maximum effect size

[5] For reasons noted in footnote 1, our total sample size has changed.
[6] Our pilot sample size has also changed.

indicated by the 95% confidence intervals. By generating and analysing 1000 datasets at varying effect sizes in this range, we calculated the minimum effect size at which 90% of the tests were statistically significant at $p < .02$ (see Table 2.2).

Although we report non-standardised coefficients in our main analyses – allowing direct interpretation of the model coefficients in relation to unit changes in the measures – we computed standardised coefficients to examine the minimum detectable effect sizes within the context of the current literature. There is a limited literature on which to base reasonable effect size estimates for the moderating role of sleep on adaptive CER strategy use and mental health outcomes. A recent cross-sectional study examined the influence of adaptive CER strategy use and sleep quality on depression, using a structural equation modelling approach (Nicholson et al., 2021) and estimated a standardised path coefficient of 0.12. Our simulations for the interaction between adaptive CER strategy use and sleep quality on depression (Model 3) estimated that we have sufficient power to test an effect of similar magnitude ($\beta = 0.19$)[7].

To determine the sensitivity of our models to false positives, we ran an additional simulation analysis with all beta coefficients for the effects of interest set to 0. Because Model 3 includes all of our effects of interest, we deemed it reasonable to carry out this simulation on Model 3 alone (separately for depression and anxiety). These simulations confirmed that the proportion of false positives produced by the models was in line with the alpha level of 0.02 (see Table A.3 in the Supplementary Material).

[7] For reasons outlined in footnote 1, the minimum detectable effect size for the interaction between adaptive CER strategy use and sleep quality on depression has changed.

Table 2.2. Minimum detectable effect sizes and 95% confidence intervals based on a simulated dataset with 90% power and 0.02 alpha level.

	Depression		***Anxiety***	
Effect Size (ES)	***B*** *[CIs]*	***β*** *[CIs]*	***B*** *[CIs]*	***β*** *[CIs]*
Model 2				
Time	0.66 *[0.65–0.68]*	0.11 *[0.11–0.11]*	0.83 *[0.78–0.87]*	0.15 *[0.15–0.16]*
Adaptive CER Strategy Use	0.17 *[0.16–0.18]*	0.19 *[0.18–0.20]*	0.16 *[0.15–0.17]*	0.19 *[0.18–0.20]*
Time × Adaptive CER Strategy Use	0.07 *[0.07–0.08]*	0.09 *[0.09–0.09]*	0.11 *[0.10–0.11]*	0.11 *[0.11–0.12]*
Model 3				
Time	0.72 *[0.70–0.74]*	0.12 *[0.11–0.13]*	1.02 *[1.01–1.04]*	0.19 *[0.18–0.19]*
Adaptive CER Strategy Use	0.17 *[0.18–0.18]*	0.17 *[0.16–0.17]*	0.16 *[0.15–0.17]*	0.16 *[0.15–0.16]*
Sleep Quality	0.31 *[0.30–0.32]*	0.17 *[0.16–0.17]*	0.36 *[0.34–0.37]*	0.20 *[0.19–0.21]*
Time × Adaptive CER Strategy Use	0.08 *[0.07–0.08]*	0.12 *[0.11–0.12]*	0.18 *[0.17–0.19]*	0.16 *[0.16–0.17]*
Time × Sleep Quality	0.03 *[0.03–0.04]*	0.14 *[0.14–0.14]*	0.46 *[0.45–0.48]*	0.22 *[0.21–0.22]*
Adaptive CER Strategy Use × Sleep Quality	0.08 *[0.07–0.08]*	0.19 *[0.18–0.19]*	0.08 *[0.08–0.08]*	0.19 *[0.18–0.20]*
Time × Adaptive CER Strategy Use × Sleep Quality	0.03 *[0.03–0.04]*	0.09 *[0.09–0.10]*	0.05 *[0.05–0.05]*	0.12 *[0.12–0.13]*

B = Non-standardised ES, β = Standardised ES[8].

[8] For reasons noted in footnote 1, our pilot sample size has changed and, as such, our minimum detectable effect sizes and 95% confidence intervals have changed.

2.3 Results

2.3.1 Pre-registered analysis

The data files and scripts for our pre-registered and exploratory analyses can be found on the OSF. Both the depression and anxiety outcome measures violated the assumptions of linearity and homoskedascity. An initial log(10) transformation did not resolve these violations so we applied a Box–Cox transformation and report the results using these transformed outcome variables. To control for multiple comparisons, we report p-values adjusted for the false discovery rate (FDR; Benjamini & Hochberg, 1995). Cohen's d for each effect of interest was calculated using the R package *EMAtools* (Kleiman, 2021). Bayes Factors were computed using the R package *BayesFactor* (Morey & Rouder, 2022) and can be interpreted in line with Jeffreys criterion (Jeffreys, 1961).

Table 2.3 shows the descriptive statistics for the depression and anxiety datasets. Table 2.4 shows correlations among all examined variables for the (a) self-reported depression models and (b) self-reported anxiety models. We found a significant negative association between adaptive CER strategy use and both depression ($r_s = -.24$, $p < .001$) and anxiety ($r_s = -.19$, $p < .001$), such that greater use of adaptive CER strategies was associated with lower depression and anxiety scores. There was also a significant positive association between sleep quality and both depression ($r_s = .51$, $p < .001$) and anxiety ($r_s = .44$, $p < .001$); with lower scores on the PSQI reflecting higher sleep quality. Thus, higher sleep quality was associated with lower depression and anxiety scores. Furthermore, there was a significant negative association between sleep quality and adaptive CER strategy use in both the depression ($r_s = -.22$, $p < .001$) and anxiety datasets ($r_s = -.21$, $p < .001$), such that higher sleep quality was associated with greater use of adaptive CER strategies.

Table 2.3. Descriptive statistics (a) for PHQ-9, GAD-7, CERQ adaptive composite score and PSQI total score. (b) Distribution of depression and anxiety severity levels, based on cut-off scores for the PHQ-9 and GAD-7 during Spring and Autumn 2020. Early and late time point PHQ-9 and GAD-7 total scores are reported for each of the depression and anxiety datasets, respectively. CERQ adaptive composite score and PSQI total score are reported for both the depression and anxiety datasets. None-minimal indicates no or minimal depression and/or anxiety symptomatology. Mild to severe indicates respective levels of depression and/or anxiety symptomatology.

(a)	**Depression dataset**		**Anxiety dataset**	
	PHQ-9*^		**GAD-7***	
Time bin	**Early**	**Late**	**Early**	**Late**
Mean [*SD*]	6.24 [*4.30*]	5.42 [*4.25*]	6.14 [*4.84*]	6.11 [*4.83*]
Median [*IQR*]	5.50 [*5.52*]	4.67 [*5.67*]	5.00 [*7.00*]	5.00 [*5.50*]
Range	0–23	0–20.30	0–21	0–21
	CERQ	**PSQI**	**CERQ**	**PSQI**
Mean [*SD*]	22.66 [*5.89*]	6.17 [*3.24*]	22.63 [*5.92*]	6.14 [*3.25*]
Median [*IQR*]	22.00 [*8.25*]	5.50 [*4.00*]	22.00 [*9.00*]	6.00 [*4.00*]
Range	9–40	0–16	9–40	0–16
(b)	**PHQ-9***		**GAD-7***	
Time bin	**Early**	**Late**	**Early**	**Late**
None-minimal	182	143	256	156
Mild	213	128	191	126
Moderate	84	38	91	37
Moderately severe	23	15	*NA*	*NA*

Severe	5	1	36	32

*Descriptive statistics and cut-off scores were calculated on the non-transformed outcome variables to facilitate interpretation. ^PHQ-9 scores were modified due to the omission of the suicidality item so total score ranges from 0–24 instead of the typical 0–27.

Table 2.4. Spearman's correlations (r_s) between all examined variables for (a) self-reported depression and (b) self-reported anxiety. Statistically significant correlations are shown in bold. Multiple comparisons correction was applied using Holm's method (Hochberg, 1988).

(a)	**Time**	**Age**	**Biological Sex**	**Mental Health Diagnosis**	**Adaptive CER Strategy Use**	**Sleep Quality**	**PHQ-9***
Time	-						
Age	.04	-					
Biological Sex	−.01	.07	-				
Mental Health Diagnosis	.02	**.13**	.09	-			
Adaptive CER Strategy Use	<.01	.11	.02	.10	-		
Sleep Quality	.01	.05	–.03	**−.19**	**−.22**	-	
PHQ-9*	−.10	**–.11**	–.03	**−.25**	**−.24**	**.51**	-

(b)	**Time**	**Age**	**Biological Sex**	**Mental Health Diagnosis**	**Adaptive CER Strategy Use**	**Sleep Quality**	**GAD-7***
Time	-						
Age	.05	-					
Biological Sex	−.02	.09	-				
Mental Health Diagnosis	.01	.10	.10	-			
Adaptive CER Strategy Use	.02	.10	.02	.10	-		

Sleep Quality	.01	.06	−.06	**−.19**	**−.21**	-	
GAD-7*	<.01	**−.13**	−.10	**−.24**	**−.19**	**.44**	-

*Total scores after Box-Cox transformation.

Model 1, effect of time: Coefficients and inferential statistics for Model 1 are shown for depression and anxiety in Table 2.5. These outcomes are also illustrated in Figure 2.2. There was a main effect of time on depression ($B = -0.25$ [−0.37, −0.14], $p < .001$, d = 0.46), such that depression decreased from Spring to Autumn 2020. However, there was no main effect of time on anxiety ($B = 0.04$ [−0.08, 0.16], $p = .777$, d = 0.07). Age significantly predicted both depression ($B = -0.01$ [−0.01, 0.00], $p = .045$, d = 0.22) and anxiety ($B = -0.01$ [−0.02, −0.01], $p = .001$, d = 0.31), such that increased age was associated with lower depression and anxiety, consistent with prior work (Cunningham, Fields, Garcia, et al., 2021; Cunningham, Fields, & Kensinger, 2021). There was no main effect of biological sex (female/male) on depression ($B = -0.03$ [−0.33, 0.27], $p = .940$, d = 0.02) or anxiety ($B = -0.24$ [−0.54, 0.06], $p = .392$, d = 0.13). For both datasets, there was a main effect of current mental health diagnosis (depression: $B = -0.76$ [−1.03, −0.49], $p < .001$, d = 0.45; anxiety: $B = -0.74$ [−1.01, −0.46], $p < .001$, d = 0.42): individuals with a currently diagnosed mental health condition had significantly higher depression and anxiety than individuals without diagnosed mental illness.

Table 2.5. Model 1 coefficients with 95% confidence intervals. Model 1 included participant variables (age, biological sex and mental health diagnosis) and time (period during which self-reported depression or anxiety measures were collected). Separate models were run for depression (PHQ-9) and anxiety (GAD-7). Statistically significant coefficients are shown in bold.

	PHQ-9*			***GAD-7****		
	B *[CIs]*	***β*** *[CIs]*	***p***	***B*** *[CIs]*	***β*** *[CIs]*	***p***
Intercept	**2.70** ***[2.59, 2.81]***	−0.02 *[−0.10, 0.05]*	-	**2.62** ***[2.51, 2.73]***	0.01 *[−0.07, 0.08]*	-
Age	**−0.01** ***[−0.01, 0.00]***	**−0.10** ***[−0.18, −0.02]***	**.045**	**−0.01** ***[−0.02, −0.01]***	**−0.15** ***[−0.22, −0.07]***	**.001**
Biological Sex	−0.03 *[−0.33, 0.27]*	−0.01 *[−0.09, 0.07]*	.940	−0.24 *[−0.54, 0.06]*	−0.06 *[−0.13, 0.01]*	.392
Mental Health Diagnosis	**−0.76** ***[−1.03, −0.49]***	**−0.22** ***[−0.30, −0.14]***	**<.001**	**−0.74** ***[−1.01, −0.46]***	**−0.20** ***[−0.28, −0.13]***	**<.001**
Time	**−0.25** ***[−0.37, −0.14]***	**−0.18** ***[−0.26, −0.09]***	**<.001**	0.04 *[−0.08, 0.16]*	0.03 *[−0.05, 0.11]*	.777

B = Non-standardised coefficients, β = Standardised coefficients
*PHQ-9 and GAD-7 outcome variables were transformed using the Box-Cox transformation

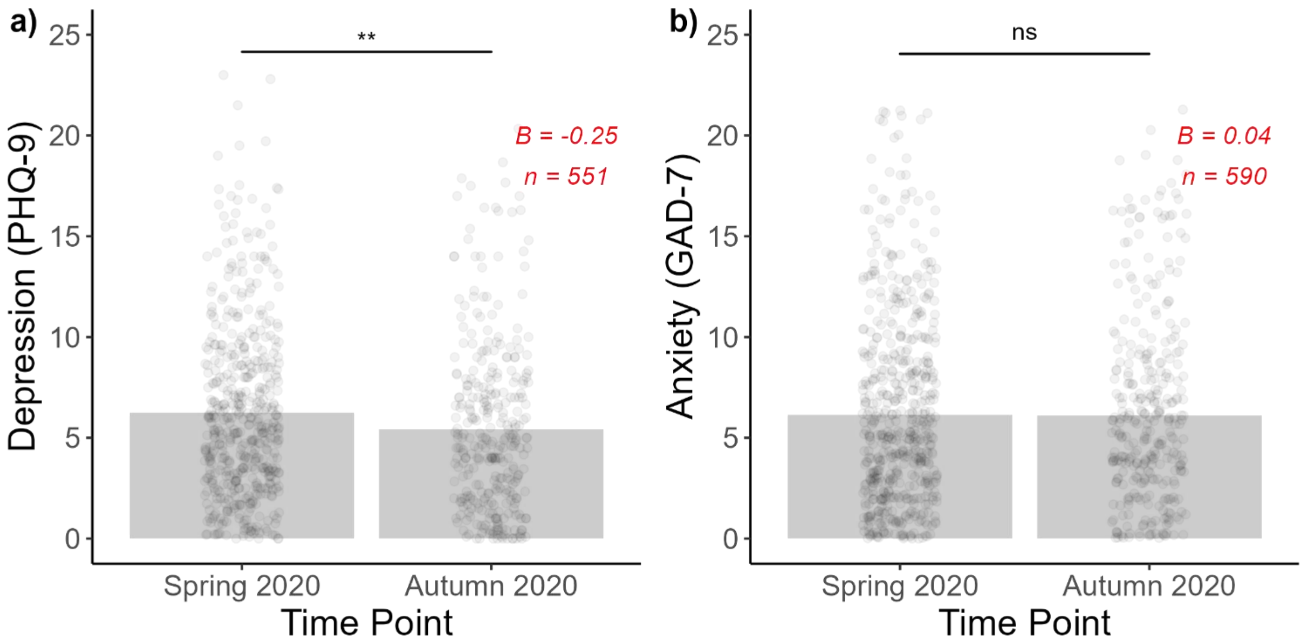

Figure 2.2. Effect of time on depression and anxiety. Changes in a) self-reported depression and b) self-reported anxiety over time (Model 1). Depression significantly decreased from Spring to Autumn 2020. However, there was no significant change in anxiety from Spring to Autumn 2020. Non-transformed outcomes are shown for visualisation purposes. ** $p < .01$, ns = non-significant ($p > .05$).

Model 2, effect of time and adaptive CER strategy use: Coefficients and inferential statistics for Model 2 are shown in Table 2.6. These outcomes are also illustrated in Figure 2.3. For depression, there was a main effect of adaptive CER strategy use ($B = -0.05$ [−0.07, −0.03], $p < .001$, d = 0.48, $BF_{10} > 100$) but no significant interaction between adaptive CER strategy use and time ($B = -0.01$ [−0.03, 0.01], $p = .441$, d = 0.12, $BF_{10} = 0.14$). Therefore, greater use of adaptive CER strategies was associated with lower depression, irrespective of time. For anxiety, there was also a main effect of adaptive CER strategy use ($B = -0.04$ [−0.05, −0.02], $p = .002$, d = 0.30, $BF_{10} > 100$) but, again, no significant interaction between adaptive CER strategy use and time ($B = 0.00$ [−0.02, 0.02], $p = .876$, d = 0.03, $BF_{10} = 0.12$). The significant effect of mental health diagnosis reported in Model 1 remained significant in both the depression ($B = -0.71$ [−0.98, −0.44], $p < .001$, d = 0.43) and anxiety models ($B = -0.72$ [−1.00, −0.45], $p < .001$, d = 0.41). The main effect of age reported in Model 1 remained significant for anxiety ($B = -0.01$ [−0.02, 0.00], $p = .004$, d = 0.28) but was no longer a significant predictor of depression ($B = -0.01$ [−0.01, 0.00], $p = .137$, d = 0.18).

Table 2.6. Model 2 coefficients with 95% confidence intervals. Model 2 included participant variables (age, biological sex and mental health diagnosis), time (period during which self-reported depression or anxiety responses were collected) and adaptive CER strategy use. Separate models were run for depression (PHQ-9) and anxiety (GAD-7). Statistically significant coefficients are shown in bold.

	PHQ-9*			***GAD-7****		
	B *[CIs]*	***β*** *[CIs]*	***p***	***B*** *[CIs]*	***β*** *[CIs]*	***p***
Intercept	**2.71** ***[2.60, 2.82]***	−0.02 *[−0.10, 0.06]*	-	**2.63** ***[2.52, 2.74]***	0.01 *[−0.06, 0.09]*	-
Age	−0.01 *[−0.01, 0.00]*	−0.08 *[−0.16, −0.01]*	.137	**−0.01** ***[−0.02, 0.00]***	**−0.13** ***[−0.21, −0.06]***	**.004**
Biological Sex	−0.01 *[−0.30, 0.27]*	−0.00 *[−0.08, 0.07]*	.989	−0.24 *[−0.53, 0.06]*	−0.06 *[−0.13, 0.01]*	.392
Mental Health Diagnosis	**−0.71** ***[−0.98, −0.44]***	**−0.20** ***[−0.28, −0.13]***	**<.001**	**−0.72** ***[−1.00, −0.45]***	**−0.20** ***[−0.27, −0.12]***	**<.001**
Time	**−0.25** ***[−0.37, −0.14]***	**−0.18** ***[−0.26, −0.10]***	**<.001**	0.04 *[−0.07, 0.16]*	0.03 *[−0.05, 0.11]*	.777
Adaptive CER Strategy Use	**−0.05** ***[−0.07, −0.03]***	**−0.22** ***[−0.30, −0.14]***	**<.001**	**−0.04** ***[−0.05, −0.02]***	**−0.14** ***[−0.21, −0.07]***	**.002**
Time × Adaptive CER Strategy Use	−0.01 *[−0.03, 0.01]*	−0.05 *[−0.13, 0.03]*	.441	0.00 *[−0.02, 0.02]*	0.01 *[−0.07, 0.09]*	.876

B = Non-standardised coefficients, β = Standardised coefficients

*PHQ-9 and GAD-7 outcome variables were transformed using the Box-Cox transformation.

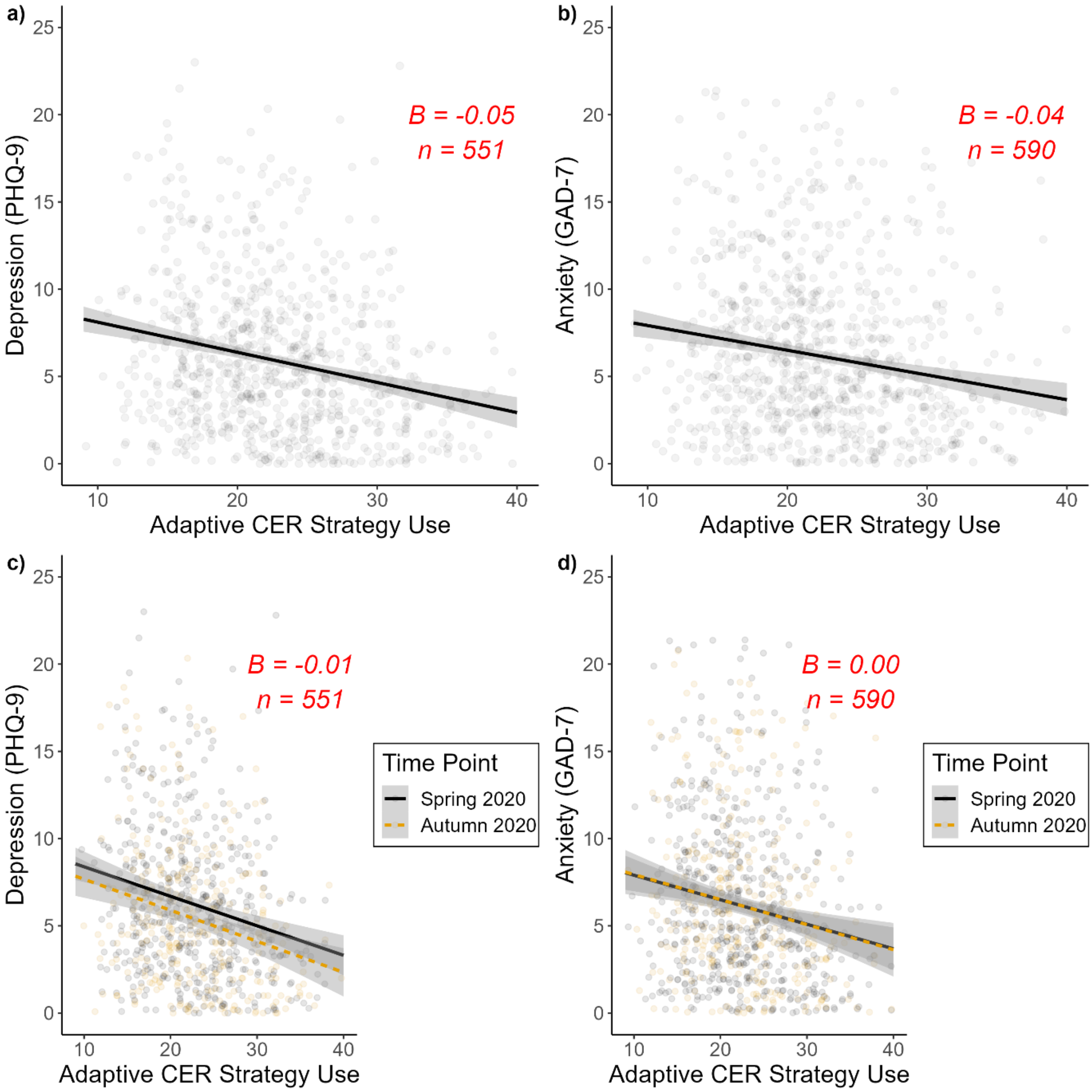

Figure 2.3. Effect of adaptive CER strategy use on depression and anxiety. Greater use of adaptive CER strategies was significantly associated with a) lower depression and b) lower anxiety across both timepoints (Spring and Autumn 2020). There was no significant interaction between adaptive CER strategy use and time for c) depression or d) anxiety (black line = Spring 2020; dashed line = Autumn 2020). Grey areas represent 95% confidence intervals. Non-transformed outcomes are shown for visualisation purposes.

Model 3, effect of time, adaptive CER strategy use and sleep quality: Coefficients and inferential statistics for Model 3 are shown in Table 2.7. These outcomes are also illustrated in Figure 2.4. The significant effect of adaptive CER strategy use on depression reported in Model 2 remained significant in this expanded model ($B = -0.03$ [−0.05, −0.01], $p = .002$, d = 0.31). However, the significant effect of adaptive CER strategy use on anxiety reported in Model 2 was no longer significant ($B = -0.02$ [−0.04, 0.00], $p = .180$, d = 0.17). There was a main effect of sleep quality on both depression ($B = 0.21$ [0.18, 0.24], $p < .001$, d = 1.17, BF > 100) and anxiety ($B = 0.19$ [0.15, 0.22], $p < .001$, d = 0.93, $BF_{10} > 100$), such that higher sleep quality was associated with lower depression and anxiety. There was no interaction between sleep quality and time or sleep quality and adaptive CER strategy use on either depression ($B = -0.03$ [−0.07, 0.01], $p = .277$, d = 0.16, $BF_{10} = 0.13$; $B = 0.00$ [−0.01, 0.00], $p = .842$, d = 0.03, $BF_{10} = 0.12$, respectively) or anxiety ($B = -0.05$ [−0.09, −0.01], $p = .065$, d = 0.25, $BF_{10} = 1.88$; $B = 0.00$ [0.00, 0.01], $p = .876$, d = 0.02, $BF_{10} = 0.18$, respectively). In addition, there was no significant three-way interaction between time, adaptive CER strategy use and sleep quality on depression ($B = 0.00$ [−0.01, 0.00], $p = .439$, d = 0.12, $BF_{10} < .01$) or anxiety ($B = 0.00$ [−0.01, 0.00], $p = .821$, d = 0.05, $BF_{10} < .01$). The significant effects of mental health diagnosis reported in Model 2 remained significant for depression ($B = -0.45$ [−0.69, −0.21], $p = .002$, d = 0.30) and anxiety ($B = -0.51$ [−0.77, −0.25], $p = .001$, d = 0.31). Age was also a significant predictor of depression ($B = -0.01$ [−0.01, 0.00], $p = .007$, d = −0.28) and anxiety ($B = -0.01$ [−0.02, −0.01], $p < .001$, d = 0.37) in this expanded model.

Table 2.7. Model 3 coefficients with 95% confidence intervals. Model 3 included participant variables (age, biological sex and mental health diagnosis), time (period during which self-reported depression or anxiety responses were collected), adaptive CER strategy use and sleep quality. Separate models were run for depression (PHQ-9) and anxiety (GAD-7). Statistically significant coefficients are shown in bold.

	PHQ-9*			***GAD-7****		
	B *[CIs]*	***β*** *[CIs]*	***p***	***B*** *[CIs]*	***β*** *[CIs]*	***p***
Intercept	**2.70** ***[2.61, 2.79]***	−0.03 *[−0.09, 0.04]*	-	**2.64** ***[2.54, 2.74]***	0.02 *[−0.05, 0.09]*	-
Age	**−0.01** ***[−0.01, 0.00]***	**−0.11** ***[−0.18, −0.04]***	**.007**	**−0.01** ***[−0.02, −0.01]***	**−0.16** ***[−0.23, −0.09]***	**<.001**
Biological Sex	0.02 *[−0.23, 0.27]*	0.01 *[−0.06, 0.07]*	.942	−0.18 *[−0.45, 0.09]*	−0.04 *[−0.11, 0.02]*	.604
Mental Health Diagnosis	**−0.45** ***[−0.69, −0.21]***	**−0.13** ***[−0.20, −0.06]***	**.002**	**−0.51** ***[−0.77, −0.25]***	**−0.14** ***[−0.21, −0.07]***	**.001**
Time	**−0.27** ***[−0.39, −0.15]***	**−0.19** ***[−0.27, −0.10]***	**<.001**	0.04 *[−0.08, 0.16]*	0.03 *[−0.05, 0.11]*	.777
Adaptive CER Strategy Use	**−0.03** ***[−0.05, −0.01]***	**−0.13** ***[−0.20, −0.06]***	**.002**	−0.02 *[−0.04, 0.00]*	−0.08 *[−0.15, −0.01]*	.180
Sleep Quality	**0.21** ***[0.18, 0.24]***	**0.48** ***[0.41, 0.54]***	**<.001**	**0.19** ***[0.15, 0.22]***	**0.40** ***[0.33, 0.47]***	**<.001**
Time × Adaptive CER Strategy Use	−0.02 *[−0.04, 0.00]*	−0.07 *[−0.15, 0.02]*	.277	0.00 *[−0.02, 0.02]*	0.00 *[−0.08, 0.08]*	.997
Time × Sleep Quality	−0.03 *[−0.07, 0.01]*	−0.07 *[−0.15, 0.02]*	.277	−0.05 *[−0.09, −0.01]*	−0.10 *[−0.18, −0.02]*	.065
Adaptive CER Strategy Use × Sleep Quality	0.00 *[−0.01, 0.00]*	−0.01 *[−0.08, 0.06]*	.842	0.00 *[0.00, 0.01]*	0.01 *[−0.06, 0.08]*	.876
Time × Adaptive CER Strategy Use × Sleep Quality	0.00 *[−0.01, 0.00]*	−0.06 *[−0.15, 0.04]*	.439	0.00 *[−0.01, 0.00]*	−0.02 *[−0.10, 0.06]*	.821

B = Non-standardised coefficients, β = Standardised coefficients
*PHQ-9 and GAD-7 outcome variables were transformed using the Box-Cox transformation.

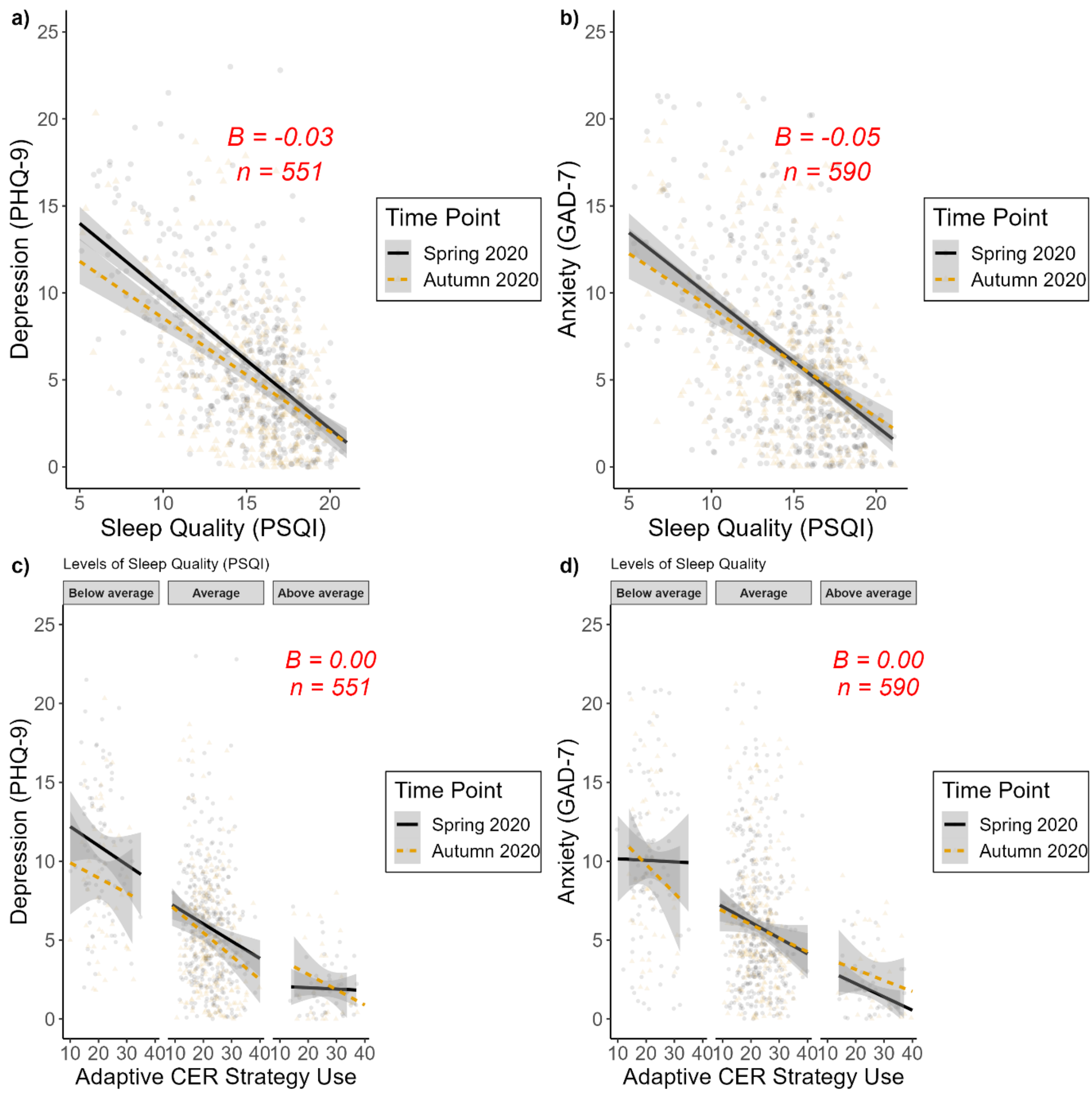

Figure 2.4. Effect of adaptive CER strategy use and sleep quality on depression and anxiety. PSQI scores have been inverted for visualisation purposes such that higher scores represent higher quality sleep. Higher sleep quality was significantly associated with a) lower depression and b) anxiety over time (black line = Spring 2020; dashed line = Autumn 2020). There was no significant interaction between adaptive CER strategy use, sleep quality and time on either c) self-reported depression or d) anxiety. Data are plotted at different levels of sleep quality (mean and +/− 1 SD). Grey areas represent 95% confidence intervals. Non-transformed outcomes are shown for visualisation purposes.

2.3.2 Exploratory analyses

Although our primary objective was to investigate the influence of adaptive CER strategies and sleep quality on mental health outcomes, we also conducted several exploratory analyses. First, given that poor sleep quality has been shown to increase the use of maladaptive CER strategies (Latif et al., 2019), we also investigated the influence of maladaptive CER strategies and sleep quality on depression and anxiety. Second, because higher levels of depression and anxiety have been reported among Black, Hispanic and Asian communities (as compared to White communities) during the COVID-19 pandemic (Czeisler et al., 2020; Wu et al., 2021), we explored the influence of race in our models. Moreover, because we included participants with and without a current mental health diagnosis in our main analysis, we ran an exploratory analysis to examine whether our findings differed when excluding individuals with a diagnosed mental health disorder. Finally, to determine how people's experience of the pandemic influenced our findings, we ran our models again but only included individuals who reported that COVID-19 had, on the whole, had a negative impact on their lives. We report these findings in the Supplementary Material.

2.4 Discussion

Previous research has suggested that the mental health benefits of using adaptive CER strategies are contingent on good quality sleep (Mauss et al., 2013; Parsons et al., 2021; Tamm et al., 2019; Zhang et al., 2019). We tested this possibility by investigating whether mental health outcomes arising during a prolonged period of stress (the COVID-19 pandemic) were dependent on adaptive CER strategy use and sleep quality, as well as the interaction of these predictors. We found that greater use of adaptive CER strategies and higher levels of sleep quality were independently associated with lower levels of depression and anxiety. However, only sleep quality was a significant predictor of self-reported anxiety in our final model. The benefits of adaptive CER strategy use for depression were not influenced by naturally varying levels of sleep quality.

The results of our baseline model indicate that depression decreased significantly from Spring to Autumn 2020, as observed in previous work (Fields et al., 2021; Rodriguez-Seijas et al., 2020). However, in contrast to earlier findings (Carr et al., 2022; Fancourt et al., 2020; Kujawa et al., 2020; O'Connor et al., 2020; van der Velden et al., 2021), anxiety did not significantly change across the same time period. The uncertainty surrounding COVID-19 during the Spring and Autumn of 2020 (e.g. job insecurity, new COVID-19 variants, lack of an approved vaccine) might have contributed to sustained anxiety symptoms. Further support for this possibility comes from evidence that anxiety was persistently worse across the first-year of the COVID-19 pandemic, as compared to before, even when lockdown measures were eased (Patel et al., 2022). It is nevertheless important to note that anxiety data was collected only once at each of the Spring and Autumn timepoints, whereas depression data was collected several times across both timepoints, meaning that the trajectory of mental health outcomes might be better captured in the depression dataset.

Greater use of adaptive CER strategies was associated with lower depression and anxiety in Model 2, supporting hypotheses 1a and 1b. This association was independent of time, demonstrating a stable relationship between adaptive CER strategy use and mental health outcomes. Our findings are well aligned with those reported in previous studies (Aldao & Nolen-Hoeksema, 2010; Cardi et al., 2021; Dimanova et al., 2022; Domaradzka & Fajkowska, 2018; Garnefski et al., 2002; Jungmann & Witthöft, 2020; Martin & Dahlen, 2005; Muñoz-Navarro et al., 2021; K. Wang et al., 2021; Waterschoot et al., 2022) and have potentially important clinical implications (e.g. deploying adaptive CER strategies could be utilised as a preventative measure when confronted with real-world emotional turmoil). It has been suggested that adaptive CER strategy use promotes well-being by reducing negative affect (Cardi et al., 2021), potentially via similar mechanisms to those underpinning the downregulation of intrusive thoughts (Engen & Anderson, 2018; Harrington & Cairney, 2021). Maintaining such self-directed and adaptive inputs to one's affective composition might be particularly important for psychological well-being when enduring chronic periods of stress. It should be noted, however, that adaptive CER strategy use was not a significant predictor of anxiety when we added sleep quality to our final model. This is in keeping with prior work showing that cognitive regulation of emotion may be less crucial in the context of anxiety than depression (Domaradzka & Fajkowska, 2018).

Higher levels of sleep quality were associated with lower depression and anxiety, supporting hypotheses 2a and 2b. This association was also independent of time, suggesting a stable relationship between sleep quality and mental health outcomes. Our findings are in keeping with previous work (Alqahtani et al., 2022; Baglioni, Spiegelhalder, et al., 2010; Bi & Chen, 2022; Franceschini et al., 2020; Freeman et al., 2017; French et al., 2022; Randall et al., 2019; A. J. Scott et al., 2021; Varma et al., 2021) and highlight sleep's role in maintaining affective well-being (Bower et al., 2010). Sleep supports cognitive processes that often go awry in mood disorders, such as emotion regulation and memory consolidation (Ashton et al., 2020;

Cairney et al., 2018; Fairholme & Manber, 2015; Guttesen et al., 2023; Harrington, Ashton, Sankarasubramanian, et al., 2021; Palmer & Alfano, 2017), which might represent mechanistic pathways linking sleep quality to mental health. It is noteworthy that many of the pandemic-related sources of sleep disruption (e.g. reduced outdoor activity and increased screen time; Landry et al., 2021) would have remained fairly constant during the study period, potentially nullifying any impact of time in our models.

There was no two-way interaction between sleep quality and adaptive CER strategy use, and no three-way interaction between sleep quality, adaptive CER strategy use and time for either depression or anxiety, refuting hypotheses 3a and 3b. Similar patterns have been observed in previous work; for example, insomnia and emotion dysregulation both predict symptom severity in depression and anxiety disorder, but show no interaction (Fairholme et al., 2013). Together with our other findings, these null effects suggest that high sleep quality and adaptive CER strategies independently support resilience to depression, as the association between adaptive CER strategy use and depression was similar at different levels of sleep quality. The same cannot be said for anxiety, however, as adaptive CER strategy use was not a significant predictor of anxiety outcomes in this final model that accounted for sleep quality. Nevertheless, because the observed effect sizes for the interactions in Models 2 and 3 were considerably smaller than the effect sizes for which the study was powered to detect, it is possible that the dataset was underpowered to detect any interaction effects, should they have existed.

It is worth noting that our data revealed a significant correlation between sleep quality and adaptive CER strategy use; whereby greater use of adaptive CER strategies was associated with higher sleep quality. Although there may be a bidirectional relationship between these variables, the observed correlation is aligned with prior work showing that poor quality sleep can negatively impact on people's ability to deploy adaptive CER strategies effectively (Mauss et al., 2013; Parsons et al., 2021; Tamm et al., 2019; Zhang et al., 2019), potentially via the disruption of cognitive control processes supported by the prefrontal cortex (Mauss et al., 2013). Overall, these data suggest that good quality sleep is tightly linked to the tendency to deploy adaptive CER strategies, but these variables do not have a synergistic influence upon depression or anxiety outcomes.

Each of our models controlled for age, biological sex and mental health diagnosis. We found that age was a significant predictor of mental health outcomes, with older adults experiencing fewer depression and anxiety symptoms than younger adults. Recent work on the same dataset has shown that younger adults felt more inconvenienced and frustrated with stay-at-home orders than older adults, resulting in a greater mental health burden (Cunningham, Fields, Garcia, et al., 2021; Cunningham, Fields, & Kensinger, 2021; Fields et al., 2021). We also found that an existing diagnosis of a mental health condition (versus no diagnosis) was associated with higher levels of depression and anxiety, as observed previously (Fancourt et al., 2020; Gémes et al., 2022; Jia et al., 2022). Contrary to evidence that females are more likely to experience depression and anxiety than males (Carr et al., 2022; Fancourt et al., 2020; French et al., 2022; Jia et al., 2022), there was no effect of biological sex on depression or anxiety outcomes in our dataset. It is important to note, however, that our sample was predominantly female (82.9% for both depression and anxiety), which may have precluded any effect of biological sex from emerging (should one exist in the context of depression and anxiety outcomes during the COVID-19 pandemic).

This is the first study to investigate the ways in which adaptive CER strategies and sleep quality influence mental health outcomes when experiencing a real-world, chronic stressor. Nevertheless, there were several limitations with our study design that might have contributed to the null effects observed in our final model. First, we relied on subjective reports to index emotion regulation and sleep quality. Previous research has shown that discrepancies exist between affective responses assessed subjectively and objectively (Zhang et al., 2019), and self-reported sleep quality is often lower than that indicated by objective measures of sleep continuity or wake-after-sleep-onset (Buysse et al., 2008; Grandner et al., 2006). Future research examining sleep and mental health in the context of real-world chronic stressors can address this limitation by combining objective and subjective assessments of sleep quality and emotion regulation, potentially through the use of wearables tracking sleep and physiological arousal (e.g. heart rate variability). Relatedly, in the data we had available, adaptive CER strategy use and sleep quality were measured only once (May 2020), whereas depression and anxiety were measured twice (Spring and Autumn 2020). Consequently, we were unable to assess any changes in adaptive CER strategy use or sleep quality that may have arisen during the initial months of the pandemic.

Second, although our decision to use a composite measure of adaptive CER strategy use allowed us to investigate how sleep quality and generalised positive thought processes influenced mental health outcomes, it prevented us from determining whether a specific strategy (or smaller combination of strategies) was particularly effective in this regard. For example, some studies have shown that positive reappraisal is a strong predictor of depression and anxiety (Aldao & Nolen-Hoeksema, 2010; Cardi et al., 2021; Dimanova et al., 2022; Garnefski et al., 2002; Martin & Dahlen, 2005; Muñoz-Navarro et al., 2021), while others have indicated that resilience to mental health problems is supported by a finely-tuned balance of adaptive and maladaptive strategies (Waterschoot et al., 2022). Our pre-registered analyses were unable to address whether specific (or different combinations of) adaptive CER strategies interact with sleep quality to support affective well-being and this will be an important endeavour for future work.

A more general limitation of our study was the lack of socio-demographic diversity in the data that we had available. Participants were predominantly female, white, well-educated individuals all residing in the US (Cunningham, Fields, Garcia, et al., 2021; Cunningham, Fields, & Kensinger, 2021). As a result, we were unable to provide appropriate control for other relevant covariates that may have influenced depression and anxiety (e.g. socioeconomic status). Furthermore, because the data were collected in an online setting, only individuals with access to a PC, tablet or smartphone were able to participate. Despite the diversity in scores on the self-report measures, our findings cannot be easily generalised to different societies, environments and cultures, and replication across broader populations will be a crucial next step.

Finally, the COVID-19 pandemic was a very unique and complex stressor, which was associated with a number of factors that may have affected depression and anxiety symptoms (e.g. job security, living situation). It is therefore difficult to draw comparisons between the impacts of COVID-19 and other prolonged stressors on mental health outcomes.

In conclusion, we found that, during the initial months of the COVID-19 pandemic, greater use of adaptive CER strategies was associated with lower depression, whereas higher sleep quality was associated with lower depression and anxiety. The relationship between adaptive CER strategy use and mental health outcomes was not contingent on good quality sleep, however. Building on a large body of laboratory-based research, our findings call attention to the potential transdiagnostic benefits of targeting sleep quality and adaptive CER strategy use when enduring chronic periods of emotional hardship.

Chapter 3: The Influence of Sleep Deprivation on the Evolution of Arousal During Exposure to Ambiguous Threat

Abstract

Sleep deprivation amplifies next-day state anxiety and impairs threat-related information processing. However, little is known about how sleep loss affects the evolution of arousal over the course of a threatening experience. In the current study, we combined virtual reality (VR) and psychophysiology to test the hypothesis that sleep deprivation amplifies in-the-moment arousal responses when exposed to prolonged ambiguous threat. Likewise, we expected sleep deprivation to amplify retrospective reports of subjective arousal. We also predicted that sleep deprivation would impair the recovery of arousal after the threat had dissipated. Reciprocally, certain properties of sleep, namely slow wave activity (SWA) has been shown to reduce next-day state anxiety, but again, whether SWA influences the evolution of arousal in response to prolonged threat remains to be established. We predicted that greater SWA would be associated with reduced arousal in response to ambiguous threat. Following a night of polysomnography (PSG)-monitored sleep or total sleep deprivation, N = 54 adults entered an immersive VR world that cycled between threatening and non-threatening environments, during which their skin conductance level (SCL) and heart rate (HR) were monitored. Participants then watched a replay of their VR experience and retrospectively rated their subjective arousal at each moment. First, we found that SCL (but not HR or subjective arousal ratings) attenuated across the threatening parts in the sleep rested condition but remained elevated in the sleep deprivation condition. However, SWA was not associated with this attenuation. Second, we found no significant differences between the sleep rested and sleep deprivation conditions in arousal responses following the dissipation of threat. Together, these findings indicate that a night of sleep is important for reducing physiological arousal in response to prolonged ambiguous threat. We propose that sleep supports cognitive control and fear learning processes that promote affect regulation.

3.1 Introduction

State anxiety can be defined as a transitory emotional state consisting of feelings of apprehension, nervousness, and physiological arousal, such as increased heart rate (HR) or respiration (Spielberger, 1979). State anxiety tends to arise in direct response to or anticipation of an emotional experience, whereas trait anxiety reflects a relatively chronic state of anxiety (Hutchins & Young, 2018). In healthy individuals, one night of sleep deprivation has been shown to amplify next-day state anxiety (Babson et al., 2010; Ben Simon et al., 2020; Goldstein et al., 2013). Disrupted sleep continuity (through forced awakenings during the night) has also been shown to increase next-day state anxiety (Reid et al., 2023). These findings were further corroborated in a meta-analysis of 24 experiments, which demonstrated that sleep deprivation (total or partial) is associated with a significant increase in self-reported next-day state anxiety (Pires et al., 2016). Furthermore, sleep disruption is a common complaint in those with clinical anxiety disorders, with insufficient sleep contributing to elevated anxiety (Breslau et al., 1996; Chellappa & Aeschbach, 2022; Harvey et al., 2011; Mellman, 2006; Neckelmann et al., 2007; Papadimitriou & Linkowski, 2005; Uhde et al., 2009). Together, these findings demonstrate the anxiogenic impact of sleep loss in both clinical and non-clinical populations.

An absence of sleep is also known to disrupt threat-related information processing. Compared to a night of sleep, total sleep deprivation increases physiological reactivity to negative stimuli (Franzen et al., 2008, 2009). Furthermore, sleep deprivation enhances threat perception (Barber & Budnick, 2015; Goldstein-Piekarski et al., 2015; Zenses et al., 2020). For example, Goldstein-Piekarski et al. (2015) demonstrated that sleep deprived individuals categorised more face stimuli as threatening, and fewer face stimuli as non-threatening compared to their sleep rested counterparts. Moreover, sleep deprivation impaired the cardiac discrimination of threatening from non-threatening face stimuli (Goldstein-Piekarski et al., 2015). However, prior research has only assessed threat-related information processing through one-shot ratings of aversive stimuli (e.g. images and film clips). In the real world, emotional experiences often fluctuate in their intensity over prolonged periods of time (Hildebrandt et al., 2016). Moreover, when an individual encounters a negative emotional experience, sometimes the exact nature of the threat is not always clear (McCall et al., 2022). For example, if we went to the theatre, then had to walk through a dark alleyway on our way home, this can be highly threatening despite the nature of the threat being uncertain. Ambiguously threatening environments result in states of hypervigilance, which, if becomes chronic, may take the form of pathological anxiety (Grillon, 2008; McCall et al., 2022). Although many individuals encounter prolonged periods of uncertain threat in their day-to-day lives, we know very little about how sleep deprivation influences the evolution of arousal, as ambiguously threatening experiences unfold.

Nevertheless, emotional responses have been shown to attenuate following prolonged exposure to threat-relevant stimuli (Johnson et al., 2019; Olatunji et al., 2012; Olatunji, Wolitzky-Taylor, Ciesielski, et al., 2009; Olatunji, Wolitzky-Taylor, Willems, et al., 2009;

Zaback et al., 2019, 2022). This not only highlights the need to understand how sleep influences this evolving process, but also suggests that individuals are able to effectively regulate their threat response as it unfolds in real time. The ability to adaptively respond to threat in the moment may rely on cognitive control (e.g. attention, working memory, and reappraisal; Ochsner & Gross, 2005; Ochsner et al., 2012). Sleep deprivation has been shown to impair cognitive control processes, such as attention, working memory, inhibition, and task-goal switching (Krause et al., 2017; Kusztor et al., 2019; Skurvydas et al., 2020; Slama et al., 2018; Zhang et al., 2019). Electroencephalography (EEG) markers of regulatory success, such as P300 and Pe amplitudes, are also disrupted following sleep deprivation (Kusztor et al., 2019). Taken together, it is plausible that sleep rested individuals can regulate their response to threat through cognitive control processes. However, because these processes are disrupted following sleep deprivation, an individual's ability to regulate their threat response may be impaired, resulting in amplified arousal.

Neuroimaging studies of neurotypical adults demonstrate that total sleep deprivation is associated with a neural profile analogous to that presented in highly anxious individuals. For example, lack of sleep increases activity in brain regions associated with greater reactivity to negative emotional stimuli, such as the amygdala, dorsal anterior cingulate cortex (dACC), and insula (Ben Simon et al., 2020; Goldstein et al., 2013; van der Helm & Walker, 2012; Yoo et al., 2007). Moreover, when individuals are sleep deprived, they display hypoactivity in the medial prefrontal cortex (mPFC) as well as impaired mPFC-amygdala connectivity when viewing aversive images or film clips (Ben Simon et al., 2020; van der Helm & Walker, 2012; Yoo et al., 2007). This neural composition is thought to reflect impaired top-down control of emotional brain regions, and thus disrupted affect regulation (Ben Simon et al., 2020; van der Helm & Walker, 2012; Yoo et al., 2007). The mPFC is also involved in the engagement of cognitive control processes (E. K. Miller, 2000; Niendam et al., 2012; Ridderinkhof et al., 2004). Together, these findings lend neurological support to the idea that sleep deprivation disrupts cognitive mechanisms that are important for adaptively responding to threat.

Individual differences in threat responses emerge not only during exposure to threat, but also in an individual's ability to return to calm over time and between disturbing events. For example, Hildebrandt et al. (2016) demonstrated that participants with higher self-reported resilience and higher heart rate variability (HRV; variability in time between adjacent heartbeats) had lower subjective arousal ratings, than those with lower resilience and lower HRV, when immersed in a threatening and evolving virtual reality (VR) environment.

Critically, they showed that this effect only emerged at the first opportunity to regulate, following the dissipation of intermittent threats (e.g. explosions), suggesting that these markers of flexible regulation play a pivotal role in the recovery of arousal. High HRV has been associated with enhanced executive functioning (Cattaneo et al., 2021; Forte et al., 2019; Gillie et al., 2014; Thayer & Lane, 2009) and successful emotion regulation (Appelhans & Luecken, 2006). Moreover, HRV and resilience have been associated with greater use of adaptive cognitive emotion regulation (CER) strategies (i.e. positive thought processes that downregulate negative emotions; Hildebrandt et al., 2016; Min et al., 2013; Volokhov & Demaree, 2010). Adaptive CER strategy use enlists a number of executive functions, such as memory updating, inhibition of prepotent responses, and flexible task switching (Joormann & Tanovic, 2015; McRae et al., 2012; Ochsner & Gross, 2005). Moreover, executive control deficits have been associated with less frequent and unsuccessful use of adaptive CER strategies (Joormann, 2010; Joormann & Gotlib, 2010; Malooly et al., 2013; Pe et al., 2013; Schmeichel & Tang, 2015; Schmeichel et al., 2008). Given that sleep deprivation impairs executive functions, as described above (Krause et al., 2017; Kusztor et al., 2019; Skurvydas et al., 2020; Slama et al., 2018; Zhang et al., 2019), it is possible that sleep deprivation prevents individuals from being able to downregulate their arousal back to baseline levels following threat. Taken together, we tested the hypothesis that sleep deprivation impairs affect regulation, leading to both (i) amplified arousal during exposure to threat and (ii) impaired recovery following the dissipation of threat.

One challenge in studying responses to prolonged stressors is measurement. Self-report assessments of affect often require participants to summarise an entire experience, thereby collapsing the unfolding of an experience into one measurement. Such summary measures may incur memory bias for the final moments of an experience (Kahneman et al., 1993; McCall et al., 2015). To avoid such bias, one approach is to have participants provide retrospective subjective arousal ratings continuously whilst watching a recording of an emotional experience (Hildebrandt et al., 2016; McCall et al., 2015). This can then be compared with physiological measures, which also provide continuous measurement. Prior work suggests we reliably encode in-the-moment arousal for an experience. Indeed, retrospective reports of subjective arousal are more coherent with physiological arousal during the original event (i.e. past-present coherence) than physiological arousal at the moment of recall (Mauss et al., 2005; McCall et al., 2015). Physiological arousal has been shown to be a key feature of a threat response (Hildebrandt et al., 2016). For example, skin conductance is higher when viewing threatening versus non-threatening images (Bradley et al., 2001). As such, the use of physiological measures, along with continuous subjective arousal ratings, provides a more complete picture of how arousal responses unfold during exposure to ambiguous threat.

Given the impact of sleep loss on threat regulation, a complementary question concerns the specific properties of sleep that restore affect regulatory processes. Individuals with anxiety disorders demonstrate reductions in non-rapid eye movement (NREM) sleep, slow wave sleep (SWS), and slow wave activity (SWA; 0.5–4 Hz), which is one of the hallmarks of SWS (Arriaga & Paiva, 1990; Baglioni et al., 2016; Forbes et al., 2008; Fuller et al., 1997). Conversely, experimental studies have shown that greater amounts of NREM SWA support the overnight reduction of state anxiety (Ben Simon et al., 2020; Chellappa & Aeschbach, 2022). Importantly, this association holds when controlling for trait anxiety and changes in mood (Ben Simon et al., 2020). Moreover, SWA enhancement has been shown to benefit memory consolidation and other cognitive processes, including executive functions such as working memory and reasoning (Wilckens et al., 2016, 2018). On a neural level, greater SWA has been associated with increased next-day restoration of cingulate regions (e.g. the ACC), and prefrontal mechanisms (Ben Simon et al., 2020; Campbell-Sills et al., 2011), both of which have been shown to be critical for the regulation of affect during threat-related information processing (Bishop, 2007; Bishop et al., 2004; M. J. Kim et al., 2011; Simmons et al., 2008). Although these findings point towards an anxiolytic benefit of SWA, *how* SWA influences the evolution of arousal in response to ambiguous threat remains unknown. Given that SWA is thought to be involved in cognitive processes and the restoration of brain mechanisms integral to affect regulation, we tested the hypothesis that SWA would be associated with reduced arousal in response to ambiguous threat.

To address whether sleep deprivation impaired affect regulation during ambiguous threat exposure, we examined physiological arousal responses whilst participants navigated through an immersive threatening VR world following a night of sleep or total sleep deprivation. Participants were then played back the world via a standard desktop computer and retrospectively rated how aroused they felt during every moment to index subjective arousal. Critically, the VR world cycled between ambiguously threatening (akin to walking through a dark alleyway) and non-threatening parts (akin to walking down a well-lit street). This allowed us to examine whether sleep deprivation amplified physiological and subjective arousal during prolonged exposure to ambiguous threat and impaired recovery following the dissipation of threat. The sleep rested condition included polysomnography (PSG) monitoring to examine whether SWA was associated with reduced arousal in response to ambiguous threat.

To examine whether the evolution of arousal across a threatening experience was influenced by markers of efficient executive functioning, we conducted an exploratory analysis to probe the influence of adaptive CER strategy use and HRV on arousal responses following a night of sleep or sleep deprivation.

3.2 Methods

The study methods and analyses were pre-registered on the Open Science Framework.

3.2.1 Participants

All participants were recruited via a publicly open university-based system (SONA). Based on a pre-study screening session (*N* = 85), participants were selected only if they reported no history of neurological, psychiatric, attention, or sleep disorders. Participants were excluded if they scored within the clinical range for depression or anxiety on the Beck Depression Index (BDI-II $\geq$ 18; Beck et al., 1996) and/or the Beck Anxiety Inventory (BAI $\geq$ 16; Beck et al., 1988), if they had extreme diurnal preference (score of < 31 or > 69) as assessed by the Morningness-Eveningness Questionnaire (MEQ; Horne & Östberg, 1976), poor sleep quality (score of > 6) as assessed by the Pittsburgh Sleep Quality Index (PSQI; Buysse et al., 1989) or had a regular bedtime of later than 2:00 am (Porcheret et al., 2015). In addition, they must have typically risen by 8:00 am after at least six hours of sleep, as indicated by self-report. None of the participants were taking any medications with the exception of the female contraceptive pill. Following standard procedures in our laboratory (Ashton et al., 2019; Harrington, Ashton, Ngo, et al., 2021; Harrington, Ashton, Sankarasubramanian, et al., 2021; Strachan et al., 2020), participants were asked to refrain from caffeine and alcohol consumption for 24 and 48 hours, respectively, before the main study sessions. Participants were given an Actiwatch on the morning of the main experimental session to ensure that they did not nap during the day and that participants assigned to the sleep deprivation condition adhered to the study protocol. All participants provided written informed consent. Ethical approval for this study was obtained by the Department of Psychology Research Ethics Committee at the University of York

64 participants completed the main experimental sessions (sleep deprivation: *N* = 36; sleep rested: *N* = 28; mean age [SD] = 19.94 years [2.18 years]). Of these 64, *N* = 8 were excluded as they did not adhere to the sleep deprivation protocol (> 2 hours of sleep), as

indicated by self-report and/or actigraphy data. A further $N = 1$ was excluded as they felt nauseated by the VR environment and $N = 1$ was excluded due to sleeping < 4 hours in the sleep rested condition. Therefore, our final sample size included 54 participants (27 sleep rested: mean [SD] age= 20.30 [2.27] years, 15 females; 27 sleep deprivation: mean [SD] age = 19.59 [2.06] years, 18 females). To avoid any possible influence of dispositional anxiety, participants in each condition were matched on trait anxiety levels as measured by the State-Trait Anxiety Inventory- Trait version (STAI-T; Spielberger, 1983; $t[52] = 0.45$, $p = .652$). Participants received £90 or bachelor's-level psychology course credit for participating in the study. To reduce demand characteristics, the study was advertised and framed to investigate the effects of sleep on memory.

Sample size was determined using a power analysis. Our estimated effect size was based on a study that examined the association between SWA and next-day state anxiety using the State-Trait Anxiety Inventory- State version (STAI-S; Ben Simon, Rossi, et al., 2020). The effect size reported for the influence of sleep deprivation on next-day state anxiety was larger than the effect size reported for the association between SWA and state anxiety ($\eta^2 = 0.34$; Ben Simon, Rossi, et al., 2020), meaning that we would only need $N = 8$ for 90% power at $\alpha = 0.05$. Therefore, it was necessary that our sleep rested condition was adequately powered to examine whether SWA influences the evolution of arousal. Using an effect size of $r = .53$ for the association between SWA and state anxiety, for 90% power at $\alpha = 0.05$ (one-tailed), we needed 27 participants in the sleep rested condition to detect an association between SWA and arousal. Altogether, our final sample size was $N = 54$ ($N = 27$ in each of the sleep rested and sleep deprived conditions). Excluded participants were replaced to meet this sample size for our main research questions.

3.2.2 Procedure and measures

A schematic overview of the study procedure is shown in Figure 3.1. Participants completed three sessions in total.

3.2.2.1 Session one

In session one, participants completed an online screening questionnaire and carried out a "taster" session to ensure that they were comfortable with the VR setup. During this taster session, participants navigated through a neutral version of the VR world used in session three. Skin conductance level (SCL) and HR were also recorded to check for non-responding (e.g. failure to elicit a skin conductance orienting response) in the SCL data and to ensure that no electrocardiography (ECG) abnormalities were present in the HR data. Session one was conducted at least 24 hours before session two.

3.2.2.2 Session two

At 9 am on the morning of session two, participants collected an Actiwatch which they wore until the end of the study (end of session three). During session two (~8:30 pm), participants completed a 5-minute recording of their resting HR before completing several questionnaires including the STAI-S (Spielberger, 1983), Stanford Sleepiness Scale (SSS; Hoddes et al., 1973), Cognitive Emotion Regulation Questionnaire– Short version (CERQ-short; Garnefski & Kraaij, 2006), and a psychomotor vigilance task (PVT). They were then informed whether they had been assigned to the sleep rested or sleep deprivation condition. When two participants were present in the laboratory on the same night, they were both assigned to either the sleep rested or sleep deprivation condition.

3.2.2.3 Overnight interval

Sessions two and three were separated by an overnight interval during which participants either slept in the sleep laboratory with PSG or remained awake at home. Electrodes were attached to participants in the sleep rested condition following the completion of session two. Lights were turned off at ~11 pm and participants were woken up at ~7 am (after ~8 hours of PSG-monitored sleep). If participants were assigned to the sleep deprivation condition, they were sent home and permitted to communicate, read, use electronic devices, watch TV, or play games. In addition, participants in the sleep deprivation condition were administered a questionnaire to complete overnight (from 11 pm to 6:30 am), which involved answering a general knowledge question every 30 minutes. This was to ensure that they were engaged in an activity throughout the night. Adherence to the sleep deprivation protocol was also verified with actigraphy, allowing for an objective assessment of whether participants had remained awake during the overnight interval. Participants were instructed to refrain from consuming caffeine and return to the laboratory the following morning for session three (after > 24 hours of sleep deprivation).

3.2.2.4 Session three

In session three (the following morning at ~8:30 am), participants repeated all the questionnaires (except the CERQ-short) and the PVT. If participants were assigned to the sleep deprivation condition, they also completed a questionnaire probing the activities that they engaged in throughout the night (see Table 3.1) as well as whether they had dozed or consumed caffeine. All participants then experienced the VR world whilst we measured their SCL and HR. This VR world cycled between parts that were ambiguously threatening and designed to induce anxiety, and parts that were non-threatening and designed to reduce anxiety following exposure to threat. Next, participants were played back the VR world via a standard desktop computer and were instructed to retrospectively rate "*how aroused they felt*" during every moment of the experience, using a joystick to continuously mark how they felt on an affect grid of valence and arousal. Arousal ratings were collected to index subjective arousal for the main analysis, and valence ratings were collected as part of an exploratory analysis not reported here. At the end of the experiment, participants returned their Actiwatch and were fully debriefed regarding the nature of the study.

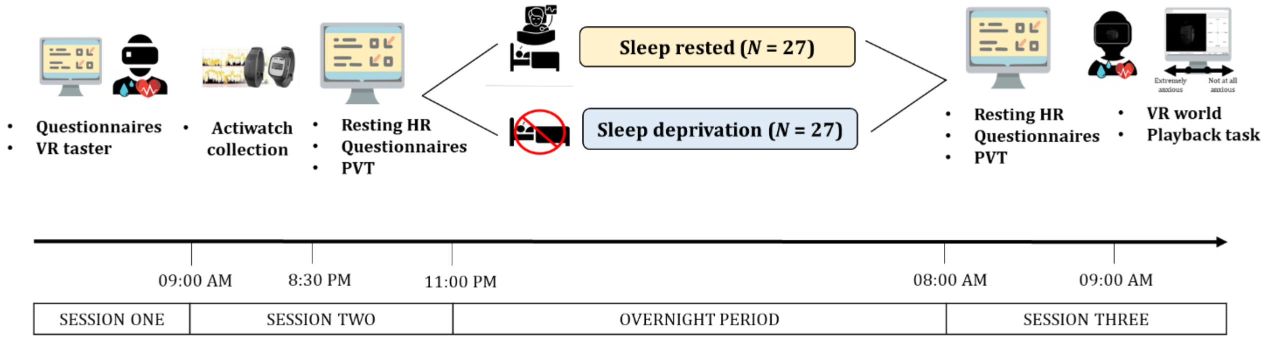

Figure 3.1. Schematic overview of study procedure. During session one, participants came to the laboratory to complete a screening questionnaire and taster session to ensure they were comfortable in a virtual reality (VR) environment. On the morning of session two, participants came to collect an Actiwatch to wear during the remaining study period. In the evening of session two, all participants came to the sleep laboratory and completed a 5-minute recording of their resting heart rate (HR) along with several questionnaires and the psychomotor vigilance task (PVT). At the end of session two, participants were informed whether they had been assigned to the sleep rested or sleep deprivation condition. Those in the sleep rested condition slept overnight in the laboratory with polysomnography (PSG), whereas those in the sleep deprivation condition went home and were instructed to stay awake overnight. In session three, all participants returned to the laboratory and repeated the 5-minute measure of resting HR, questionnaires, and the PVT. Following this, they were immersed in a VR world, whilst their skin conductance level (SCL) and HR were continuously monitored. They were then played back their experience in the VR world via a standard desktop computer and were instructed to retrospectively rate how aroused they felt during every moment.

Table 3.1. A list of activities those in the sleep deprivation condition reported engaging in during the overnight interval. These categories were based on self-report and are therefore data-driven.

Self-reported activity	Percentage of participants who self-reported engaging in the activity
Watching TV	88.89
University work	48.15
Organising/cleaning	44.44
Exercising	37.04
Preparing/eating food	37.04
Gaming	33.33
Recreational activities	29.63
Browsing social media	29.63
Socialising with friends	29.63
Self-care	18.52
Other	7.41

N = 27.

3.2.2.5 VR world

In the VR world, participants navigated through a series of rooms, each with their own unique features. Critically, the nature of these rooms deviated between ambiguously threatening and non-threatening environments. Ambiguously threatening rooms (e.g. hospital room, storage room, autopsy room) were designed to elicit anxiety and harnessed environmental features from psychological research and horror game design (McCall et al., 2022). For example, participants viewed these rooms through a dim torchlight (Habel & Kooyman, 2014), and each room contained occluded areas where an assailant may hide (Rigoli et al., 2016). Moreover, ambient audio was used to prime fear of the unknown (Roberts, 2014), as well as discrete sounds to allude to the presence of an assailant (e.g. footsteps, screams; Demarque & de Lima, 2013). Non-threatening rooms (e.g. office rooms) were designed to reduce anxiety. They included features such as ample light, open spaces, and neutral music. Importantly, the rooms designed to induce anxiety were navigated through sequentially to create an ambiguously threatening environment. From this, we were able to examine the influence of sleep deprivation (versus a night of sleep) on the magnification of arousal responses during exposure to ambiguous threat. Moreover, the non-threatening environments always followed the threatening environments. This allowed us to examine the influence of sleep deprivation (versus a night of sleep) on the attenuation of arousal responses following the dissipation of threat. Participants navigated through two threatening and two non-threatening environments during the VR world (see Figure 3.2a). Each environment consisted of three rooms in total, with the exception of the second non-threatening environment, which consisted of only one room.

Before beginning, participants listened to a prelude that set the scene for the VR world. This prelude explained to participants that they were about to enter a research lab which was working on a new drug to eradicate evil. Participants were informed that a terrible event had occurred and the researchers were being held captive by a group of evil masterminds wanting to destroy their new drug. To encourage participants to move around and explore the ambiguously threatening rooms, they were instructed to collect cannisters that appeared sequentially throughout each room by walking into them. Participants were told to collect all of the cannisters in order to save the researchers and defeat the evil mastermind.

Participants started in a neutral office room, and their average arousal response in this room was used to index their baseline levels of arousal. A freight elevator then took participants down to the basement level, where they experienced the first set of threatening rooms ($P1_{theat}$). After finishing the first threatening environment, participants navigated through a series of neutral office rooms during the first non-threatening environment ($P1_{non\text{-}threat}$), before returning to a final set of threatening rooms during the second threatening environment ($P2_{threat}$). The freight elevator then took participants back to a brightly lit upper level where they entered the last neutral office room during the second non-threatening environment ($P2_{non\text{-}threat}$) before the experience ended (see Figure 3.2b for sample images, and a video of the VR world can be viewed online). Participants took on average 10.53 minutes to navigate through the VR world (SD = 0.77 minutes).

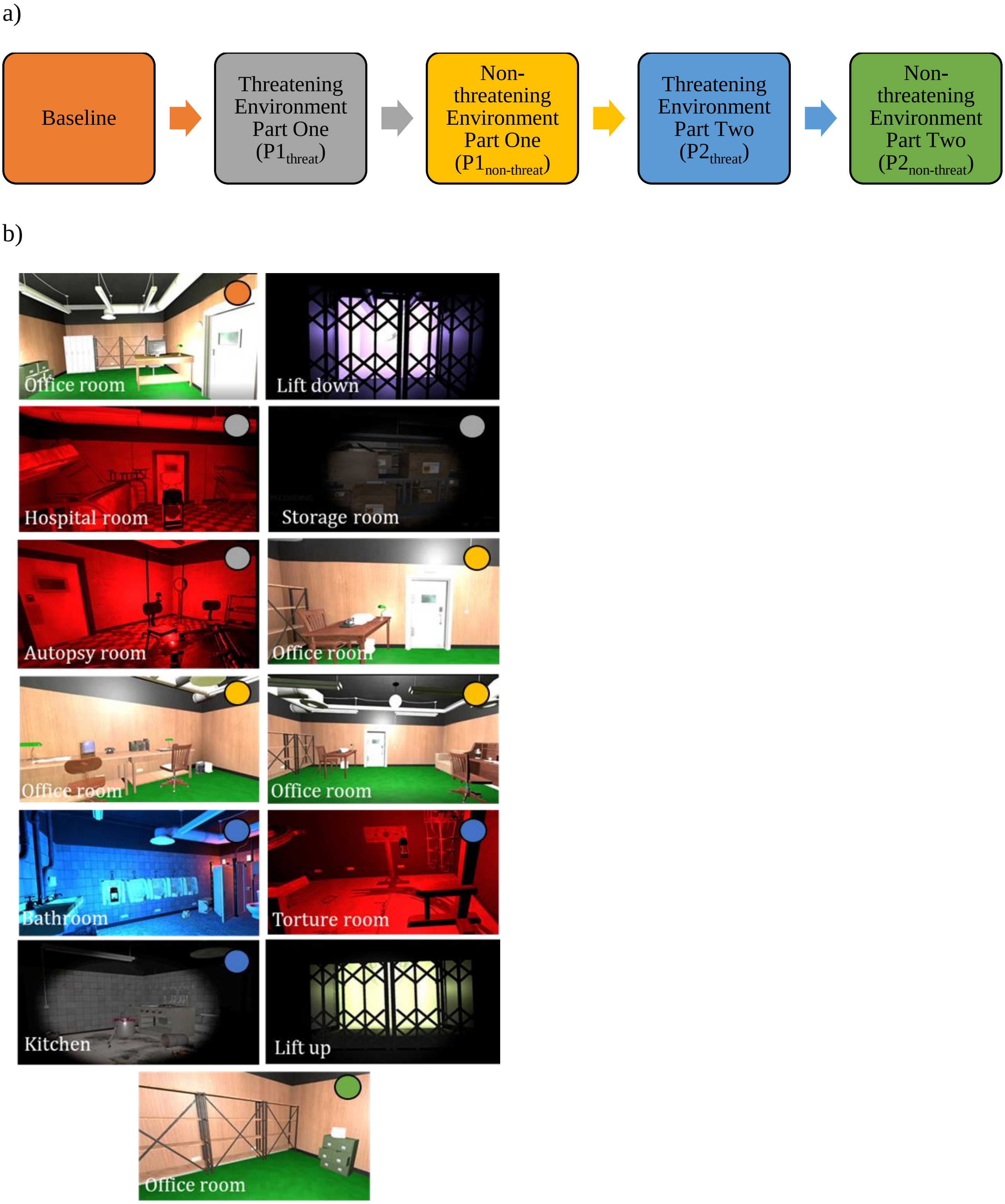

Figure 3.2. VR environment. a) Critical parts of the VR world. Participants began in a neutral room to index their baseline arousal (Baseline). They then navigated through three ambiguously threatening rooms which formed the first threatening environment ($P1_{threat}$). Following this, they navigated through three neutral rooms which formed the first non-threatening environment ($P1_{non\text{-}threat}$). Next, they navigated through three ambiguously threatening rooms again, which formed the second threatening environment ($P2_{threat}$) before

finishing in a neutral room comprising the second non-threatening environment ($P1_{non-threat}$). b) Screenshots from the VR environment. Coloured circles, corresponding to figure part a, symbolise which part of the VR world is shown in the image.

3.2.2.6 VR playback

Participants were instructed to watch a first-person recording of their experience and continuously rate how aroused they felt during every moment in the VR world using a joystick (McCall et al., 2015). Specifically, they were instructed to remember how they felt during the VR world and not how they felt while watching back the experience. Participants rated how they felt on an affect grid (Russell, 1980) with valence (*unpleasant* – *pleasant*) on the x-axis and arousal (*excited* – *not at all excited*) on the y-axis (see Figure 3.3). The magnitude of each axis varied from −100 to 100. A moving circle depicted the current position of the joystick. The position of the joystick was sampled at a rate of 20 Hz. At the beginning, this moving circle was in the middle of the scale, and participants were instructed to move the circle to the appropriate position on the affect grid once the recording had begun.

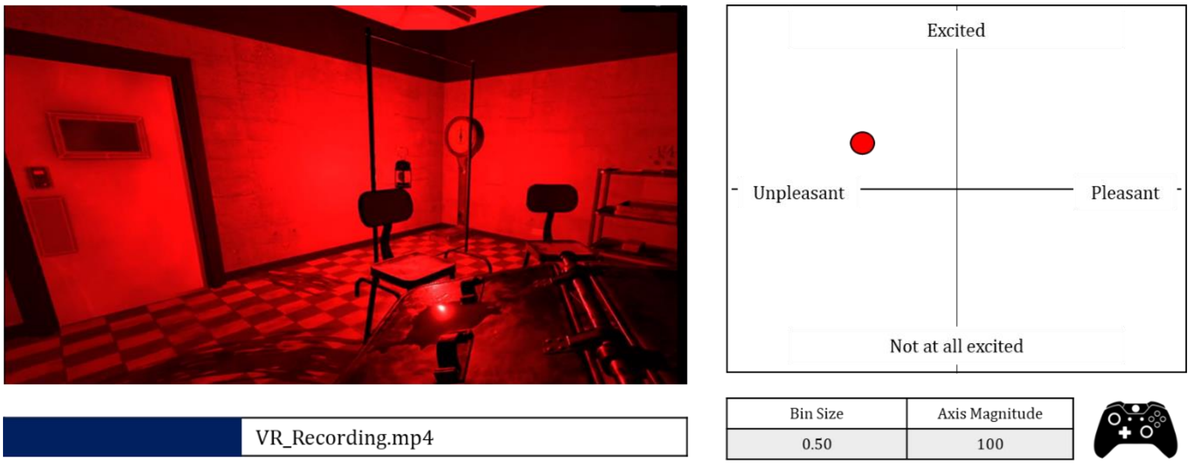

Figure 3.3. Overview of the playback task. Participants used a joystick to continuously rate how they felt using the affect grid of valence (unpleasant - pleasant) and arousal (excited - not at all excited) whilst watching a playback of their experience in the VR world.

3.2.2.7 Self-reported anxiety

Participants completed the State-Trait Anxiety Inventory- State version (STAI-S; Spielberger, 1983). They completed this in the evening and again in the morning prior to experiencing the VR world. The STAI-S consists of 20 items and measures a participant's feelings of anxiety in the current moment. Responses on each item vary from 1 (*not at all*) to 4 (*very much so*). Total state anxiety scores range from 20–80, with higher scores reflecting higher levels of state anxiety. To assess the internal consistency of this total score, we computed Cronbach's alpha, which was estimated to be very good ($\alpha = 0.90$).

3.2.2.8 Adaptive CER strategy use

Participants completed the Cognitive Emotion Regulation Questionnaire– Short version (CERQ-short; Garnefski & Kraaij, 2006). In this eighteen-item self-report questionnaire, participants were asked to rate how often they use nine conceptually different strategies (two items per strategy) after experiencing a negative event or situation, on a scale ranging from 1 (*almost never*) to 5 (*almost always*). Individual scores for each CER strategy are then obtained by summing the two questionnaire items associated with each strategy to form an overall score (ranging from 2–10). The higher the score, the more a CER strategy is used. The CER strategies defined in this questionnaire were dichotomised as adaptive or maladaptive (Garnefski et al., 2001). Adaptive CER strategies include *refocus on planning* (i.e. thinking about the next steps and how to handle the negative event), *positive refocusing* (i.e. turning thoughts towards joyful and pleasant matters), *positive reappraisal* (i.e. attaching a positive meaning to an event), and *putting into perspective* (i.e. downregulating the seriousness of the event and comparing it to other events).

To assess adaptive CER strategy use, a composite score was created by summing the scores for all adaptive items in the CERQ-short (*positive refocusing, refocus on planning, positive reappraisal,* and *putting into perspective*). Scores ranged from 8–40 (two questionnaire items per adaptive CER strategy), with higher scores indicating more frequent use of adaptive CER strategies. Internal consistency of this composite measure was estimated to be acceptable ($\alpha = 0.68$).

3.2.2.9 HRV

To index basal HRV, a 5-minute ECG measure was obtained during session two. Following electrode placement, participants sat still for 7-minutes. The first 2-minutes were excluded due to an acclimatisation period. They were then instructed to relax for 5-minutes without closing their eyes or crossing their feet. We calculated the root mean square of successive difference (RMSSD) between normal heartbeats (a measure of vagally mediated HRV). RMSSD was chosen because it is the primary time-domain measure to estimate HRV (Shaffer & Ginsberg, 2017) and has been shown to be reliable for short recordings (Nussinovitch et al., 2011).

3.2.2.10 Alertness

A psychomotor vigilance task (PVT) was administered to assess participants alertness levels (Khitrov et al., 2014). Participants were instructed to respond as fast as possible with a mouse click when a digital counter appeared on the screen. The inter-stimulus interval (ISI) varied from 2 to 10 seconds and participants received immediate feedback on their response time. The task lasted 3-minutes in total with this duration showing high reliability and validity in detecting nuances as a result of sleep loss in previous research (Benderoth et al., 2021). Participants also completed the Standard Sleepiness Scale (SSS; Hoddes et al., 1973) to assess subjective sleepiness.

3.2.3 Equipment

3.2.3.1 VR environment

The VR environment was adapted from the Underwood Project, a modular virtual environment kit built in the Unity game creation environment (version 2020.3.21f1), using standard packages with C# scripting (McCall et al., 2022). 3D models within the Underwood Project kit were developed in 3ds Max 2017. Participants experienced the world through an HTC Vive head-mounted display (HMD) unit with an integrated Dual AMOLED 3.6-inch diagonal screen with a resolution of 1080 × 1200 pixels per eye, a refresh rate of 90 Hz, and a 110° field of view. A wireless Vive controller was used so that participants could navigate around the VR world using the dual-stage trigger. Audio was played through DOQUAS wireless headphones from a standard desktop computer. Subjective arousal was assessed with a "playback" of the VR world (see "VR playback" described above). The recorded experience (including audio) was played back to participants on a standard desktop computer using the open-source software DARMA (Girard & Wright, 2018). Participants rated how they felt during every moment using the joystick of an Xbox wireless controller.

3.2.3.2 Physiological equipment

While participants were in the VR world, physiological signals were recorded using AcqKnowledge 5.0 software (Biopac Systems Inc., Santa Barbara, CA) and Biopac MP160 acquisition system. All physiological signals were sampled at 2000 Hz. SCL was recorded using a wireless Biopac BioNomadix amplifier (BN-PPGED) with a BioNomadix dual electrode lead and disposable Ag/AgCl foam electrodes (Biopac, EL507a). The electrodes were attached to the middle phalanges of the left middle and index fingers using an isotonic electrode paste (Biopac Gel 101a). HR was recorded using a wireless Biopac BioNomadix ECG (BN-RSPEC) amplifier with a three-lead set and disposable Ag/AGCl foam electrodes (Biopac, EL503). Electrodes were placed on the sternal end of the right clavicle, left mid-clavicle (ground electrode), and lower left rib cage. Event related timestamps were recorded on the rendering computer and onset time of physiological acquisition was recorded on the physiological acquisition computer (along with subsequent event related timestamps). The system clocks on both computers were synced, which allowed us to align these data series.

To measure resting HR (to calculate basal HRV), data were recorded using a BioPac MP36R data acquisition system and AcqKnowledge (ACQ) 4.4.1 software.

3.2.3.3 PSG

PSG was recorded in the sleep rested condition to ensure that participants obtained a sufficient amount of sleep and to characterise sleep physiology. This was recorded using an Embla N7000 PSG system (Embla Systems, Broomfield, CO, USA). The scalp was cleaned with NuPrep exfoliating agent before gold-plated electrodes were attached at eight standard locations according to the international 10-20 system (Homan et al., 1987): F3, F4, C3, C4, P3, P4, O1, and O2, each referenced to the contralateral mastoid (A1 or A2). Left and right electrooculogram, left, right, and upper electromyogram, and a ground electrode (forehead) were also attached. All electrodes were verified to have a connection impedance of < 5 kΩ. All signals were digitally sampled at 200 Hz.

3.2.3.4 Actigraphy

Participants wore wristwatch actigraphy devices (Actiwatch 2, Philips Respironics, United States) throughout the study, allowing us to monitor their sleep outside the laboratory.

3.2.4 Pre-processing

3.2.4.1 SCL

Data was first visually inspected for the presence of artefacts. All artefacts < 2 seconds were retained. The raw data was then exported into R studio and downsampled to 500 Hz. Event markers were also exported into R studio. Aggregated SCL data was then computed over each of the threatening and non-threatening environments in the VR world.

3.2.4.2 HR and HRV

R-peaks (the maximum amplitude of an R wave in a QRS complex of an ECG) were identified using Acqknowledge software. The R-R tachograms were then visually inspected for the presence of artefacts. Artefacts > 2 seconds were removed from the analysis (seven artefacts across 5 participants). Next, we removed any misclassified R peaks and added missing R peaks (e.g. labelled peaks that fell below the algorithm threshold). A list of R-peaks was then exported into R studio. Instantaneous HR was then calculated using the R package *RHRV* (Rodriguez-

Linares et al., 2022). HR data was then aggregated over each of the threatening and non-threatening environments in the VR world.

To calculate our measure of HRV during session two, R-peaks were automatically detected using Acqknowledge software and visually inspected for accuracy, as described above. The interbeat interval time series was then exported into Kubios HRV Standard 3.5.0 Software (Tarvainen et al., 2014). To obtain a time domain-specific index of HRV, the RMSSD was obtained, with a higher value representing higher HRV.

3.2.4.3 Subjective arousal ratings

Subjective arousal ratings obtaining during the playback task were exported into R studio. Subjective arousal ratings were then aggregated over each of the threatening and non-threatening environments in the VR world.

3.2.4.4 PSG

Using RemLogic 3.4, PSG data were partitioned into 30 second epochs and scored as wakefulness, N1, N2, N3 (SWS), or rapid eye movement (REM) sleep according to standardised criteria (Iber et al., 2007). Epochs scored as N2 and N3 were exported to MATLAB 2019a using the FieldTrip toolbox (Oostenveld et al., 2011, v10/04/18) for spectral analysis. Artefacts were identified and removed using Fieldtrip's data browser and noisy channels (identified at scoring) were removed (seven channels across 6 participants). A band-pass filter between 0.3 Hz and 30 Hz was applied to the remaining data.

Our spectral analysis of the PSG data included frontal (F3 and F4), central (C3 and C4), and parietal (P3 and P4) channels. Using functions from the Fieldtrip toolbox, artefact-free N2 and N3 epochs were applied to a Fast Fourier Transformation with a 10.24 second Hanning window and 50% overlap. Spectral power was determined across standard PSG frequency bands: delta (0.8–4.6 Hz), theta (4.8–8.0 Hz), alpha (8.2–12.0 Hz), sigma (12.25–15.0 Hz), slow beta (15.2–20.0 Hz), fast beta (20.2–35.0 Hz), and gamma (35.2–45 Hz). Values were divided by absolute power across all frequency bands to produce normalised spectral power values. Normalised power values were averaged across three channel derivations: frontal (F3 and F4), central (C3 and C4), and posterior (P3 and P4). Normalised power values in the delta band (0.8–4.6 Hz) were used as our index of SWA, in accordance with previous work (Ben Simon et al., 2020).

3.3 Statistical analysis

Unless otherwise specified, all analyses were run in R 4.2.3 (64), and all plots were created using the R package *ggplot2* (Wickham, 2016). To quantify the evidence in support of the experimental (H_1) or null hypotheses (H_0), Bayes Factors were calculated for each effect of interest (Wetzels & Wagenmakers, 2012) using Jeffreys (1961) conventional cut-offs to determine the strength of the evidence.

To address our first research question (i.e. *Does sleep deprivation amplify arousal during exposure to ambiguous threat?*), we ran a mixed ANOVA to measure physiological (SCL and HR) and subjective arousal during the two ambiguously threatening environments in the VR world. The between-subjects factor was Condition (Sleep rested/Sleep deprivation). The within-subjects factor was Part (One/Two), with part one corresponding to the first threatening environment ($P1_{threat}$) and part two corresponding to the second threatening environment ($P2_{threat}$). To index the magnification of arousal during exposure to ambiguous threat we calculated change scores by subtracting mean arousal in the first neutral room (Baseline) from mean arousal in threat part one ($P1_{threat}$ − Baseline) and threat part two ($P2_{threat}$ − Baseline). Separate ANOVAs were performed for each outcome measure (SCL, HR, and subjective arousal ratings), resulting in three ANOVAs in total. In the case of a significant interaction between Condition and Part, post-hoc two-sided t-tests with Bonferroni corrected p-values were run. All ANOVAs and post-hoc tests were analysed using the R package *rstatix* (Kassambara, 2023).

To address our second research question (i.e. *Does sleep deprivation impair the recovery of arousal following the dissipation of threat?*), we performed a similar ANOVA to above. However, physiological (SCL and HR) and subjective arousal were measured during the two non-threatening parts of the VR world. To index the recovery of arousal following the dissipation of threat, we calculated change scores. To calculate our first recovery index, we subtracted mean arousal during threat part one ($P1_{threat}$) from mean arousal during non-threat part one ($P1_{non\text{-}threat} - P1_{threat}$). To calculate our second recovery index, we subtracted mean arousal during threat part two ($P2_{threat}$) from mean arousal during non-threat part two ($P2_{non\text{-}threat} - P2_{threat}$). As such, negative scores correspond to a reduction in arousal. Separate ANOVAs were carried out for each outcome measure (SCL, HR, and subjective arousal ratings), resulting in three ANOVAs in total. All ANOVAs and post-hoc tests were analysed as above.

To address our final research question (i.e. *Is SWA associated with reduced arousal in response to ambiguous threat?*), six correlational analyses were conducted. The first three examined the association between SWA and arousal during threat part one ($P1_{threat}$) for each outcome measure (SCL, HR, and subjective arousal ratings). The second three examined the association between SWA and arousal during threat part two ($P2_{threat}$) for each outcome measure (SCL, HR, and subjective arousal ratings). To account for multiple comparisons, Bonferroni correction was applied to the resulting p-values from these correlations. All correlations were analysed using the R package *Hmisc* (Harrell, 2023).

To address our exploratory research questions, we ran linear mixed models (LMMs). All LMMs were fitted using the R packages *lme4* (Bates et al., 2014) and *lmerTest* (Kuznetsova et al., 2017). We obtained p-values for F and t-tests using the *lmerTest* ANOVA function using Satterthwaite's method. Estimated marginal means were calculated using the R package *emmeans* (Lenth et al., 2023). Post-hoc pairwise comparisons were also calculated using *emmeans* corrected for the false discovery rate (FDR). LMMs were conducted for each outcome measure (SCL, HR, and subjective arousal ratings). Each of these models predicted arousal using a fixed effect for Condition (Sleep rested/Sleep deprivation) and Room (Room in the VR world, see Figure 3.2b for sample images of each room). A random effect for participant intercept was also included in each model. To examine the influence of adaptive CER strategy use and HRV on arousal responses, these predictors were added as additional fixed effects in separate LMMs. Adaptive CER Strategy Use and HRV were categorised into high and low groups based on a median split and were thus entered into the LMMs as categorical predictors.

3.3.1 Deviations from the pre-registration

Here, we note several deviations from our pre-registration. First, we stated that SCL obtained during the VR world would be square-root transformed due to the possibility of a non-normal distribution. However, SCL values were instead z-scored within-participants to maintain consistency with our other outcome measures (HR and subjective arousal ratings). Second, we stated that for each of the threatening and non-threatening parts of the VR world, arousal (as indexed by SCL, HR, and subjective arousal ratings) would be calculated by subtracting mean arousal in each part from mean arousal in the preceding part (as is the case for research question 2). However, to address research question 1, we wanted to track the magnification of arousal during exposure to ambiguous threat relative to participants' initial arousal levels. To do this, we instead subtracted mean arousal during the first neutral room

(Baseline) from mean arousal during threat part one ($P1_{threat}$ − Baseline) and threat part two ($P2_{threat}$ − Baseline). Finally, for our correlational analysis, we stated that we would examine the associations between SWA and arousal during $P1_{threat}$ and $P1_{non\text{-}threat}$. Because we are primarily interested in the magnification of arousal in response to prolonged threat, we instead examined the relationships between SWA and arousal during $P1_{threat}$ and $P2_{threat}$.

3.4 Results

3.4.1 Does sleep deprivation increase next-day state anxiety?

When examining self-reported state anxiety, as assessed by the STAI-S, a 2 (Condition: Sleep rested/Sleep deprivation) × 2 (Session: Evening/Morning) mixed ANOVA demonstrated a main effect of Session ($F(1, 52) = 13.84$, $p = .001$, $\eta^2 = 0.21$, $BF_{10} = 5.01$), such that across all participants, state anxiety was significantly higher in the morning than the evening. There was also a main effect of Condition ($F(1, 52) = 8.98$, $p = .004$, $\eta^2 = 0.15$, $BF_{10} = 9.32$), such that state anxiety was significantly higher in the sleep deprivation condition than the sleep rested condition. There was also a significant interaction between Session and Condition ($F(1, 52) = 45.28$, $p < .001$, $\eta^2 = 0.47$, $BF_{10} > 100$). Post-hoc tests indicated that participants had equivalent levels of state anxiety in the evening ($t(51.7) = 0.27$, $p = .788$, $d = 0.07$). However, the following morning, state anxiety levels were significantly higher in the sleep deprivation condition, compared to the sleep rested condition ($t(44.8) = 5.07$, $p < .001$, $d = 1.38$; see Table 3.2). Notably, whereas state anxiety significantly decreased overnight in sleep rested participants ($t(26) = 2.74$, $p = .011$, $d = 0.53$), state anxiety significantly increased overnight in sleep deprived participants ($t(26) = 6.25$, $p < .001$, $d = 1.20$; see Figure 3.4). These results replicate previous studies showing that acute sleep deprivation amplifies next-day state anxiety, as assessed using the STAI-S (Ben Simon et al., 2020; Goldstein et al., 2013; Pires et al., 2016).

Table 3.2. Means and standard errors for STAI-S total score across sessions.

Condition	**Sleep rested (*N* = 27)**	**Sleep deprivation (*N* = 27)**
STAI-S	**M *[SE]***	**M *[SE]***
Evening	32.26 *[1.31]*	31.78 *[1.21]*
Morning	29.59 *[1.23]*	41.04 *[1.89]*

STAI-S = State Trait Anxiety Inventory– State version.

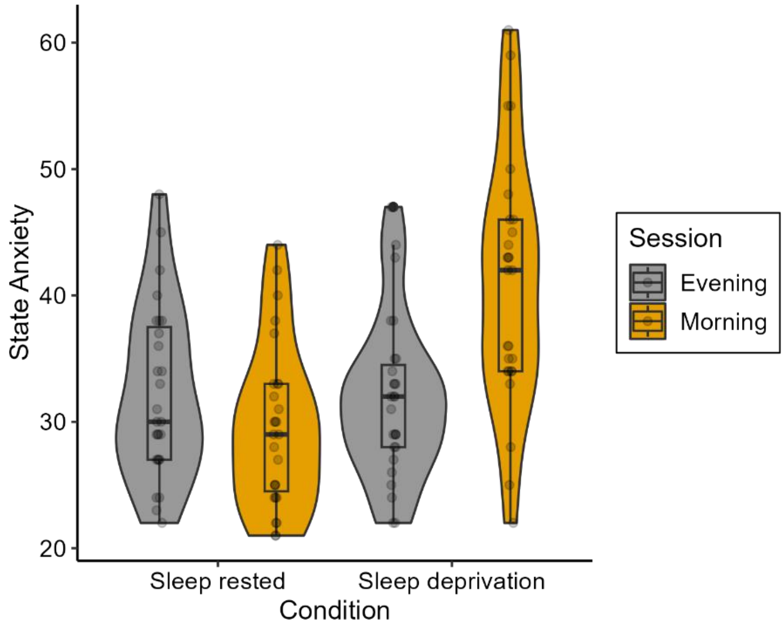

Figure 3.4. State anxiety (STAI-S) separated by Session (evening and morning) and Condition (sleep rested versus sleep deprivation). Whereas there was no difference between conditions in the evening session, sleep deprived individuals experienced greater state anxiety than sleep rested individuals in the morning session. The violin plot illustrates the kernel probability density i.e. the width of the shaded area represents the proportion of data located there. Boxplots depict the minimum, first quartile, median, third quartile, and maximum values.

3.4.2 Does sleep deprivation amplify arousal during exposure to ambiguous threat?

3.4.2.1 SCL

Next, we examined the hypothesis that individuals who are sleep deprived (versus sleep rested) exhibit amplified arousal during exposure to ambiguous threat. For SCL, a 2 (Condition) × 2 (Part) mixed ANOVA revealed a significant main effect of Part ($F(1,52) = 24.75$, $p < .001$, $\eta^2 = 0.32$, $BF_{10} > 100$), such that across all participants, SCL was higher in the first threatening part relative to the second. Although sleep deprived participants had higher SCL compared to sleep rested participants, the main effect of Condition did not reach statistical significance ($F(1,52) = 3.95$, $p = .052$, $\eta^2 = 0.07$, $BF_{10} = 1.54$). However, there was a significant interaction between Part and Condition ($F(1,52) = 4.98$, $p = .030$, $\eta^2 = 0.09$, $BF_{10} = 1.89$). Post-hoc tests indicated that SCL significantly decreased from threat part one to threat part two in the sleep rested condition ($t(26) = 5.58$, $p < .001$, $d = 1.07$; see Table 3.3). However, those in the sleep deprivation condition had statistically similar levels of SCL in threat part one and two ($t(26) = 1.80$, $p = .084$, $d = 0.35$). These results suggest that well-rested participants could regulate their physiological arousal during exposure to ambiguous threat, whereas sleep deprived participants could not (see Figure 3.5a).

3.4.2.2 HR

For HR, we found a significant main effect of Part ($F(1, 52) = 4.83$, $p = .032$, $\eta^2 = 0.01$, $BF_{10} = 1.61$), such that across participants, HR was lower in threat part one compared to threat part two. However, we found no significant effect of Condition ($F(1,52) = 0.31$, $p = .580$, $\eta^2 < 0.01$, $BF_{10} = 0.41$) and no significant interaction between Part and Condition ($F(1,52) = 0.31$, $p = .580$, $\eta^2 < 0.01$, $BF_{10} = 0.32$; see Table 3.3). These results demonstrate that HR did not significantly differ between the sleep rested and sleep deprivation conditions during exposure to ambiguous threat (see Figure 3.5b).

3.4.2.3 Subjective arousal ratings

Subjective arousal ratings were obtained during the playback task with participants retrospectively rating their arousal levels. We found a significant main effect of Part ($F(1,52) = 8.07$, $p = .006$, $\eta^2 = 0.13$, $BF_{10} = 6.19$), such that across all participants, subjective arousal ratings were higher in threat part one compared to threat part two. However, we found no significant effect of Condition ($F(1,52) = 0.96$, $p = .331$, $\eta^2 = 0.02$, $BF_{10} = 0.67$), nor a significant interaction between Part and Condition ($F(1,52) = 0.08$, $p = .777$, $\eta^2 < 0.01$, $BF_{10} = 0.27$; see Table 3.3). These findings indicate no significant difference in subjective arousal ratings between the sleep rested and sleep deprivation conditions during exposure to ambiguous threat (see Figure 3.5c).

Table 3.3. Means and standard errors for SCL, HR and subjective arousal ratings across the threatening parts of the VR world.

Condition	**Sleep rested (*N* = 27)**	**Sleep deprivation (*N* = 27)**
Arousal Measure	**M *[SE]***	**M *[SE]***
SCL		
Threat Part One	0.58 *[0.23]*	1.05 *[0.25]*
Threat Part Two	−0.42 *[0.31]*	0.67 *[0.35]*
HR		
Threat Part One	0.38 *[0.11]*	0.40 *[0.13]*
Threat Part Two	0.55 *[0.12]*	0.50 *[0.11]*
Subjective arousal ratings		
Threat Part One	0.25 *[0.20]*	0.59 *[0.22]*
Threat Part Two	0.10 *[0.24]*	0.40 *[0.26]*

SCL = Skin conductance level. HR = Heart rate (BPM). SCL, HR and subjective arousal ratings were z-scored.

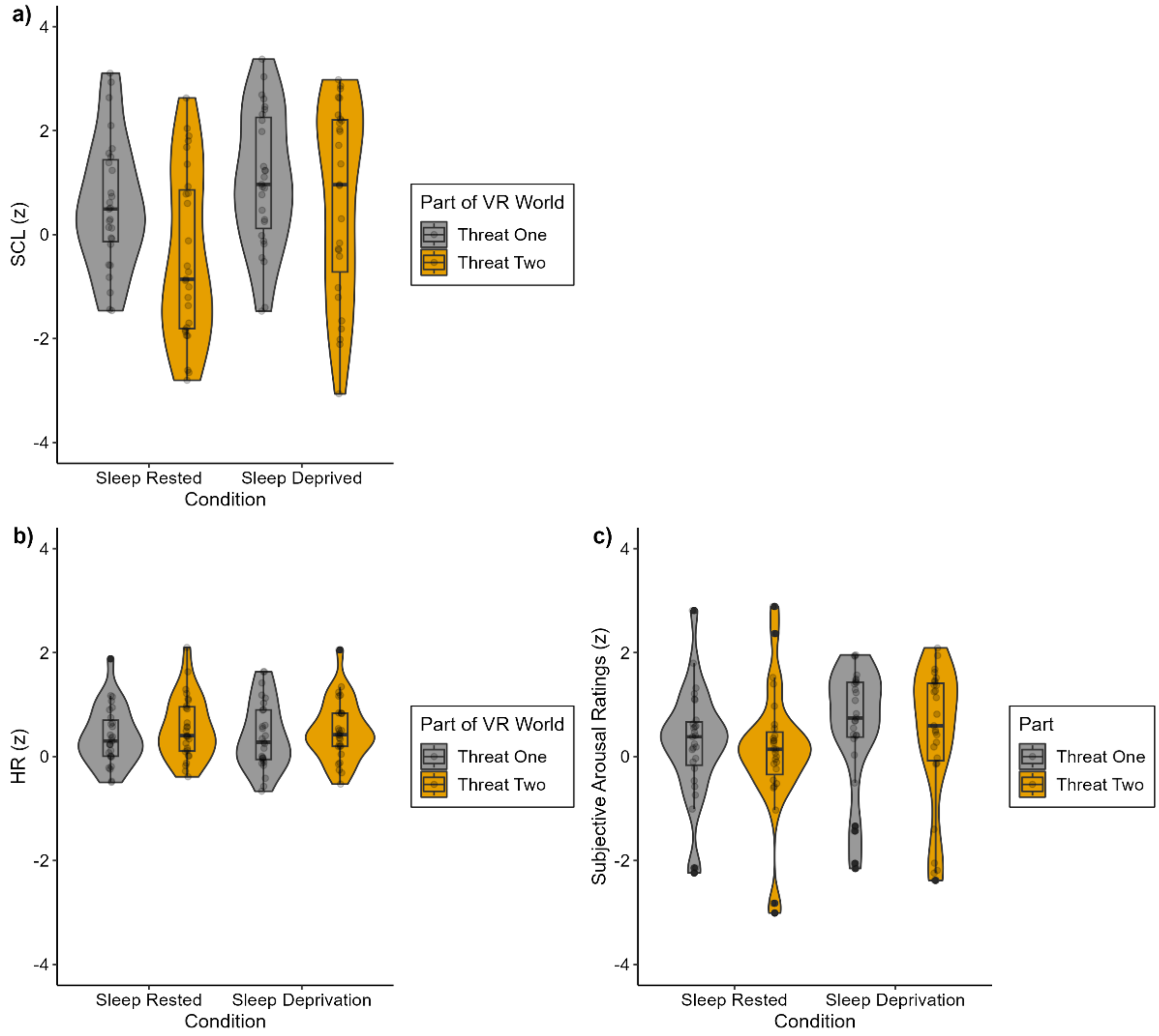

Figure 3.5. Arousal during prolonged exposure to threat. a) Skin conductance level (SCL) significantly declined from threat one to threat two in the sleep rested but not the sleep deprivation condition, b) there was no significant difference between the sleep rested and sleep deprivation conditions in heart rate (HR) during threat one and threat two, and c) there was no significant difference between the sleep rested and sleep deprivation conditions in subjective arousal ratings during threat one and threat two. All outcome measures were z-scored.

3.4.3 Does sleep deprivation impair the recovery of arousal following the dissipation of threat?

Next, we examined the hypothesis that individuals who are sleep deprived (versus sleep rested) exhibit impaired recovery from a threatening experience after the threat has dissipated. Recovery was calculated as the change in arousal from the threatening to the non-threatening parts of the VR world. As negative arousal responses correspond to a reduction in arousal, lower values indicate a greater arousal recovery following the dissipation of threat.

3.4.3.1 SCL

For SCL, a 2 (Condition) × 2 (Part) mixed ANOVA revealed a significant main effect of Part ($F(1,52) = 7.83$, $p = .007$, $\eta^2 = 0.13$, $BF_{10} = 6.96$), such that across all participants, recovery of SCL was greater during the first non-threatening part relative to the second. However, there was no significant main effect of Condition ($F(1,52) = 0.72$, $p = .400$, $\eta^2 = 0.01$, $BF_{10} = 0.32$), nor was there a significant interaction between Part and Condition ($F(1,52) = 2.98$, $p = .090$, $\eta^2 = 0.05$, $BF_{10} = 0.96$; see Table 3.4). These findings indicate that SCL did not significantly differ between sleep rested and sleep deprived participants when recovering from threat (see Figure 3.6a).

3.4.3.2 HR

For HR, there was also a significant main effect of Part ($F(1,52) = 4.25$, $p = .044$, $\eta^2 = 0.08$, $BF_{10} = 1.27$), such that recovery of HR was greater during the first non-threatening part compared to the second. However, we found no significant main effect of Condition ($F(1,52) = 0.18$, $p = .677$, $\eta^2 < 0.01$, $BF_{10} = 0.39$), nor a significant interaction between the Part and Condition ($F(1,52) = 0.26$, $p = .610$, $\eta^2 = 0.01$, $BF_{10} = 0.29$; see Table 3.4). These results demonstrate that sleep rested and sleep deprived participants do not significantly differ in HR when recovering from threat (see Figure 3.6b).

3.4.3.3 Subjective arousal ratings

Finally, for subjective arousal ratings, we found no significant main effect of Part ($F(1,52) = 1.03$, $p = .316$, $\eta^2 = 0.02$, $BF_{10} = 0.32$) or Condition ($F(1,52) = 0.57$, $p = .453$, $\eta^2 = 0.01$, $BF_{10} = 0.48$). We also found no significant interaction between Part and Condition ($F(1,52) = 0.00$, $p = .950$, $\eta^2 < 0.01$, $BF_{10} = 0.27$; see Table 3.4). The data here suggest that subjective arousal levels do not significantly differ between sleep rested and sleep deprived participants when recovering from threat (see Figure 3.6c).

Table 3.4. Means and standard errors for SCL, HR and subjective arousal ratings across the non-threatening parts of the VR world.

Condition	**Sleep rested (*N* = 27)**	**Sleep deprivation (*N* = 27)**
Arousal Measure	**M *[SE]***	**M *[SE]***
SCL		
Non-threat Part One	−0.88 *[0.15]*	−0.50 *[0.15]*
Non-threat Part Two	−0.26 *[0.15]*	−0.36 *[0.16]*
HR		
Non-threat Part One	0.04 *[0.10]*	0.01 *[0.10]*
Non-threat Part Two	0.20 *[0.12]*	0.11 *[0.10]*
Subjective arousal ratings		
Non-threat Part One	−1.05 *[0.18]*	−0.82 *[0.22]*
Non-threat Part Two	−1.19 *[0.27]*	−0.94 *[0.28]*

SCL = Skin conductance level. HR = Heart rate (BPM). SCL, HR and subjective arousal ratings were z-scored.

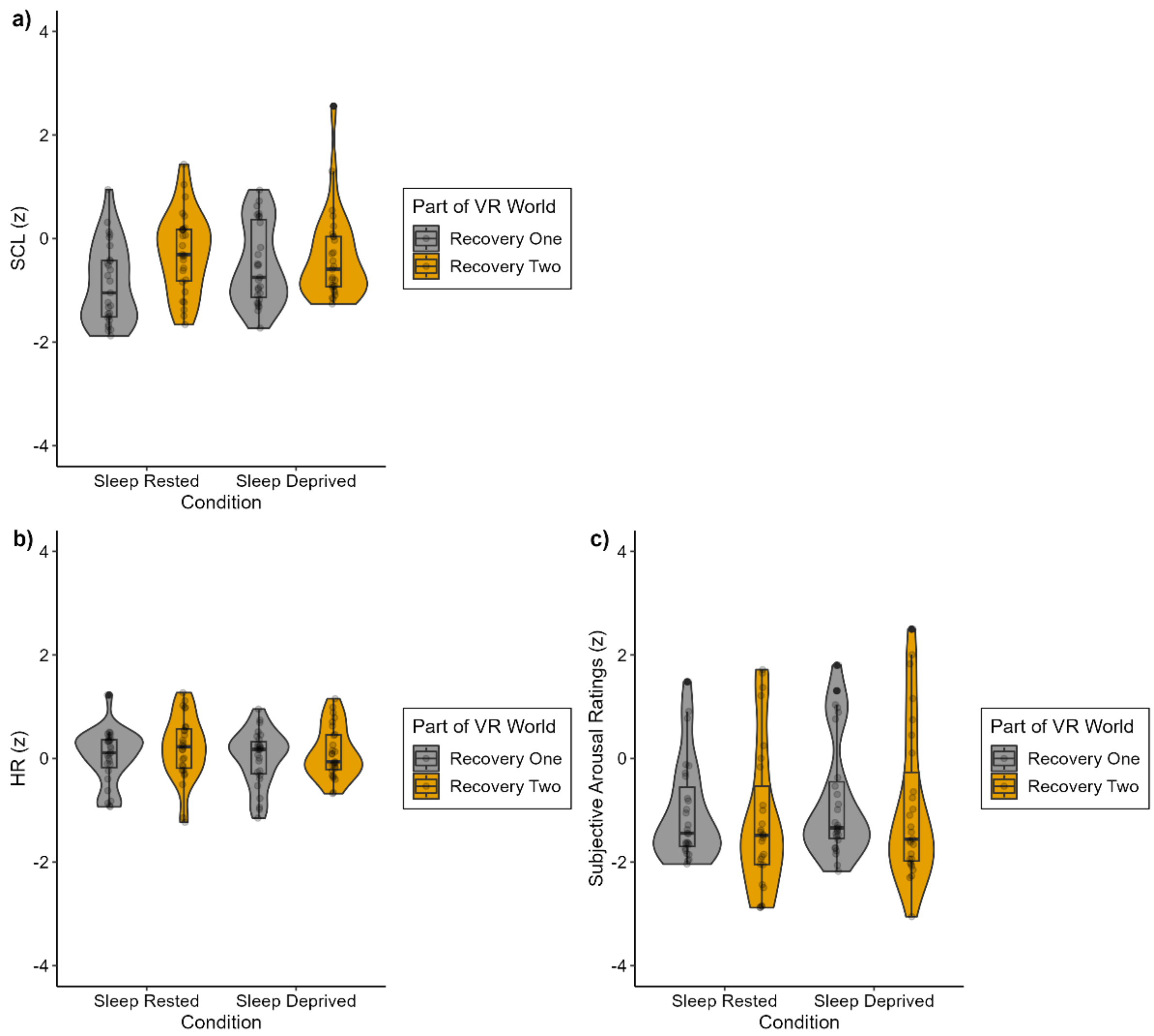

Figure 3.6. Recovery of arousal following the dissipation of threat. There were no significant differences between the sleep rested and sleep deprived individuals when recovering from threat for a) SCL, b) HR, and c) subjective arousal ratings. All outcome measures were z-scored.

3.4.4 Is SWA associated with reduced arousal in response to ambiguous threat?

We found no significant association between SWA and state anxiety, either for morning STAI-S scores or overnight change in these scores (see Table 3.5). This result is at odds with previous work demonstrating a significant association between greater SWA and lower next-day state anxiety, as well as a greater overnight reduction in state anxiety (Ben Simon et al., 2020).

Next, we tested our hypothesis that greater SWA would be associated with reduced arousal during exposure to initial ($P1_{threat}$) and repeated threat ($P2_{threat}$). SWA was examined across different electrode clusters given the topographical effects reported in previous work (Ben Simon et al., 2020). For each of our outcome measures (SCL, HR, and subjective arousal ratings), we found no significant association between SWA and $P1_{threat}$ or SWA and $P2_{threat}$ (see Table 3.5)[9]. These findings suggest that, although sleep attenuated physiological arousal (SCL) during exposure to ambiguous threat, SWA was not significantly associated with this reduction.

As part of an exploratory analysis, we also examined whether arousal responses during initial threat ($P1_{threat}$) and repeated threat ($P2_{threat}$) were associated with the amount of time spent in REM sleep. We examined these associations because previous work demonstrates an important role for REM sleep in the regulation of arousal responses (Greenberg et al., 1972; Gujar, McDonald, et al., 2011; Hutchison et al., 2021; Rosales-Lagarde et al., 2012; van der Helm et al., 2011). However, for each of our outcome measures (SCL, HR, and subjective arousal ratings), we found no significant relationship between REM sleep duration and $P1_{threat}$, or REM sleep duration and $P2_{threat}$ (see Table 3.5).

[9] We also investigated whether greater SWA was associated with reduced arousal following the dissipation of initial ($P1_{non\text{-}threat}$) and repeated threat ($P2_{non\text{-}threat}$). Again, for each of our outcome measures (SCL, HR, and subjective arousal ratings), we found no significant associations between SWA and $P1_{non\text{-}threat}$ or SWA and $P2_{non\text{-}threat}$.

Table 3.5. Correlations between SWA and anxiety, as indexed by the STAI-S and arousal responses during threatening parts one and two of the VR world.

Variable	Frontal SWA (% power)	Central SWA (% power)	Posterior SWA (% power)	REM (minutes)
STAI-S Morning	−.05, BF_{10} = 0.43	.06, BF_{10} = 0.43	.15, BF_{10} = 0.53	.30, BF_{10} = 1.10
STAI-S Overnight Change	−.05, BF_{10} = 0.43	.07, BF_{10} = 0.44	.20, BF_{10} = 0.64	.00, BF_{10} = 0.42
SCL $P1_{threat}$	.09, BF_{10} = 0.45	.12, BF_{10} = 0.49	.11, BF_{10} = 0.48	−.16, BF_{10} = 0.55
SCL $P2_{threat}$	.01, BF_{10} = 0.42	.09, BF_{10} = 0.45	.03, BF_{10} = 0.42	−.21, BF_{10} = 0.68
HR $P1_{threat}$	−.04, BF_{10} = 0.43	.00, BF_{10} = 0.42	.02, BF_{10} = 0.42	−.09, BF_{10} = 0.46
HR $P2_{threat}$	−.14, BF_{10} = 0.51	−.15, BF_{10} = 0.53	−.13, BF_{10} = 0.50	−.12, BF_{10} = 0.49
Subjective arousal $P1_{threat}$	.11, BF_{10} = 0.48	.08, BF_{10} = 0.45	.11, BF_{10} = 0.48	.17, BF_{10} = 0.58
Subjective arousal $P2_{threat}$	.29^, BF_{10} = 0.63	.31^, BF_{10} = 0.61	.32^, BF_{10} = 0.72	.25^, BF_{10} = 0.67

STAI-S = State Trait Anxiety Inventory- State version. SCL = Skin conductance level, HR = Heart rate, P1 = Part one, P2 = Part two, $_{threat}$ = Threatening VR environment, SWA = Slow wave activity. REM = Rapid eye movement sleep. BF_{10} are the Bayes Factors for each correlation. All *p* values were Bonferroni corrected and were > .05. ^ indicates non-parametric Spearman's rank correlations were run instead of Pearson's due to violation of the normality assumption.

3.4.5 Alertness

The influence of sleep deprivation (versus restful sleep) on alertness levels was examined using the psychomotor vigilance task (PVT) and the Stanford Sleepiness Scale (SSS). For the PVT, a 2 (Condition: Sleep rested/Sleep deprivation) × 2 (Session: Evening/Morning) mixed ANOVA revealed a main effect of Session ($F(1, 52) = 19.36$, $p < .001$, $\eta^2 = 0.27$, $BF_{10} > 100$), such that all participants were significantly slower at responding in the morning compared to the evening. There was no significant effect of Condition ($F(1, 52) = 2.29$, $p = .136$, $\eta^2 = 0.04$, $BF_{10} = 0.75$) but there was a significant interaction between Session and Condition ($F(1,52) = 11.94$, $p = .001$, $\eta^2 = 0.19$, $BF_{10} = 26.97$). Post-hoc tests showed equivalent response times between conditions in the evening session ($t(45.3) = 0.14$, $p = .887$, $d = 0.04$). However, sleep deprived participants were slower at responding in the morning session compared to sleep rested participants ($t(51.8) = 2.58$, $p = .013$, $d = 0.70$; see Table 3.6). For the SSS, the ANOVA indicated a main effect of Session ($F(1, 52) = 22.49$, $p < .001$, $\eta^2 = 0.13$, $BF_{10} = 31.74$), such that all participants felt sleepier in the morning compared to the evening. The results also revealed a main effect of Condition ($F(1, 52) = 27.11$, $p < .001$, $\eta^2 = 0.25$, $BF_{10} > 100$), such that sleep deprived participants reported feeling sleepier than sleep rested participants. Finally, there was a significant interaction between Session and Condition ($F(1,52) = 59.38$, $p < .001$, $\eta^2 = 0.29$, $BF_{10} > 100$). Post-hoc tests revealed equivalent levels of self-reported sleepiness in the evening ($t(51.9) = 0.38$, $p = .788$, $d = 0.10$), whereas in the morning, participants in the sleep deprivation condition reported greater feelings of sleepiness relative to participants in the sleep rested condition ($t(48.3) = 8.16$, $p < .001$, $d = 2.22$; see Table 3.6).

Table 3.6. Means and standard errors for alertness measures (PVT and SSS) across sessions.

Condition	**Sleep rested (*N* = 27)**	**Sleep deprivation (*N* = 27)**
Alertness Measure	**M *[SE]***	**M *[SE]***
PVT		
Evening	273.85 *[7.82]*	272.51 *[5.22]*
Morning	278.21 *[8.10]*	308.76 *[8.65]*
SSS		
Evening	2.70 *[0.21]*	2.59 *[0.20]*
Morning	2.15 *[0.21]*	4.93 *[0.27]*

PVT = Psychomotor vigilance task as assessing by examining response times in milliseconds. SSS = Stanford Sleepiness Scale (maximum score 7).

3.4.6 Exploratory analysis

3.4.6.1 Adaptive CER strategy use

In an exploratory analysis, we examined whether the evolution of arousal following a night of sleep or sleep deprivation was influenced by the tendency to engage in adaptive CER strategies. To do this, we ran LMMs with Room, Condition and Adaptive CER Strategy Use as fixed effects.

SCL. There was no significant main effect of Adaptive CER Strategy Use (F(1, 50) = 0.43, p = .516, η^2 < 0.01), nor a significant interaction between Condition and Adaptive Strategy Use (F(1, 50) = 3.43, p = .070, η^2 = 0.01). Interestingly, there was a significant interaction between Room and Adaptive Strategy Use (F(9, 450) = 2.91, p = .002, η^2 = 0.06), indicating that high adaptive CER strategy users had higher SCL than low adaptive CER strategy users, particularly during the later rooms (see Figure 3.7a). However, pairwise comparisons revealed no significant differences in SCL between high- and low- adaptive CER strategy users in any of the rooms. We also found no significant three-way interaction between Room, Condition and Adaptive CER Strategy Use (F(9, 450) = 0.49, p = .880, η^2 = 0.01). Consistent with our ANOVA results, we found a significant main effect of Room (F(9, 450) = 21.24, p < .001, η^2 = 0.30). We also found a significant main effect of Condition (F(1, 50) = 4.08, p = .049, η^2 = 0.01), such that across all rooms, and in both high and low adaptive CER strategy user groups, sleep deprived individuals had higher SCL than sleep rested individuals.

However, we did not find a significant interaction between Room and Condition ($F(9, 450) = 1.75$, $p = .077$, $\eta^2 = 0.03$).

HR. We found no significant effect of Adaptive CER Strategy Use ($F(1, 50.21) = 0.82$, $p = .369$, $\eta^2 < 0.01$), nor a significant two-way interaction between Condition and Adaptive CER Strategy Use ($F(1, 50.21) = 0.82$, $p = .369$, $\eta^2 < 0.01$), or Adaptive CER Strategy Use and Room ($F(9, 427.31) = 1.87$, $p = .055$, $\eta^2 = 0.04$). There was also no significant three-way interaction between Room, Condition and Adaptive CER Strategy Use ($F(9, 427.31) = 1.10$, $p = .361$, $\eta^2 = 0.02$, see Figure 3.7b). Consistent with our ANOVA findings, there was a significant main effect of Room ($F(9, 427.31) = 3.63$, $p < .001$, $\eta^2 = 0.07$), but no significant main effect of Condition ($F(1, 50.21) = 0.32$, $p = .574$, $\eta^2 < 0.01$), nor a significant two-way interaction between Room and Condition ($F(9, 427.31) = 0.39$, $p = .940$, $\eta^2 = 0.01$).

Subjective arousal ratings. We found no significant main effect of Adaptive CER Strategy Use ($F(1, 50) = 2.11$, $p = .152$, $\eta^2 = 0.01$). We also found no significant two-way interaction between Condition and Adaptive CER Strategy Use ($F(1, 50) = 0.36$, $p = .551$, $\eta^2 < 0.01$), and Adaptive CER Strategy Use and Room ($F(9, 450) = 0.30$, $p = .976$, $\eta^2 = 0.01$). Interestingly, there was a significant three-way interaction between Condition, Room and Adaptive Strategy Use ($F(9, 450) = 3.05$, $p = .001$, $\eta^2 = 0.06$). Pairwise comparisons revealed that first, for low adaptive CER strategy users, subjective arousal ratings were significantly higher in the sleep deprivation condition compared to the sleep rested condition in two of the non-threatening rooms (office 3 and office 4 ($t(139) = 2.13$, $p = .035$, $d = 1.17$; $t(139) = 2.33$, $p = .022$, $d = 1.28$, respectively). Second, for high adaptive strategy users, subjective arousal ratings were significantly higher in the sleep deprivation condition compared to the sleep rested condition during a different non-threatening room: office 2 ($t(139) = 2.09$, $p = .039$, $d = 1.24$). In summary, these results suggest that low adaptive CER strategy users suffer more following sleep deprivation during the parts of the VR world when they are trying to recover (i.e. the non-threatening parts; see Figure 3.7c). However, these comparisons were no longer significant after adjusting for the FDR. Consistent with our main analysis, we also found a significant effect of Room ($F(9, 450) = 20.87$, $p < .001$, $\eta^2 = 0.29$), but not Condition ($F(1, 50) = 3.53$, $p = .066$, $\eta^2 = 0.01$), and no significant two-way interaction between Room and Condition ($F(9, 450) = 0.62$, $p = .779$, $\eta^2 = 0.01$).

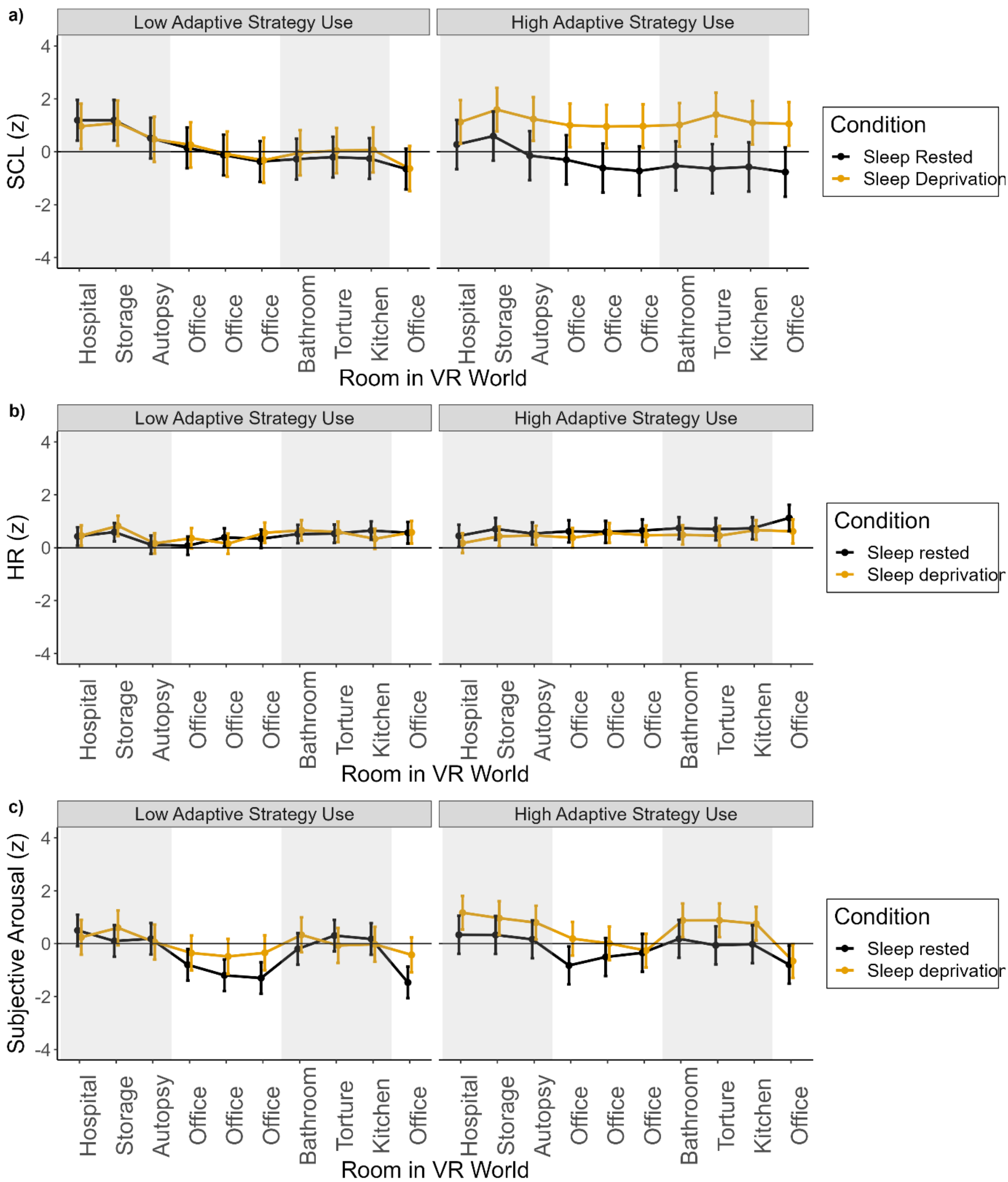

Figure 3.7. Linear mixed models (LMMs) for Adaptive CER Strategy Use. Estimated marginal means and 95% confidence intervals for a) SCL, b) HR, and c) subjective arousal ratings in each room of the VR world. Adaptive CER strategies are separated by low and high use based on a median split. The order of the rooms (x axis) is chronological. Shaded areas signify the ambiguously threatening parts of the VR world. All outcome measures have been z-scored.

3.4.6.2 HRV

We also examined whether the evolution of arousal responses following a night of sleep or sleep deprivation was associated with HRV. To do this, we ran LMMs with Room, Condition and HRV as fixed effects.

SCL. There was no significant main effect of HRV ($F(1, 50) = 0.69$, $p = .411$, $\eta^2 < 0.01$), nor a significant two-way interaction between Room and HRV ($F(9, 450) = 0.54$, $p = .846$, $\eta^2 = 0.01$), or Condition and HRV ($F(1, 50) = 1.75$, $p = .192$, $\eta^2 < 0.01$). We also found no significant three-way interaction between Room, Condition and HRV ($F(9, 450) = 0.66$, $p = .746$, $\eta^2 = 0.01$; see Figure 3.8a). Consistent with our ANOVA findings, there was a significant main effect of Room ($F(9,450) = 19.65$, $p < .001$, $\eta^2 = 0.28$) and a significant interaction between Condition and Room ($F(9, 450) = 2.30$, $p = .016$, $\eta^2 = 0.04$). We also found a significant main effect of Condition ($F(1, 50) = 4.27$, $p = .044$, $\eta^2 = 0.01$), such that across all rooms, and low and high HRV groups, sleep deprived individuals had higher SCL than sleep rested individuals.

Subjective arousal ratings. Although we found no significant main effect of HRV ($F(1, 50) = 0.11$, $p = .737$, $\eta^2 < 0.01$), there was a significant interaction between Condition and HRV ($F(1, 50) = 8.40$, $p = .006$, $\eta^2 = 0.02$). Pairwise comparisons revealed that subjective arousal ratings were significantly higher in the sleep deprivation condition compared to the sleep rested condition among participants with low HRV ($t(50) = 3.48$, $p = .002$, $d = 1.43$), whereas there was no significant difference in subjective arousal ratings between the sleep rested and sleep deprivation conditions among participants with high HRV ($t(50) = 0.62$, $p = .541$, $d = 0.25$). These findings suggest that sleep deprivation has the greatest impact on subjective arousal responses among individuals with low HRV (see Figure 3.8b). However, we found no significant two-way interaction between Room and HRV ($F(9,450) = 0.37$, $p = .948$, $\eta^2 = 0.01$), nor a significant three-way interaction between Room, Condition and HRV ($F(9,450) = 1.49$, $p = .148$, $\eta^2 = 0.03$). Consistent with our main analysis, there was a significant main effect of Room ($F(9,450) = 22.72$, $p < .001$, $\eta^2 = 0.31$) and no significant interaction between Room and Condition ($F(9,450) = 0.78$, $p = .640$, $\eta^2 = 0.02$). However, there was a main effect of Condition ($F(1, 50) = 4.11$, $p = .048$, $\eta^2 = 0.01$), such that across all rooms, and low and high HRV groups, subjective arousal ratings were higher when participants were sleep deprived compared to sleep rested.

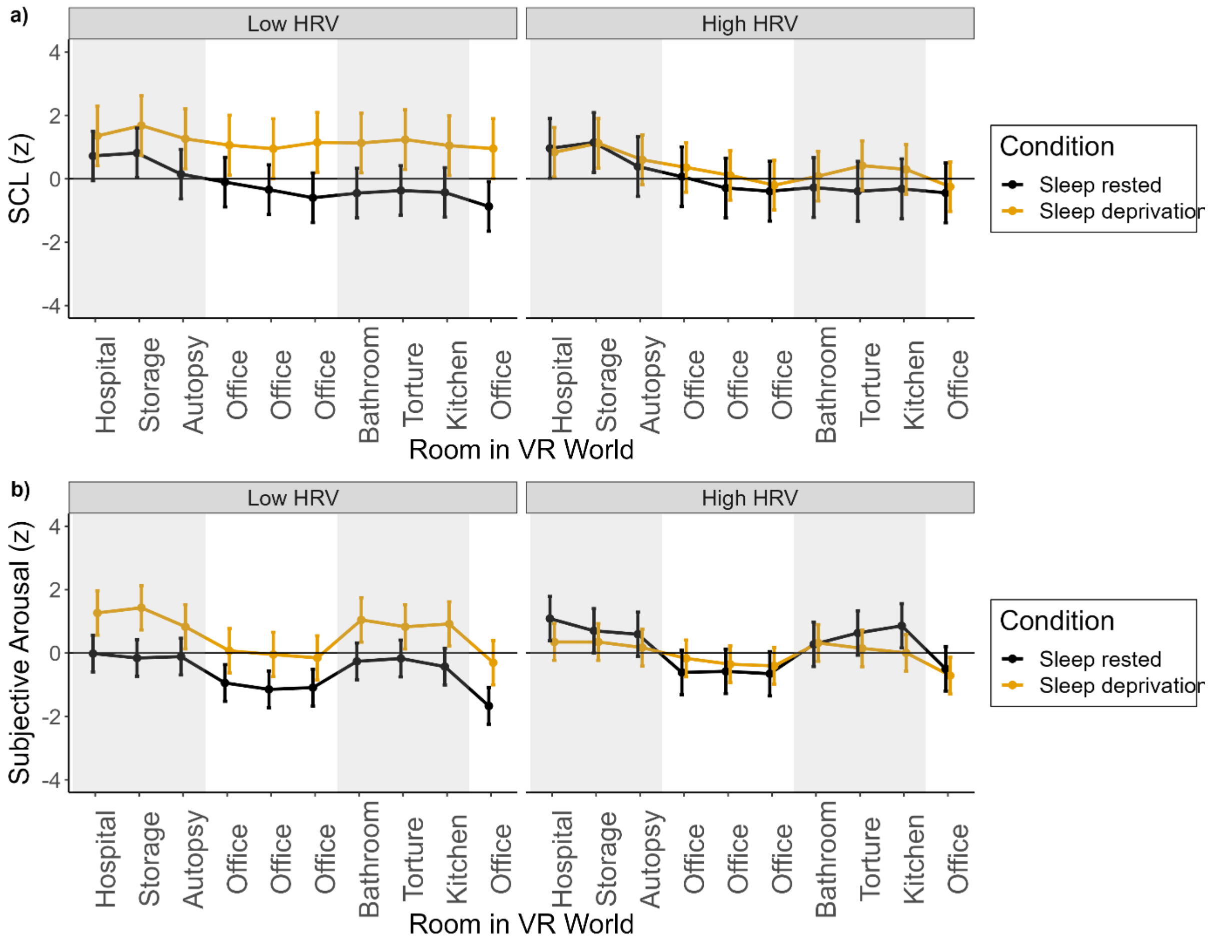

Figure 3.8. Linear mixed models (LMMs) for HRV. Estimated marginal means and 95% confidence intervals for a) SCL and b) subjective arousal ratings in each room of the VR world. HRV is separated by low and high based on a median split analysis. The order of the rooms (x axis) is chronological. Shaded areas signify the ambiguously threatening parts of the VR world. All outcome measures have been z-scored.

3.5 Discussion

Prior work indicates that sleep deprivation increases next-day state anxiety and impairs threat-related information processing. However, these studies have only assessed threat-related information processing at discrete moments in time and in response to direct threat. Resultantly, little is known about how arousal responses unfold during exposure to ambiguous threat and how this might be influenced by an absence of sleep. We addressed this gap in the literature by examining how sleep deprivation, compared to a night of sleep, influences physiological and subjective arousal responses to ambiguous threat. Following a night of sleep deprivation or sleep, participants navigated through an immersive VR world that cycled between ambiguously threatening and non-threatening environments. During this time, their SCL and HR were continuously monitored to provide physiological indices of arousal. Participants then watched a playback of their navigation through the emotional experience and continuously rated how aroused they remembered feeling during every moment, providing a subjective measure of arousal. Participants who had a night of sleep were monitored with PSG to index SWA. Our pre-registered analyses focused on whether sleep deprivation amplified arousal during exposure to ambiguous threat and impaired recovery following the dissipation of threat. We also examined whether greater SWA was associated with reduced arousal when exposed to ambiguous threat, given that greater amounts of SWA support the overnight reduction of state anxiety in prior work.

First, our findings replicated previous work showing that sleep deprivation increases next-day state anxiety, as assessed using the STAI-S (Ben Simon et al., 2020; Goldstein et al., 2013; Pires et al., 2016; Reid et al., 2023). Indeed, we found that state anxiety significantly increased overnight in the sleep deprivation condition. We also found that state anxiety significantly decreased overnight in the sleep rested condition, demonstrating the anxiety-reducing benefit of sleep. Such findings support the high comorbidity of sleep disturbances and clinical anxiety (Breslau et al., 1996; Chellappa & Aeschbach, 2022; Harvey et al., 2011; Mellman, 2006; Neckelmann et al., 2007; Papadimitriou & Linkowski, 2005; Uhde et al., 2009) and demonstrate that sleep loss can directionally elevate next-day state anxiety levels in the absence of a clinical anxiety disorder. Conversely, these findings also support the therapeutic potential of sleep for reducing next-day state anxiety levels.

Next, we examined whether sleep deprivation amplifies arousal when individuals are exposed to ambiguous threat. Our data showed that SCL increased during initial threat exposure in both the sleep rested and sleep deprivation conditions. However, sleep rested individuals demonstrated a reduction in SCL during prolonged threat exposure. Conversely, SCL remained elevated in those who were sleep deprived. These findings supported our hypothesis that those who were sleep deprived would show amplified arousal during prolonged exposure to ambiguous threat.

These between-condition differences may be explained by the influence of sleep deprivation on cognitive control mechanisms. Sleep deprivation has been shown to impair cognitive control functions that are important for adaptively responding to threat (Ochsner & Gross, 2005; Ochsner et al., 2012), such as attention, working memory, task switching, and inhibition (Krause et al., 2017; Kusztor et al., 2019; Slama et al., 2018). Furthermore, sleep loss has been associated with lower self-reported distress tolerance (i.e. an individual’s ability to withstand unpleasant, aversive, or uncomfortable emotions; Kechter & Leventhal, 2019; Reitzel et al., 2017; Short et al., 2016; L. J. Smith et al., 2019). Together, these findings support the suggestion that those who slept were better able to regulate their affective response to threat than those who were sleep deprived, resulting in attenuated physiological arousal during prolonged threat exposure.

Alternatively, these between-condition differences may be explained by the effects of sleep deprivation on fear learning mechanisms. The ability to learn and remember that a stimulus is no longer threatening is pivotal for affect regulation (Britton et al., 2011; Foa & McLean, 2016). Sleep deprivation has been shown to curtail the formation of fear memories (Menz et al., 2013) and impair the recall of extinguished fear (P. Davidson & Pace-Schott, 2020; Straus et al., 2017). Therefore, those who had slept, relative to those who were sleep deprived, may have been able to effectively learn and remember the nature of the environment during initial threat exposure. Thus, when presented with a similar threatening environment a second time, well-rested individuals knew what to expect and were better able to regulate their affective response to threat. Nonetheless, it is important to note that regulatory control and fear learning explanations are not mutually exclusive. In fact, it is likely that impaired fear learning mechanisms arise from poor regulatory control, and vice versa.

Our finding that SCL was reduced in sleep rested, but not sleep deprived, individuals during exposure to prolonged ambiguous threat aligns with the theoretical framework linking sleep loss to exacerbated anxiety (Ben Simon et al., 2020). Sleep deprivation has been associated with decreased mPFC activity (Ben Simon et al., 2020; van der Helm & Walker, 2012; Yoo et al., 2007), a critical brain region that is important in the top-down regulation of affect (Ben Simon et al., 2020; Bishop et al., 2004; M. J. Kim et al., 2011). The mPFC is also thought to support cognitive control and adaptive fear learning processes (Feng et al., 2018; Giustino & Maren, 2015; E. K. Miller, 2000; Ridderinkhof et al., 2004). Together, these findings support the assumption that well-rested participants, in comparison to sleep deprived participants, were able to restore prefrontal brain networks overnight, allowing for next-day regulation of affect in response to repeated threat. To corroborate this claim, future work should examine whether mPFC activity and mPFC-amygdala connectivity are associated with reduced arousal responses during prolonged threat exposure.

The above effects of sleep deprivation on threat responses could also be explained by differences in recovery. However, we found no significant difference between sleep rested and sleep deprived participants in arousal responses following the dissipation of threat. These findings do not support our hypothesis that those who were sleep deprived would show impaired recovery of arousal following the dissipation of threat. Nonetheless, recovery values were negative for both SCL and subjective arousal ratings, suggesting that all participants were able to recover to some extent following the dissipation of threat.

Despite these null results, our exploratory analysis demonstrated that adaptive CER strategy use and HRV moderated the effect of sleep deprivation on the recovery of arousal responses. First, we found that lower habitual adaptive CER strategy users had higher subjective arousal ratings when they were sleep deprived compared to sleep rested following the dissipation of threat. This result suggests that low habitual adaptive CER strategy users suffer more from sleep deprivation than their sleep rested counterparts when trying to recover following threat. This finding aligns with previous work showing that those who use the adaptive CER strategy positive reappraisal less frequently were more likely to hyper-focus on negative emotional stimuli following sleep deprivation, compared to those who use positive reappraisal more frequently (Cote et al., 2015). We also found that participants in the low HRV group had higher subjective arousal ratings when sleep deprived compared to when they were sleep rested following the dissipation of threat. However, no such difference was observed among participants in the high HRV group. Similar to the above, these findings imply that sleep deprivation impairs the ability to recover from threat among participants with low HRV. Greater use of adaptive CER strategies and higher HRV have been associated with lower anxiety (Hildebrandt et al., 2016; Mather & Thayer, 2018; Schäfer et al., 2017; Sullivan et al., 2023) and superior executive functioning (Cattaneo et al., 2021; Forte et al., 2019; Gillie et al., 2014; Joormann & Tanovic, 2015; Mather & Thayer, 2018; McRae et al., 2012; Ochsner & Gross, 2005). Therefore, it is possible that these individual differences safeguard against the subjective effects of threat under sleep deprivation, enabling individuals to recover following threat.

Given the impact of sleep loss on threat regulation, in a complementary analysis, we examined whether SWA restored affect regulation processes. We found no significant relationship between SWA and self-reported state anxiety, neither when examining morning state anxiety nor overnight change in state anxiety. We also found no significant association between SWA and arousal responses during initial or repeated exposure to ambiguous threat, irrespective of whether arousal was assessed with SCL, HR, or subjective arousal ratings. These findings did not support our hypothesis that greater SWA would be associated with reduced arousal in response to ambiguous threat and is at odds with previous work demonstrating that greater amounts of NREM SWA support the overnight reduction of next-day state anxiety (Ben Simon et al., 2020; Chellappa & Aeschbach, 2022), Given that SWA has been shown to support executive functioning and restore the brain regions integral for affect regulation (Bishop, 2007; Bishop et al., 2004; M. J. Kim et al., 2011; Simmons et al., 2008; Wilckens et al., 2018), our results are surprising. One interpretation of these null results is that sleep might exert a broader influence on regulatory control (beyond the SWA mechanism). This is supported by our findings that a night of sleep promoted the overnight reduction of state anxiety, along with the attenuation of physiological arousal following exposure to prolonged ambiguous threat. However, in our exploratory analysis, we found no significant association between REM sleep duration and arousal responses. Therefore, future work should consider a broader range of sleep properties.

We did not find any significant effects of sleep deprivation on HR. It has been argued that arousal is more closely associated with increased SCL than HR (Barry & Sokolov, 1993). Moreover, whereas SCL reflects sympathetic activity (i.e. fight or flight), HR reflects a combination of both sympathetic and parasympathetic activity (i.e. rest and digest; Mauss & Robinson, 2009). Given that parasympathetic activity is associated with relaxation, HR measures may not capture amplified arousal in response to threat. In addition, although HR generally increases in response to threat (Croft et al., 2004; Kreibig et al., 2007; Williams et al., 2017), this response may be preceded by deceleration of HR immediately after threat onset (Bradley et al., 1996), particularly in highly anxious individuals (Murakami et al., 2010). As this study intended to measure subtle changes in physiological arousal across several minutes, SCL is arguably a more reliable measure of physiological responding than HR.

Subjective arousal ratings were captured retrospectively during the playback task. In this task, participants were instructed to report their remembered arousal during the VR world. Retrospective reports of arousal have demonstrated strong coherence with physiological arousal (skin conductance and HR) measured during a VR experience (i.e. past-present coherence; McCall et al., 2015). These findings accord with the arousal-encoding hypothesis which proposes that memory is able to reliably encode physiological signals during an experience (McCall et al., 2015). However, a lack of sleep prior to encoding decreases the ability to encode negative events and results in worse subsequent retention (Kaida et al., 2015; Krause et al., 2017; Yoo et al., 2007). Consequently, it is possible that encoding deficits following a night of sleep deprivation impaired participants' ability to encode physiological signals and/or retrieve their remembered arousal accurately. Although subjective data revealed the effects of sleep deprivation when controlling for adaptive CER strategy use and HRV, we cannot tease apart whether sleep deprivation influenced the encoding of physiological signals during the emotional experience and/or the ability to retrospectively retrieve these signals. Future work should therefore incorporate study designs that allow us to delineate these memory processes to examine whether they influence subjective arousal ratings when participants are sleep deprived.

This is the first study to move beyond assessing arousal responses at a single point in time and examine the impact of sleep deprivation on the evolution of arousal during exposure to ambiguous threat. However, several limitations should be noted. First, participants in the sleep deprivation condition were sent home and instructed to stay awake overnight. Although they were given explicit instructions, there was limited experimental control over what activities they engaged in and whether they refrained from consuming caffeine. However, given that actigraphy data indicated that participants did not sleep during the overnight period, we can be confident that all participants were acutely sleep deprived. We also have a clear record of the activities participants engaged in during the night, which conformed to the study instructions (see Table 3.1). Although this study design allowed participants in the sleep deprivation condition to remain awake in the comfort of their own home and reduced experimenter burden, future work should replicate this study with participants being sleep deprived in the laboratory to allow for more stringent experimental control.

Second, although we had two non-threatening parts in our VR world, the second non-threatening part consisted of only one room, whereas all the other parts contained three rooms. Consequently, as participants only navigated through one room, there may not have been sufficient time to capture recovery. To address this, in future work using this VR world, two non-threatening rooms could be added to the end of the experience. This would ensure that participants spend equivalent amounts of time in each of the non-threatening parts and allow us to map the recovery of arousal across similar time intervals.

In conclusion, we found that physiological expressions of arousal in response to ambiguous threat were reduced in those who had slept but remained elevated in those who were sleep deprived. However, greater SWA was not associated with this reduction. Moreover, sleep deprivation, relative to a night of sleep, did not impair the recovery of arousal following the dissipation of threat. A potential interpretation for these findings is that those who slept were better able to regulate their affective response to threat than those who were sleep deprived. Exploratory analyses highlight greater adaptive CER strategy use and higher basal HRV as two variables of interest for further study that may buffer the subjective effects of threat under sleep deprivation. These novel findings provide important insights into how a night of sleep regulates arousal in response to threat, helping us understand how sleep (or a lack of sleep) influences anxiety when encountering the threats and uncertainties we face in our day-to-day lives.

Chapter 4: The Influence of Emotion Regulation and Sleep Quality on Emotional Inertia

Abstract

Emotional inertia reflects the tendency for emotions to persist over time. Higher persistence of negative affect (i.e. higher emotional inertia) has consistently been associated with lower well-being. Yet, we know little about the mechanisms underlying this association. Prior work suggests that frequent use of adaptive cognitive emotion regulation (CER) strategies (i.e. positive thought processes) reduces the persistence of negative affect (NA) over time. Moreover, recent studies have begun to examine the association between sleep and emotional inertia but have produced mixed findings. This study examined the combined influence of adaptive CER strategy use and sleep quality on emotional inertia. Specifically, we examined whether the association between greater adaptive CER strategy use and lower NA inertia is contingent on high quality sleep. Participants (N = 245) watched a series of emotionally negative, positive, and neutral film clips in a fixed order and rated how they felt on both negative (*sad, angry, depressed,* and *anxious*) and positive dimensions (*relaxed* and *happy*). They provided these ratings following the presentation of each film clip and again after a subsequent rest period which followed each of the film clips. They then completed standardised questionnaires to index the frequency with which they typically employed CER strategies and sleep quality levels. Using an autoregressive modelling approach, which modelled the association between NA at each time point (t) and NA at the preceding time point ($t - 1$), we found that greater use of adaptive CER strategies and high sleep quality were independently associated with lower NA inertia. However, the association between greater adaptive CER strategy use and lower NA inertia was observed at different levels of sleep quality. Together, these findings highlight the importance of both adaptive CER strategies and sleep quality in predicting NA persistence over time.

4.1 Introduction

Emotions are not static experiences (Dejonckheere et al., 2019; Frijda & Mesquita, 1998; Kuppens & Verduyn, 2017), but instead vary substantially throughout our daily lives. These emotional fluctuations may be driven by the experiences we encounter. For example, one morning we might feel sad as a result of an argument with a loved one; then, several hours later, we might feel happy after a friend bought us a coffee. However, on another day, we might continue to feel sad, despite our friend buying us a coffee. The extent to which an emotion state persists from one time point to the next is defined as emotional inertia (Koval et al., 2021). If an individual's emotional inertia is high, their emotion state (e.g. sadness) will likely persist from one moment to the next and they will be relatively resistant to internal and external influences (Kuppens, Allen, et al., 2010). Conversely, if an individual's emotional inertia is low, their emotion state will likely be highly variable from one moment to the next, and they will be more susceptible to psychological and environmental demands (Kuppens, Allen, et al., 2010). The ability to adapt flexibly to these demands has been shown to be an important indicator of well-being and mental health. For example, higher inertia of negative affect (NA) has been associated with depressive symptomatology (Brose et al., 2015; Koval & Kuppens, 2012; Koval et al., 2012, 2013), the onset of depression (Kuppens et al., 2012; van de Leemput et al., 2014), neuroticism (Suls et al., 1998), and low self-esteem (Kuppens, Allen, et al., 2010). However, we know relatively little about the mechanisms underlying the association between NA inertia and mental health outcomes (Houben et al., 2015; Koval et al., 2016)

Cognitive emotion regulation (CER) strategies may play an important role in the maintenance and modification of emotion states over time (i.e. emotional inertia; Gross, 2014; Koval, Butler, et al., 2015). Indeed, higher NA inertia has been associated with difficulties regulating emotions effectively (Brose et al., 2015; Koval & Kuppens, 2012; Koval et al., 2012, 2013). For instance, greater use of maladaptive CER strategies, such as expressive suppression (Bean et al., 2021; Koval, Butler, et al., 2015) and rumination (Blanke et al., 2022; Koval et al., 2012), have been associated with higher NA inertia. It has been suggested that using maladaptive CER strategies contributes to the maintenance and even enhancement of NA, thereby promoting the rigidity of NA over time (Koval, Butler, et al., 2015; Koval et al., 2012). In addition, more frequent use of maladaptive CER strategies has been associated with greater depression and anxiety symptoms when encountering emotional hardship (Sullivan et al., 2023), suggesting that, overall, these strategies are ineffective at regulating NA following an emotional event, leading to higher NA inertia.

Given that maladaptive CER strategies are associated with higher NA inertia, a reciprocal question concerns whether adaptive CER strategies are related to lower NA inertia. Some studies have demonstrated a negative association between dispositional mindfulness, a technique thought to downregulate NA as well as facilitate and strengthen the capacity for positive reappraisal, and NA inertia (Keng & Tong, 2016; Rowland et al., 2020). Moreover, greater use of positive reappraisal has been associated with a more rapid decline of NA following an emotional experience (Kuppens, Oravecz, et al., 2010). Nonetheless, other studies have shown no or only a weak association between positive reappraisal and NA inertia (Bean et al., 2021; Koval, Butler, et al., 2015). Importantly, previous studies have examined only how individual adaptive (i.e. positive reappraisal) and maladaptive (i.e. rumination) CER strategies influence NA inertia. Therefore, in this study, we aimed to expand this work and determine how adaptive and maladaptive CER strategies are associated with emotional inertia using composite measures that encompass a range of adaptive and maladaptive CER strategies.

Sleep is another factor that may influence emotional inertia. Given that sleep loss contributes to mood disturbance (Fairholme & Manber, 2015), emotion dysregulation (Ben Simon et al., 2020; Harrington, Ashton, Sankarasubramanian, et al., 2021; Harrington & Cairney, 2021; Yoo et al., 2007) and the development of mental health conditions (Baglioni, Spiegelhalder, et al., 2010; Bi & Chen, 2022; Freeman et al., 2017), it is expected that sleep loss would be associated with higher NA inertia. Indeed, X. Wen et al. (2020) found that shorter sleep duration (measured with actigraphy) was associated with higher persistence of depressive mood states over one week. However, no studies have yet found an association between sleep (either duration or quality) and NA inertia more broadly (Frérart et al., 2023; Minaeva et al., 2021; X. Wen et al., 2020).

One explanation for the lack of a significant association between sleep and NA inertia in previous work may be due to emotional inertia being measured using experience sampling methodology (ESM; Houben et al., 2015; Koval et al., 2016). ESM involves asking participants several times a day over a period of days or weeks to report how they feel on a range of emotion states (Kuppens, Allen, et al., 2010). Although studying emotion fluctuations in an individual's daily life affords high ecological validity and provides insights on a fine temporal scale, it is caveated by limited control over environmental factors. This makes it difficult to determine whether individual differences in emotional inertia result from endogenous processes (e.g. emotion regulation), exogenous factors (e.g. exposure to different life events), or both. Indeed, individuals who encounter more intense negative life events (but not more frequent negative life events) display higher levels of NA inertia in ESM paradigms (Koval, Brose, et al., 2015). Given that CER strategy use and sleep have been associated with individual differences in emotional inertia, we cannot rule out the possibility that emotional inertia was driven by differences in the intensity of emotional events that participants encountered.

To address this issue, a mood induction procedure (MIP) has been developed to measure emotional inertia by exposing participants to an identical sequence of emotional events. During this MIP, participants watch a series of film clips in a fixed order and are instructed to rate how they feel after the presentation of each film clip and again after a subsequent rest period, following each of the film clips (Koval, Brose, et al., 2015; Koval et al., 2013, 2016). The findings from these studies replicated ESM paradigms, as heightened NA inertia was associated with higher scores on negative indicators of well-being such as depressive symptoms, ruminative tendencies, and neuroticism (Koval et al., 2013, 2016). Therefore, we used this MIP to investigate the independent influence of CER strategy use and sleep quality on NA inertia.

It has been argued that the use of staged film clips decreases a participant's ability to accept the event depicted in the film as real, which is paramount for inducing strong emotional responses (Rottenberg et al., 2007; Samson et al., 2016). Critically, the film clips used in previous studies were obtained from films with scripted actors, special effects, and intensive editing (Koval, Brose, et al., 2015; Koval et al., 2013, 2016). To address this issue, we used amateur recordings of real-life events to assimilate emotional responses to naturalistic events occurring in one's daily life (Samson et al., 2016).

To date, no study has examined whether emotional inertia can be attributed to the interaction between CER strategies and sleep quality. Poor sleep has been shown to increase the use of maladaptive CER strategies (Latif et al., 2019) and reduce the effectiveness of adaptive CER strategies (Mauss et al., 2013; Zhang et al., 2019). These findings point to a potential mechanism linking adaptive CER strategies and emotional inertia, wherein the effective deployment of adaptive CER strategies (to reduce the persistence of NA) is contingent on obtaining good sleep quality. Therefore, we tested the hypothesis that the relationship between CER strategy use and NA inertia is influenced by sleep quality.

In this study, 245 participants completed our MIP to assess emotional inertia. They also completed standardised questionnaires to index the frequency with which they employed CER strategies and their sleep quality levels. As pre-registered, we first hypothesised that greater use of adaptive CER strategies and high sleep quality would be independently associated with lower NA inertia. Second, we predicted that the relationship between greater use of adaptive CER strategies and lower NA inertia would be stronger among individuals with high sleep quality.

In addition to our main research questions, we were interested in several exploratory avenues. First, as greater adaptive CER strategy use, lower maladaptive CER strategy use, and high sleep quality have all been shown to increase positive affect (PA; Bower et al., 2010;

Brans et al., 2013; Ong et al., 2017; Tugade & Fredrickson, 2007), we investigated whether CER strategy use and sleep quality were associated with PA inertia. Second, in accordance with previous studies (Houben et al., 2015), we examined whether greater depression and anxiety symptomatology were associated with higher inertia of NA.

4.2 Methods

Our study methods and analysis plans were pre-registered on the Open Science Framework.

4.2.1 Participants

We initially recruited N = 259 participants from Prolific.co. Of these 259 participants, N = 14 were excluded: N = 13 for self-reporting that they did not complete the study in a quiet low-lit room with headphones, and N = 1 as the proportion of film clip trials for which they made a response was less than 90%. Therefore, our final sample size included N = 245 participants (79 female, 164 male, 2 undisclosed), aged between 18 and 30 years (M ± SD age = 25.77 ± 3.33 years). Participants reported no history of neurological, psychiatric, or sleep disorders and declared that they had never worked for the emergency services (e.g. paramedic, firefighter, police), armed forces, or in healthcare (e.g. nurse, doctor). Participants received £8 as compensation for completing the study. Ethical approval was obtained from the Department of Psychology Research Ethics Committee at the University of York.

The sample size was determined by power analysis using the method described by Murayama et al. (2020). Effect size estimates were obtained from Koval et al. (2016), as this study included a MIP similar to the one we used. We chose an effect size from their meta-analysed results from study one (N = 100) and two (N = 202) regarding the association between trait rumination and NA inertia. We converted the effect size of r = .19 (raw emotion ratings) to a t-value (t = 3.35), and determined that we needed a sample size of 245 to achieve 85% power (α = 0.05). Excluded participants were replaced to meet the required sample size.

4.2.2 Procedure

Participants completed the study online via Qualtrics. They were instructed to undertake the study in a quiet low-lit room whilst wearing headphones. They first completed the MIP to index NA inertia, followed by standardised questionnaires to measure CER strategy use and sleep quality levels.

4.2.3 Measures

4.2.3.1 Mood induction procedure

At the beginning of the task, participants were asked to rate how they felt on four negative dimensions (*sad*, *angry, depressed,* and *anxious*) and two positive dimensions (*relaxed* and *happy*), on a scale from 0 [*not at all*] to 6 [*very much*]. This served as a baseline assessment of affect. Participants then watched several film clips that were emotionally negative, positive, or neutral. They viewed a total of 11 film clips. The film clips were shown in the following fixed order: neutral (practice trial), negative, negative, neutral, positive, neutral, negative, positive, positive, negative, and positive. Exposing participants to a series of emotional film clips in a fixed order helped rule out individual differences in event exposure (Koval et al., 2013). Descriptions of the film clips can be found in the Supplementary Material (see Table A.4). All film clips were validated in a pilot study (see "Stimulus validation"). The MIP is a modified version of the tasks described by Koval et al. (Koval, Brose, et al., 2015; Koval et al., 2013, 2016).

Following the presentation of each film clip, participants were instructed to indicate how the clip made them feel on each of the dimensions described above. There was a 10 second time limit for each rating. Participants were explicitly instructed to rate how each clip made them feel, as opposed to how they felt in general, or how they thought they should feel. Between each film clip, participants viewed a neutral image (a ball of string) for 20 seconds before rating their feelings again (see Figure 4.1). In total, they rated their feelings on 21 occasions (at baseline, following each of the ten film clips, and following each of the ten rest periods). For each participant, ratings on the four negative dimensions (*sad, angry, depressed,* and *anxious*) were averaged at each occasion to compute a composite NA rating. To assess the internal consistency of our composite NA rating, we estimated within-person reliability using multilevel structural equation modelling (Koval et al., 2016; Nezlek, 2012). The estimated coefficient omega for our composite NA rating was good (0.92).

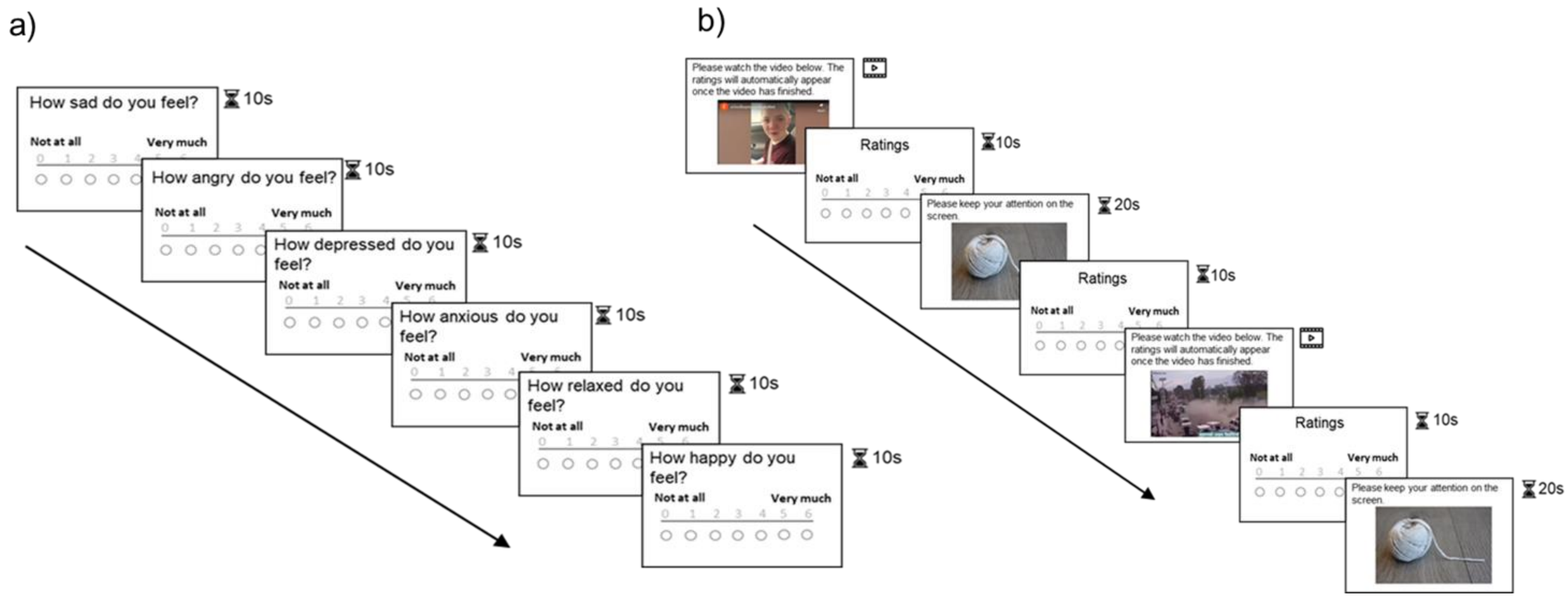

Figure 4.1. Mood induction procedure (MIP). a) Participants rated how they felt on four negative dimensions (*sad*, *angry*, *depressed*, and *anxious*) and two positive dimensions (*relaxed* and *happy*), from 0 [*not at all*] to 6 [*very much*]. b) Participants watched a series of negative, positive, and neutral film clips presented in a fixed order. After each film clip, participants rated how they felt on each of the negative and positive dimensions. Following each film clip, participants viewed a neutral image before providing the same ratings again. Arrows depict the order of presentation.

4.2.3.2 Stimulus validation

The film clips were validated through a pilot experiment. An independent set of participants ($N = 31$) were randomly assigned to one of two film clip subsets (12 in each subset). These clips included amateur footage of real-life negative, positive, and neutral events, sourced from YouTube. Following each of the film clips, participants were instructed to rate how pleasant they felt in response to the film, from 1 [*unpleasant*] to 9 [*pleasant*], and how excited they felt in response to the film, from 1 [*calm*] to 9 [*excited*], using the Self-Assessment Manikin (SAM; Bradley & Lang, 1994). Participants also indicated whether they had seen each film clip before.

Film clips that were familiar to $\geq$ 30% of the participants were excluded from the analysis (3 in total). Of the remaining 21 film clips, we selected four positive film clips with the highest valence rating (mean > 6), four negative film clips with the lowest valence rating (mean < 3), and two neutral film clips (mean 4–6) for the MIP (see Figure 4.2).

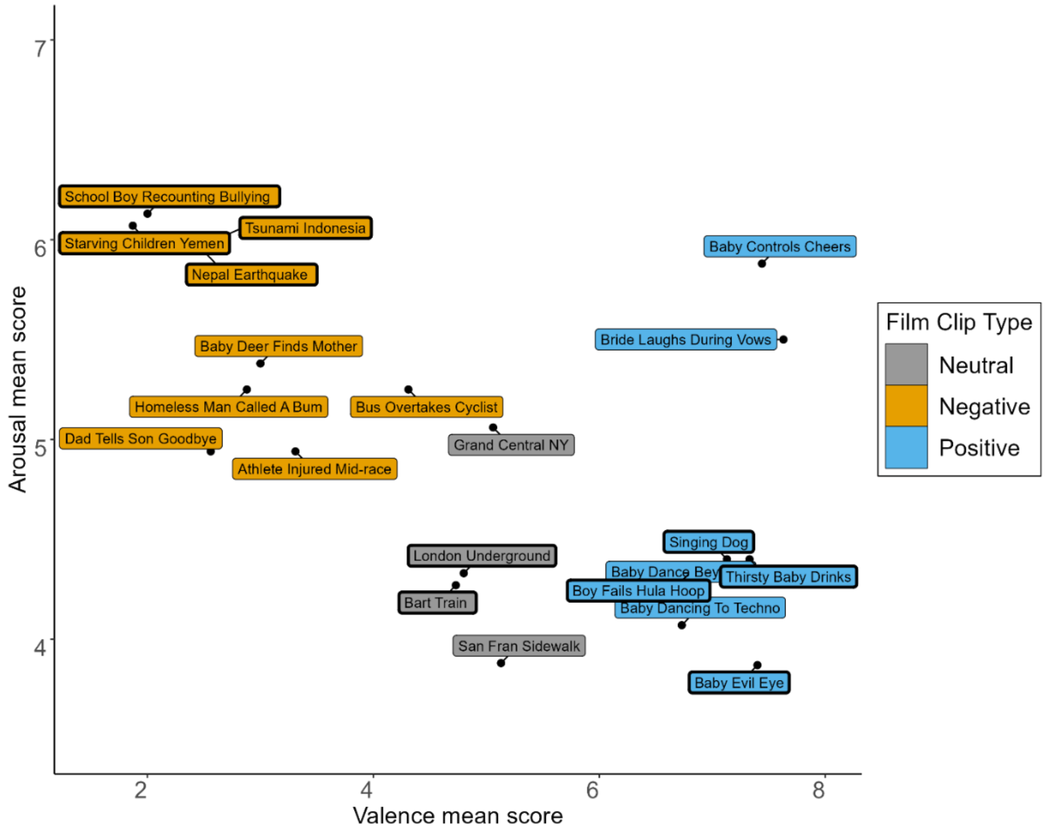

Figure 4.2. Mean valence and arousal ratings for each film clip in the pilot experiment. Film clips are separated by film type, which was defined when selecting the initial film clips for validation. The film clips chosen for the mood induction procedure (MIP) are outlined in bold.

4.2.3.3 Cognitive emotion regulation

CER strategy use was assessed using the Cognitive Emotion Regulation Questionnaire-short version (CERQ-short; Garnefski & Kraaij, 2006). The CERQ-short is an eighteen-item, self-report questionnaire designed to identify the emotion regulation strategies that people use after experiencing a negative event or situation. Participants were asked to rate how often they use nine conceptually different CER strategies (two questionnaire items per strategy) on a scale ranging from 1 (*almost never*) to 5 (*almost always*). Individual scores for each CER strategy are obtained by summing the two questionnaire items associated with each strategy to form an overall score (ranging from 2–10). The higher the overall score, the more a CER strategy is used.

CER strategies were dichotomised as either adaptive or maladaptive (Aldao et al., 2010; Garnefski et al., 2001). Adaptive CER strategies include *refocus on planning* (i.e. thinking about the next steps and how to handle the negative event), *positive refocusing* (i.e. turning thoughts towards joyful and pleasant matters), *positive reappraisal* (i.e. attaching a positive meaning to an event), and *putting into perspective* (i.e. downregulating the seriousness of the event and comparing it to other events). Although *acceptance* (i.e. coming to terms with the situation that has occurred) has been previously classified as an adaptive CER strategy, there are concerns that it may only be adaptive under certain circumstances (Martin & Dahlen, 2005). Consequently, it was not considered as an adaptive or maladaptive CER strategy in the current study. Maladaptive CER strategies include *self-blame* (i.e. blaming oneself for what they have experienced), *other-blame* (i.e. blaming others for what they have experienced), *rumination* (i.e. dwelling on the negative feelings or thoughts associated with an event), and *catastrophising* (i.e. overemphasising the negative parts of an experience).

To compute a composite measure of adaptive CER strategy use, the scores for all adaptive items on the CERQ-short were summed. Scores ranged from 8–40 (two questionnaire items per adaptive CER strategy), with higher scores indicating more frequent use of adaptive CER strategies. To assess the internal consistency of this composite measure, we computed Cronbach's alpha, which was estimated to be good ($\alpha = 0.80$). Scores for all maladaptive items on the CERQ-short were also summed to create a composite score of maladaptive CER strategy use. Again, scores ranged from 8–40 (two questionnaire items per maladaptive CER strategy), with higher scores indicating more frequent use of maladaptive CER strategies. The internal consistency of this composite measure was estimated to be good ($\alpha = 0.76$).

4.2.3.4 Sleep quality

Sleep quality was assessed using the Pittsburgh Sleep Quality Index (PSQI; Buysse et al., 1989), a self-report questionnaire designed to assess sleep quality over the preceding month. The questionnaire consists of 19 items, grouped to form seven sub-scores: (1) subjective sleep quality, (2) sleep latency, (3) sleep duration, (4) sleep efficiency, (5) sleep disturbance, (6) use of sleep medication, and (7) daytime dysfunction. Each sub-score ranges from 0–3, with 3 indicating the poorest sleep quality. Sub-scores were then summed to produce a global score, which ranged from 0–21. Higher global scores indicate poorer sleep quality. The internal consistency of this global score was estimated to be acceptable ($\alpha = 0.67$).

4.2.3.5 Depression

As part of an exploratory analysis, we assessed depression severity using the Beck Depression Index (BDI-II; Beck et al., 1996). The BDI-II is a 21-item self-report instrument intended to assess the existence and severity of symptoms of depression over the preceding two weeks. Each of the 21 items corresponds to a symptom of depression and is rated on a four-point Likert scale from 0 (*not at all*) to 3 (*severely*). The BDI-II was scored by summing the ratings for the 21 items. Total score ranges from 0–63. A total score of 0–13 is considered minimal depression, 14–19 is considered mild depression, 20–28 is considered moderate depression, and 29–63 is considered severe depression.

4.2.3.6 Anxiety

We also assessed anxiety severity as part of our exploratory analysis using the Beck Anxiety Inventory (BAI; Beck et al., 1988). The BAI is a self-report inventory that is used to measure anxiety symptom severity. It consists of 21 items, each of which describes a common symptom of anxiety. Participants are asked to rate how much they have been bothered by each symptom over the past week on a four-point Likert scale ranging from 0 (*not at all*) to 3 (*severely*). Total score is computed by summing scores across all items and ranges from 0–63. A total score of 0–7 suggests minimal anxiety, 8–15 suggests mild anxiety, 16–25 suggests moderate anxiety, and 26–63 suggests severe anxiety.

4.3 Statistical analysis

4.3.1 Statistical modelling

We ran multilevel mixed models to test our hypotheses using the *lme4* (Bates et al., 2014) and *lmerTest* (Kuznetsova et al., 2017) R packages (R version 4.2.3). These packages were used to model regressions and calculate Satterthwaite-adjusted p-values. Plots were created with the R package *ggplot2* (Wickham, 2016). We ran separate analyses modelling NA inertia using raw and within-person standardised NA ratings for each research question. Each model included a random intercept and a random (autoregressive) slope. It is important to note that some of our models did not converge with this maximal effects structure. In this case, we removed the random slope and re-ran the model. Our findings were generally robust when we replicated the model without the random slope. Therefore, we retained the random slope in our main analysis and report the model estimates without the random slope in the Supplementary Material (see Tables A.5 and A.6). The standard $p < .05$ criteria was used to determine if our statistical tests suggested that the results were significantly different from those expected under the null hypothesis. We report p-values adjusted for the false discovery rate (FDR) to control for multiple comparisons (Benjamini & Hochberg, 1995). Cohen's d for each effect of interest was calculated using the R package *EMAtools* (Kleiman, 2021). To quantify the evidence in support of the experimental (H_1) or null hypotheses (H_0), we calculated Bayes Factors for each effect of interest (Wetzels & Wagenmakers, 2012) using the Bayesian information criterion (BIC) approximation method (Wagenmakers, 2007).

Standard assumptions of multilevel mixed models (i.e. linearity, homogeneity of variance, multicollinearity, normality of residuals, and influential data points) were checked throughout the modelling process. As multilevel mixed models are relatively robust to violations of distributional assumptions (such as normality of residuals; Schielzeth et al., 2020), any model issues that were not satisfactorily resolved were reported, and the results were interpreted with necessary caution.

4.3.1.1 Raw emotion ratings

First, we modelled NA inertia using raw NA ratings obtained from the MIP (Koval et al., 2016). A composite score of NA was computed by averaging across all NA ratings (*sad, angry, depressed,* and *anxious*) at each time point. At Level-1 (across time points), we modelled the autoregressive slope of emotions (representing emotional inertia) as shown in (1).

$$\mathbf{NA}_{ti} = \boldsymbol{\pi}_{0i} + \boldsymbol{\pi}_{1i}\,(\mathbf{NA}_{t-1i}) + \boldsymbol{e}_{ti} \tag{1}$$

In the above equation, the outcome measure at Level-1 (NA_{ti}) reflects participant *i's* level of NA at time *t*. The lagged predictor (NA_{t-1i}) represents participant *i's* level of NA at time $t-1$. The autoregressive slope (π_{1i}) assesses how strongly participant *i's* level of NA at time t is associated with their level of NA at time $t - 1$. This autoregressive slope is comparable to an autocorrelation and typically ranges between 0 and 1 (Hamaker, 2012; Koval et al., 2016).

To obtain unbiased estimates of NA inertia in a preliminary analysis, the lagged predictor (NA_{t-1i}) was added to the multilevel model in the absence of any Level-2 predictors. For the main analysis, the lagged predictor was person-mean centred to remove individual differences from Level-1 parameter estimates (Enders & Tofighi, 2007; Hamaker & Grasman, 2015; Koval et al., 2016). Therefore, the Level-1 intercept (π_{0i}) reflects each participant's mean NA level across all time points. In other words, each participant's 'NA baseline'. The Level-1 intercept and (autoregressive) slope were allowed to randomly vary across participants at Level-2.

At Level-2 (across participants) we first examined the association between CER strategy use and NA inertia (*RQ1*), as shown in (2) and (3). Adaptive and maladaptive CER strategy use composite scores were standardised before being entered as Level-2 predictors in the model (Koval, Brose, et al., 2015; Koval et al., 2016). In this model, the Level-2 intercept (β_{10}) represents the average level of NA inertia at the mean value of adaptive/maladaptive CER strategy use. The Level-2 slope (β_{11}) reflects the association between adaptive/maladaptive CER strategy use and NA inertia. Thus, a significant interaction between the lagged predictor and adaptive/maladaptive CER strategy use would provide evidence for an association between adaptive/maladaptive CER strategy use and NA inertia.

$$\boldsymbol{\pi_{1i} = \beta_{10} + \beta_{11}\,(z\text{Adaptive CER Strategy Use}_i) + r_{1i}} \tag{2}$$

$$\boldsymbol{\pi_{1i} = \beta_{10} + \beta_{11}\,(z\text{Maladaptive CER Strategy Use}_i) + r_{1i}} \tag{3}$$

Second, at Level-2, we examined the association between sleep quality and NA inertia (*RQ2*), as shown in (4). PSQI total score was standardised before being added as a Level-2 predictor to the model (Koval, Brose, et al., 2015; Koval et al., 2016). In this model, the Level-2 intercept (β_{10}) represents the average level of NA inertia at the mean value of sleep quality and the Level-2 slope (β_{11}) reflects the association between sleep quality and NA inertia. A significant interaction between the lagged predictor and sleep quality would provide evidence for an association between sleep quality and NA inertia.

$$\boldsymbol{\pi_{1i} = \beta_{10} + \beta_{11}\,(z\text{Sleep Quality}_i) + r_{1i}}$$

(4)

Finally, to examine the moderating role of sleep quality on the association between adaptive/maladaptive CER strategy use and NA inertia (*RQ2*), we added adaptive/maladaptive CER strategy use and sleep quality as Level-2 predictors to the model, as shown in (5) and (6). Here, the Level-2 slope (β_{13}) reflects the three-way association between adaptive/maladaptive CER strategy use, sleep quality, and NA inertia. A significant three-way interaction between the lagged predictor, adaptive/maladaptive CER strategy use, and sleep quality would provide evidence for a moderating role of sleep quality on the association between adaptive/maladaptive CER strategy use and NA inertia, or likewise, a moderating role of adaptive/maladaptive CER strategy use on the association between sleep quality and NA inertia.

$$\boldsymbol{\pi_{1i} = \beta_{10} + \beta_{11}\,(\text{zAdaptive Strategy Use}_i) + \beta_{12}\,(\text{zSleep Quality}_i) + \beta_{13}\,(\text{zAdaptive Strategy Use}_i * z\text{Sleep Quality}_i) + r_{1i}}$$

(5)

$$\boldsymbol{\pi_{1i} = \beta_{10} + \beta_{11}\,(\text{zMaladaptive Strategy Use}_i) + \beta_{12}\,(\text{zSleep Quality}_i) + \beta_{13}\,(\text{zMaladaptive Strategy Use}_i * z\text{Sleep Quality}_i) + r_{1i}}$$

(6)

In each of the models described above, Level-2 slopes can be interpreted as standardised regression weights. For example, for equation (2), if $\beta_{11} = -0.05$, a participant scoring 1 standard deviation (SD) above the sample-mean on adaptive CER strategy use is predicted to have a NA inertia level 0.05 units lower than the sample average, whereas a participant scoring 1 SD below the sample-mean on adaptive strategy use is predicted to have a NA inertia level 0.05 units higher than the sample average.

4.3.1.2 Standardised emotion ratings

We re-ran our multilevel models using within-person standardised NA ratings, which hold constant individual differences in mean levels and variability of NA (i.e. SD of NA over time; Koval et al., 2013, 2016; Moeck et al., 2022). To compute our standardised NA ratings, raw NA ratings were z-scored within-person. These standardised NA ratings were analysed using the multilevel models described above. Because standardisation removes individual differences in mean level and variability of NA, the lagged predictor was not person-mean centered in these models (Koval et al., 2016). The inclusion of both raw and standardised ratings allowed us to run an analysis that is commonplace within the literature and thus compare our findings with those of other studies.

4.3.1.3 Deviations from the pre-registration

In the pre-registration, we stated that we would examine NA inertia using only standardised emotion ratings. However, in our analysis, we ran an additional non-preregistered analysis to model NA inertia using raw ratings. We decided to do this as most previous research modelling NA inertia uses raw ratings, therefore we wanted our results to be comparable (Koval et al., 2016; Kuppens, Allen, et al., 2010; Suls et al., 1998). Moreover, the inclusion of both raw and standardised ratings allowed us to run our pre-registered analysis and ensure that individual differences in mean levels and variability of NA were held constant in our models.

4.4 Results

4.4.1 Descriptive statistics

Descriptive statistics and correlations between adaptive/maladaptive CER strategy use and sleep quality are presented in Table 4.1. We found a significant negative association between adaptive CER strategy use and maladaptive CER strategy use ($r = -.09$, $p < .001$), such that greater use of adaptive CER strategies was associated with less frequent use of maladaptive CER strategies. Furthermore, there was a significant negative association between adaptive CER strategy use and sleep quality ($r = -.26$, $p < .001$); with lower PSQI scores reflecting higher sleep quality. Thus, greater use of adaptive CER strategies was associated with higher sleep quality. Conversely, there was a significant positive association between maladaptive CER strategy use and sleep quality ($r = .23$, $p < .001$), such that greater use of maladaptive CER strategies was associated with poorer sleep quality.

Table 4.1. Mean, standard deviations, and correlations between all Level-2 predictors included in the main analysis.

Predictor	M	SD	Range	Adaptive CER Strategy Use	Maladaptive CER Strategy Use
Adaptive CER Strategy Use	22.75	5.78	10–40		
Maladaptive CER Strategy Use	21.52	5.31	9–37	−.09***, $BF_{10} > 100$	
Sleep Quality	5.37	2.71	0–14	−.26***, $BF_{10} > 100$	.23***, $BF_{10} > 100$

M and *SD* represent the mean and standard deviation, respectively. Adaptive and maladaptive CER strategy use were computed using the Cognitive Emotion Regulation Questionnaire-short version (CERQ-short), sleep quality was computed using the Pittsburgh Sleep Quality Index (PSQI). *** indicates $p < .001$. Multiple comparison correction was applied using Holm’s method (Hochberg, 1988).

4.4.2 Preliminary analysis

In a preliminary analysis, we estimated average levels of NA inertia using multilevel models without Level-2 predictors (Koval et al., 2016). Following recommendations (Hamaker & Grasman, 2015; Koval et al., 2016), the lagged predictor (NA rating at t – 1) was entered into each of our models uncentred. We found a significant positive association between NA ratings at time t and NA ratings at time $t - 1$ when NA inertia was modelled using both raw (β = 0.22, [0.19, 0.25], $p < .001$, d = 1.75, $BF_{10} > 100$) and standardised ratings (β = 0.16, [0.14, 0.19], $p < .001$, d = 0.33, $BF_{10} > 100$; see Table 4.2). These results demonstrate that NA showed significant moment-to-moment predictability (see Figure 4.3).

Table 4.2. Coefficients and 95% confidence intervals from the preliminary multilevel model estimating average levels of negative affect (NA) inertia across the sample in the absence of Level-2 predictors.

	Fixed effect		
Model	**Estimate *(SE)***	**95% CIs**	***p***
NA Inertia (Raw)	**0.22 (*0.02*)**	**0.19–0.25**	**< .001**
NA Inertia (Standardised)	**0.16 (*0.01*)**	**0.14–0.19**	**< .001**

NA = Negative affect. SE = Standard error of the mean.

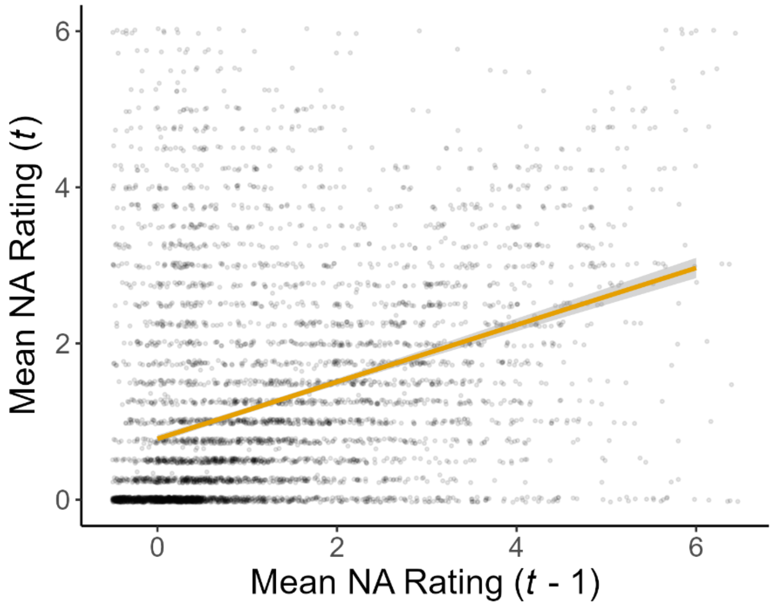

Figure 4.3. Autoregressive slope plotting the association between mean negative affect (NA) rating at time t and mean NA rating at time $t - 1$ (i.e. the lagged NA predictor). NA inertia was modelled using raw ratings. Steeper slopes reflect a stronger association between NA at time t and NA at the previous time point (t − 1) (i.e. higher NA inertia). We found a significant positive association between mean NA at time t and NA at the previous time point (t − 1),

indicating that NA inertia showed significant moment-to-moment predictability. Grey areas represent 95% confidence intervals.

4.4.3 Is there an association between CER strategy use and NA inertia?

Next, we investigated the association between CER strategy use and NA inertia. First, we added adaptive CER strategy use as a Level-2 predictor to our models. We found a significant negative association between adaptive CER strategy use and NA inertia when NA inertia was modelled using raw ratings ($\beta = -0.03$, [−0.06, 0.00], $p = .041$, d = 0.17, $BF_{10} = 0.14$), but not when NA inertia was modelled using standardised ratings ($\beta = -0.02$ [−0.05, 0.01], $p = .197$, d = 0.04, $BF_{10} = 0.04$; see Table 4.3). These results revealed that greater use of adaptive CER strategies was associated with lower persistence of NA for raw ratings only (i.e. lower NA inertia; see Figure 4.4a). Similarly, when maladaptive CER strategy use was added as a Level-2 predictor in our models, we found a significant positive association between maladaptive CER strategy use and NA inertia when NA inertia was modelled using raw ratings ($\beta = 0.03$, [0.00, 0.06], $p = .031$, d = 0.28, $BF_{10} = 0.14$), but not when NA inertia was modelled using standardised ratings ($\beta = 0.03$, [0.00, 0.05], $p = .149$, d = 0.05, $BF_{10} = 0.07$). These findings indicate that greater use of maladaptive CER strategies was associated with higher persistence of NA for raw ratings only (i.e. higher NA inertia; see Figure 4.4b).

Table 4.3. Coefficients and 95% confidence intervals from the multilevel models examining the associations between CER strategy use and negative affect (NA) inertia.

	Fixed effect		
Model	**Estimate *(SE)***	**95% CI**	***p***
Adaptive CER Strategy Use			
NA Inertia (Raw)	**−0.03 (*0.02*)**	**−0.06–0.00**	**.041**
NA Inertia (Standardised)	−0.02 (*0.01*)	−0.05–0.01	.197
Maladaptive CER Strategy Use			
NA Inertia (Raw)	**0.03 (*0.02*)**	**0.00–0.06**	**.031**
NA Inertia (Standardised)	0.03 (*0.01*)	0.00–0.05	.149

NA = Negative affect. SE = Standard error of the mean. Statistically significant coefficients are shown in bold.

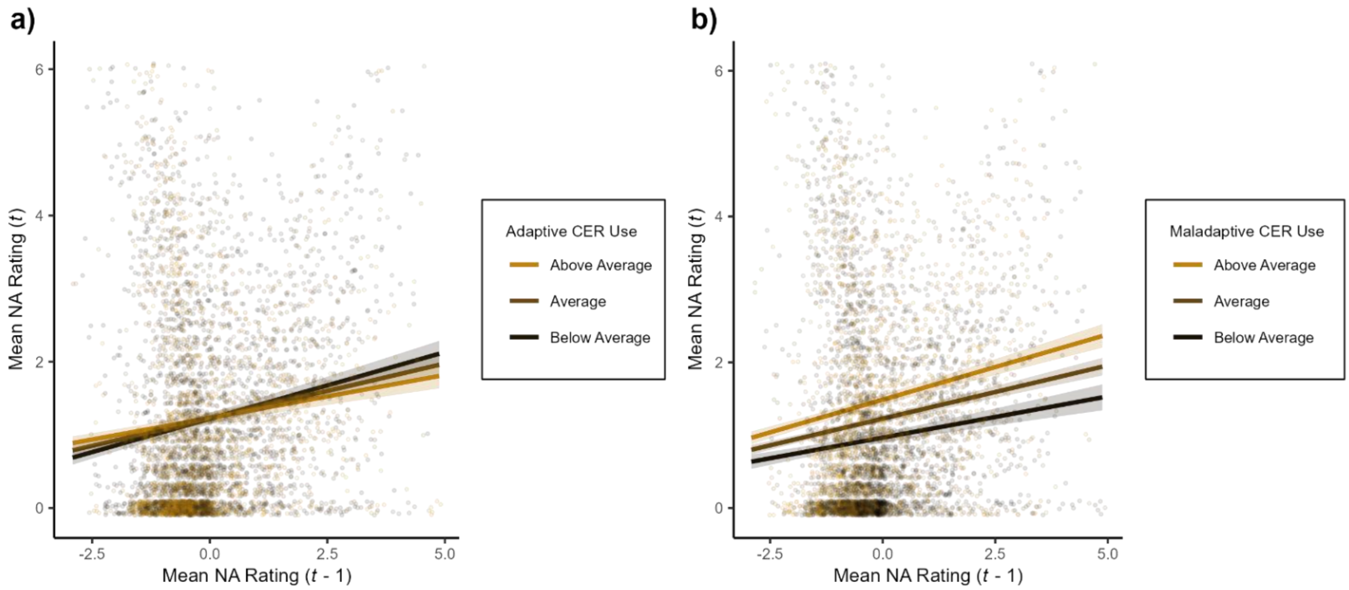

Figure 4.4. Association between CER strategy use and NA inertia. a) Greater adaptive CER strategy use was associated with lower NA inertia, b) Greater use of maladaptive CER strategies was associated with higher NA inertia. Mean NA ratings at $t-1$ (x-axis) were person-mean centred to remove between-person differences from Level-1 parameter estimates. Therefore, 0 on the x-axis represents each participant's mean NA level. Data are plotted at different levels of adaptive/maladaptive CER strategy use (mean and +/− 1 SD).

4.4.4 Is the association between CER strategy use and NA inertia influenced by sleep quality?

We were also interested in determining whether there was an association between sleep quality and NA inertia. To probe this question, we included sleep quality as a Level-2 predictor in our models. We found a significant positive association between sleep quality and NA inertia when NA inertia was modelled using both raw ($\beta = 0.03$, [0.00, 0.06], $p = .044$, d = 0.25, $BF_{10} = 0.11$) and standardised ratings ($\beta = 0.04$, [0.01, 0.07], $p = .007$, d = 0.08, $BF_{10} = 0.99$; see Table 4.4). These findings indicate that higher sleep quality (i.e. lower PSQI scores) was associated with lower NA inertia (see Figure 4.5a).

Because CER strategy use and sleep quality were both associated with NA inertia, in a final analysis, we were also interested in whether the association between CER strategy use and NA inertia was influenced by sleep quality, or vice versa. To investigate this, we first added adaptive CER strategy use and sleep quality as Level-2 predictors in our models. Our results showed no significant three-way interaction between adaptive CER strategy use, sleep quality, and NA inertia when NA inertia was modelled using either raw ($\beta = -0.03$, [−0.06, 0.00], $p = .122$, d = 0.13, $BF_{10} < 0.01$) or standardised ratings ($\beta = -0.02$, [−0.05, 0.00], $p = .230$, d = 0.05, $BF_{10} < 0.01$; see Figure 4.5b). Next, we added maladaptive CER strategy use and sleep quality as Level-2 predictors in our models. Again, we found no significant three-way interaction between maladaptive CER strategy use, sleep quality, and NA inertia when NA inertia was modelled using either raw (β = 0.02, [−0.01, 0.04], *p* = .331, d = 0.13, BF_{10} < 0.01) or standardised ratings (β = 0.01, [−0.02, 0.04], *p* = .783, d = 0.02, BF_{10} < 0.01; see Figure 4.5c). Given that all Bayes Factors in support of the null (BF_{01}) were > 100, these findings suggest that the associations between greater adaptive CER strategy use and lower NA inertia and greater maladaptive CER strategy use and higher NA inertia were unaffected by sleep quality.

Table 4.4. Coefficients and 95% confidence intervals from the multilevel models examining the associations between CER strategy use, sleep quality and negative affect (NA) inertia.

	Fixed effect		
Model	**Estimate *(SE)***	**95% CI**	***p***
Sleep Quality			
NA Inertia (Raw)	**0.03 (*0.02*)**	**0.00–0.06**	**.044**
NA Inertia (Standardised)	**0.04 (*0.01*)**	**0.01–0.07**	**.007**
Adaptive CER Strategy Use × Sleep Quality			
NA Inertia (Raw)	−0.03 (*0.02*)	−0.06–0.00	.122
NA Inertia (Standardised)	−0.02 (*0.01*)	−0.05–0.00	.230
Maladaptive CER Strategy Use × Sleep Quality			
NA Inertia (Raw)	0.02 (*0.02*)	−0.01–0.04	.331
NA Inertia (Standardised)	0.01 (*0.01*)	−0.02–0.04	.783

NA = Negative affect. SE = Standard error of the mean. Statistically significant coefficients are shown in bold.

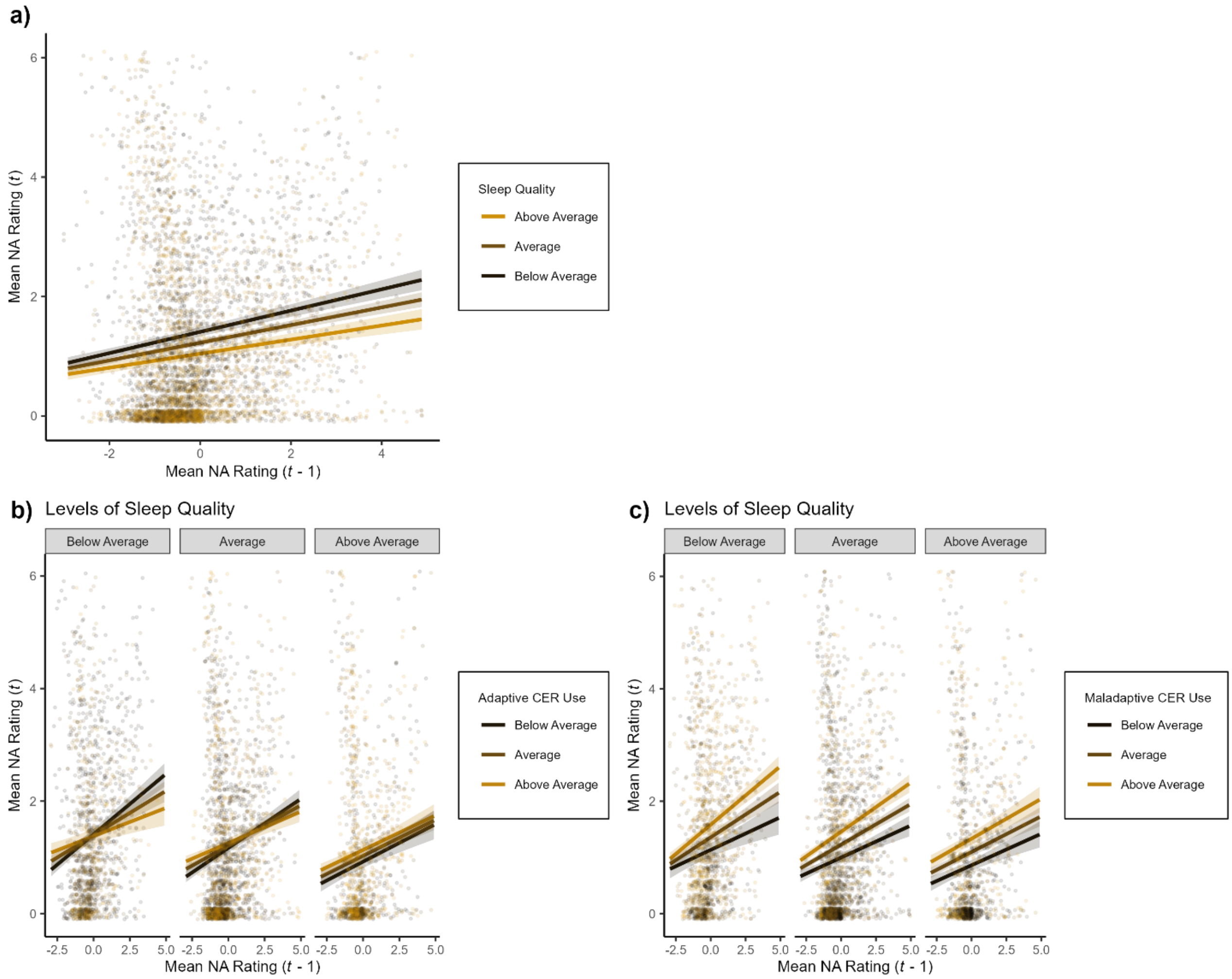

Figure 4.5. Association between CER strategy use, sleep quality and NA inertia. a) Higher sleep quality was associated with lower NA inertia. b) The association between greater use of adaptive CER strategies and lower NA inertia was unaffected by sleep quality. c) Similarly, the association between greater use of maladaptive CER strategies and higher NA inertia was unaffected by sleep quality. Data are plotted at different levels of sleep quality (mean and +/− 1 SD).

4.4.5 Exploratory analysis

4.4.5.1 CER strategy use, sleep quality, and PA inertia

Previous research has demonstrated a significant association between higher PA inertia and lower well-being, albeit to a lesser extent than NA inertia (Houben et al., 2015; Koval et al., 2016). To corroborate this relationship, in an exploratory analysis, we examined whether CER strategy use and sleep quality were associated with PA inertia.

A composite score for PA was computed by averaging across the two positive dimensions (*happy* and *relaxed*) at each time point. As mentioned above, we estimated within-person reliability of our composite PA rating using multilevel structural equation modelling.

The estimated coefficient omega for our composite PA rating was good (0.87). In a preliminary analysis, we estimated average levels of PA inertia using multilevel models in the absence of Level-2 predictors. Autoregressive slopes were positive and significant when PA inertia was modelled using both raw ($\beta = 0.27$, [0.24, 0.30], $p < .001$, d = 2.01, $BF_{10} > 100$) and standardised ratings ($\beta = 0.20$, [0.17, 0.23], $p < .001$, d = 0.41, $BF_{10} > 100$), demonstrating that PA showed significant moment-to-moment predictability (see Table 4.5).

Table 4.5. Coefficients and 95% confidence intervals from the preliminary multilevel model estimating average levels of positive affect (PA) inertia across the sample in the absence of Level-2 predictors.

	Fixed effect		
Model	**Estimate *(SE)***	**95% CIs**	***p***
PA Inertia (Raw)	**0.27 (*0.02*)**	**0.24–0.30**	**< .001**
PA Inertia (Standardised)	**0.20 (*0.01*)**	**0.17–0.23**	**< .001**

PA = Positive affect. SE = Standard error of the mean.

Next, we examined whether CER strategy use was associated with PA inertia by adding adaptive CER strategy use as a Level-2 predictor to our models. The data indicated no significant association between adaptive CER strategy use and PA inertia when PA inertia was modelled using either raw ($\beta = -0.02$, [−0.05, 0.02], $p = .291$, d = 0.13, $BF_{10} = 0.03$) or standardised ratings ($\beta = -0.02$, [−0.04, 0.01], $p = .306$, d = 0.03, $BF_{10} = 0.03$; see Table 4.6). In a similar manner, when maladaptive CER strategy use was added as Level-2 predictor to our models, we found no significant association between maladaptive CER strategy use and PA inertia when PA inertia was modelled using either raw ($\beta = 0.01$, [−0.03, 0.04], $p = .651$, d = 0.06, $BF_{10} = 0.02$) or standardised ratings ($\beta = -0.01$, [−0.03, 0.02], $p = .958$, d = 0.01, $BF_{10} = 0.02$; see Table 4.6).

We also found no significant association between sleep quality and PA inertia when PA inertia was modelled using either raw ($\beta = 0.01$, [−0.02, 0.04], $p = .513$, d = 0.08, $BF_{10} = 0.02$) or standardised ratings ($\beta = 0.02$, [−0.01, 0.04], $p = .371$, d = 0.03, $BF_{10} = 0.03$). Consistent with our main analysis, we also found no significant three-way interaction between adaptive CER strategy use, sleep quality and PA inertia when PA inertia was modelled using either raw ($\beta = -0.01$, [−0.04, 0.03], $p = .773$, d = 0.05, $BF_{10} < 0.01$) or standardised ratings ($\beta = -0.01$, [−0.03, 0.02], $p = .906$, d = 0.01, $BF_{10} < 0.01$). Likewise, we found no significant interaction between maladaptive CER strategy use, sleep quality and PA inertia when PA inertia was modelled using either raw ($\beta = -0.01$, [-0.04, 0.02], $p = .576$, d = 0.09, $BF_{10} < 0.01$) or standardised ratings ($\beta = 0.00$, [-0.02, 0.03], $p = .974$, d = 0.01, $BF_{10} < 0.01$; see Table 4.6).

Table 4.6. Coefficients and 95% confidence intervals from the multilevel models examining the associations between CER strategy use, sleep quality and positive affect (PA) inertia.

	Fixed effect		
Model	**Estimate *(SE)***	**95% CI**	***p***
Adaptive CER Strategy Use			
PA Inertia (Raw)	−0.02 *(0.02)*	−0.05–0.02	.291
PA Inertia (Standardised)	−0.02 *(0.01)*	−0.04–0.01	.306
Maladaptive CER Strategy Use			
PA Inertia (Raw)	0.01 *(0.02)*	−0.03–0.04	.651
PA Inertia (Standardised)	−0.01 *(0.01)*	−0.03–0.02	.958
Sleep Quality			
PA Inertia (Raw)	0.01 (*0.02*)	−0.02–0.04	.513
PA Inertia (Standardised)	0.02 (*0.01*)	−0.01–0.04	.371
Adaptive CER Strategy Use × Sleep Quality			
PA Inertia (Raw)	−0.01 (*0.02*)	−0.04–0.03	.773
PA Inertia (Standardised)	−0.01 (*0.01*)	−0.03–0.02	.906
Maladaptive CER Strategy Use × Sleep Quality			
PA Inertia (Raw)	–0.01 (*0.02*)	−0.04–0.02	.576
PA Inertia (Standardised)	0.00 (*0.01*)	−0.02–0.03	.974

PA = Positive affect. SE = Standard error of the mean.

4.4.5.2 Depression severity and NA inertia

We also sought to replicate the positive association between depression severity and NA inertia using our MIP. To do this, we added depression severity (measured using the BDI-II) as a Level-2 predictor to our models. We found a significant positive association between depressive severity and NA inertia when NA inertia was modelled using raw ($\beta = 0.03$, [0.01, 0.06], $p = .022$, d = 0.30, $BF_{10} = 0.19$) and standardised ratings ($\beta = 0.04$, [0.01, 0.06], $p = .028$, d = 0.07, $BF_{10} = 0.29$; see Table 4.7), demonstrating that greater depression severity was associated with higher NA inertia (see Figure 4.6a). However, we found no significant interaction between depression severity, adaptive CER strategy use, and NA inertia when NA inertia was modelled using either raw ($\beta = -0.02$, [−0.05, 0.01], $p = .158$, d = 0.12, $BF_{10} < 0.01$) or standardised ratings ($\beta = -0.02$, [−0.04, 0.01], $p = .322$, d = 0.04, $BF_{10} < 0.01$). Similarly, we found no significant association between depression severity, maladaptive CER strategy use, and NA inertia when NA inertia was modelled using either raw ($\beta = 0.01$, [−0.02, 0.04], $p = .465$, d = 0.10, $BF_{10} < 0.01$) or standardised ratings ($\beta = 0.01$, [−0.01, 0.04], $p = .772$, d = 0.03, $BF_{10} < 0.01$). We also found no significant association between depression severity, sleep quality and NA inertia when NA inertia was modelled using either raw ($\beta = 0.01$, [−0.01, 0.04], $p = .477$, d = 0.12, $BF_{10} < 0.01$) or standardised ratings ($\beta = 0.01$, [−0.02, 0.03], $p = .831$, d = 0.02, $BF_{10} < 0.01$; see Table 4.7).

4.4.5.3 Anxiety severity and NA inertia

We also examined whether there was an association between anxiety severity and NA inertia. To address this question, we added anxiety severity (measured using the BAI) as a Level-2 predictor to our models. We found a significant positive association between anxiety severity and NA inertia when NA inertia was modelled using raw ($\beta = 0.04$, [0.01, 0.07], $p = .005$, d = 0.35, $BF_{10} = 0.71$) and standardised ratings ($\beta = 0.04$, [0.01, 0.07], $p = .013$, d = 0.08, $BF_{10} = 0.60$), such that greater anxiety severity was associated with higher NA inertia (see Figure 4.6b). However, there was no significant association between anxiety severity, adaptive CER strategy use, and NA inertia when NA inertia was modelled using either raw ($\beta = -0.02$, [−0.04, 0.01], $p = .183$, d = 0.11, $BF_{10} < 0.01$) or standardised ratings ($\beta = -0.02$, [−0.05, 0.00], $p = .255$, d = 0.05, $BF_{10} < 0.01$). Similarly, there was no significant association between anxiety severity, maladaptive CER strategy use, and NA inertia when NA inertia was modelled using either raw ($\beta = 0.02$, [−0.01, 0.05], $p = .239$, d = 0.17, $BF_{10} < 0.01$) or standardised ratings ($\beta = 0.02$, [0.00, 0.05], $p = .331$, d = 0.05, $BF_{10} < 0.01$). Moreover, there was no significant association between anxiety severity, sleep quality, and NA inertia when NA inertia was modelled using either raw (β = 0.00, [−0.02, 0.03], p = .837, d = 0.02, BF_{10} < 0.01) or standardised ratings (β = 0.00, [−0.02, 0.02], p = .955, d < 0.01, BF_{10} < 0.01; see Table 4.8).

Table 4.7. Coefficients and 95% confidence intervals from the multilevel models examining the associations between depression severity and negative affect (NA) inertia.

	Fixed effect		
Model	**Estimate *(SE)***	**95% CI**	***p***
Depression			
NA Inertia (Raw)	**0.03 (*0.02*)**	**0.01–0.06**	**.022**
NA Inertia (Standardised)	**0.04 (*0.01*)**	**0.01–0.06**	**.028**
Depression × Adaptive CER Strategy Use			
NA Inertia (Raw)	−0.02 *(0.01)*	−0.05–0.01	.158
NA Inertia (Standardised)	−0.02 *(0.01)*	−0.04–0.01	.322
Depression × Maladaptive CER Strategy Use			
NA Inertia (Raw)	0.01 *(0.01)*	−0.02–0.04	.465
NA Inertia (Standardised)	0.01 *(0.01)*	−0.01–0.04	.772
Depression × Sleep Quality			
NA Inertia (Raw)	0.01 *(0.01)*	−0.01–0.04	.477
NA Inertia (Standardised)	0.01 (*0.01*)	−0.02–0.03	.831

NA = Negative affect. SE = Standard error of the mean. Statistically significant coefficients are shown in bold.

Table 4.8. Coefficients and 95% confidence intervals from the multilevel models examining the associations between anxiety severity and negative affect (NA) inertia.

	Fixed effect		
Model	**Estimate *(SE)***	**95% CI**	***p***
Anxiety			
NA Inertia (Raw)	**0.04 (*0.01*)**	**0.01–0.07**	**.005**
NA Inertia (Standardised)	**0.04 (*0.01*)**	**0.01–0.07**	**.013**
Anxiety × Adaptive CER Strategy Use			
NA Inertia (Raw)	−0.02 *(0.01)*	−0.04–0.01	.183
NA Inertia (Standardised)	−0.02 *(0.01)*	−0.05–0.00	.255
Anxiety × Maladaptive CER Strategy Use			
NA Inertia (Raw)	0.02 *(0.01)*	−0.01–0.05	.239
NA Inertia (Standardised)	0.02 *(0.01)*	0.00–0.05	.331
Anxiety × Sleep Quality			
NA Inertia (Raw)	0.00 (*0.01*)	−0.02–0.03	.837
NA Inertia (Standardised)	0.00 (*0.01*)	−0.02–0.02	.955

NA = Negative affect. SE = Standard error of the mean. Statistically significant coefficients are shown in bold.

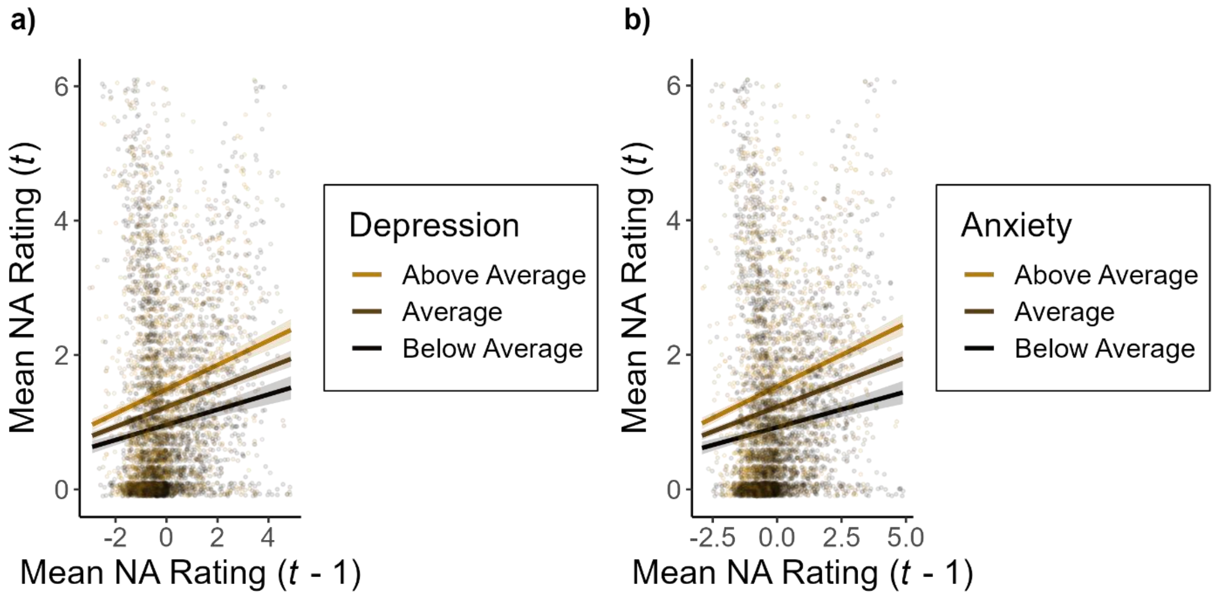

Figure 4.6. Association between depression severity, anxiety severity and NA inertia. Greater depression (a) and anxiety (b) symptomatology were associated higher NA inertia. Data are plotted at different levels of depression and anxiety (mean and +/− 1 SD).

4.5 Discussion

The present study examined whether composite measures of adaptive and maladaptive CER strategy use are differentially associated with NA inertia. We also investigated whether the association between greater adaptive CER strategy use and lower NA inertia is contingent on obtaining high sleep quality. Although previous studies have found no association between poor sleep and heightened NA inertia, they used ESM to index NA inertia. As a result, they cannot rule out the possibility that NA inertia is driven by individual differences in the intensity of emotional events that participants encounter in daily life. To address this, we employed a MIP to help control for differences in emotional event exposure. Given that the rigidity of NA appears to be more characteristic of poorer mental health than the rigidity of PA (Houben et al., 2015; Koval et al., 2016; A. Wen & Yoon, 2019), our main analysis focused on the associations between CER strategies, sleep quality, and NA inertia.

Greater use of adaptive CER strategies was significantly associated with lower NA inertia, thus supporting our first hypothesis. This finding is at odds with previous studies that found no association between the adaptive CER strategy positive reappraisal and NA inertia (Bean et al., 2021; Koval, Butler, et al., 2015). This discrepancy may result from previous studies focusing on the association between only one adaptive CER strategy (positive reappraisal) rather than the use of several adaptive CER strategies. It is possible that greater use of a combination of adaptive CER strategies is more predictive of lower NA inertia than greater use of one adaptive CER strategy alone. Moreover, prior work used ESM to measure NA inertia, whereas we used a MIP, exposing participants to the same sequence of emotional events. Therefore, the lack of an association in prior work may be obscured by differences in the emotional events that participants encountered in their daily life.

Mindfulness interventions have been thought to promote adaptive CER strategy use by increasing trait mindfulness, self-compassion, and meta-awareness while decreasing emotional reactivity and rumination in response to unpleasant experiences (Guendelman et al., 2017). Therefore, our findings are also consistent with those of studies demonstrating an association between trait mindfulness and lower NA inertia (Keng & Tong, 2016; Rowland et al., 2020), suggesting that adaptive CER strategy use might rely on similar mechanisms to reduce the persistence of NA. Taken together, our findings provide evidence to support the argument that greater use of adaptive CER strategies results in a steeper decline in NA, back to one's emotional baseline, following an emotional experience (i.e. lower NA inertia; Kuppens, Allen, et al., 2010).

In contrast, greater use of maladaptive CER strategies was associated with higher NA inertia, again supporting our first hypothesis. This finding is consistent with previous studies using ESM, which have demonstrated an association between both expressive suppression and rumination (maladaptive CER strategies), and higher NA inertia (Bean et al., 2021; Blanke et al., 2022; Koval, Butler, et al., 2015; Koval et al., 2012). It has been suggested that maladaptive CER strategies contribute to the maintenance and enhancement of NA through various mechanisms (Koval, Butler, et al., 2015; Koval et al., 2012). For instance, rumination may impede the ability to engage in problem-solving strategies (i.e. adaptive CER strategies) critical for reducing NA (Blanke et al., 2022), thereby promoting the rigidity of NA over time. Other studies have suggested that engaging with maladaptive CER strategies, such as expressive suppression, is cognitively demanding and depletes cognitive resources (Franchow & Suchy, 2015; Y. Wang et al., 2014). This can impair an individual's ability to respond flexibly and adaptively to both internal and external demands (Koval, Butler, et al., 2015). Maladaptive CER strategy use may thus promote heightened NA inertia through the impairment of problem solving and the consumption of cognitive resources that would otherwise be used for flexible responding. As previous work has focused on the use of only rumination and expressive suppression, this is the first study to find that greater use of a combination of maladaptive CER strategies is also associated with higher NA inertia.

Despite the foregoing findings, it is important to acknowledge that the above associations were not significant when NA inertia was modelled using within-person standardised ratings. The analysis of standardised NA ratings holds constant individual differences in both mean levels and variability of NA (Koval et al., 2016; Moeck et al., 2022). Given that the association between both adaptive and maladaptive CER strategies and NA inertia became non-significant when NA inertia was modelled using standardised ratings, it is possible that the associations between CER strategy use and NA inertia may be partly driven by mean levels and/or variability of NA. Therefore, although CER strategy use and NA inertia are related, CER strategy use may also influence mean and/or variability of NA. Consequently, more work is needed to examine how strongly mean levels and variability of NA are associated with CER strategy use (Koval et al., 2016; Wenzel & Brose, 2023). This can be achieved through autoregressive models that allow for simultaneous estimation of mean levels, variability, and inertia of NA in relation to CER strategy use and sleep quality (Jongerling et al., 2015; Koval et al., 2016).

Higher sleep quality was significantly associated with lower NA inertia when modelled using both raw and standardised ratings, such that obtaining good sleep quality was associated with lower persistence of NA, thus supporting our hypothesis. This finding aligns with previous work demonstrating an association between shorter sleep duration and higher inertia of a depressed affect state using ESM (X. Wen et al., 2020). We expanded on this finding by demonstrating an association between high sleep quality and lower NA inertia as a composite of sadness, anger, depression, and anxiety. More broadly, this result is in accordance with prior work suggesting that good sleep quality can help people regulate their emotion states back to baseline levels (Goldstein & Walker, 2014), whereas poor sleep contributes to emotion dysregulation (Ben Simon et al., 2020; Harrington, Ashton, Sankarasubramanian, et al., 2021; Harrington & Cairney, 2021; Yoo et al., 2007).

It is possible that the association between sleep quality and NA inertia is underpinned by executive functions. Waugh et al. (2017) postulated that lower NA inertia reflects the ability to inhibit negative emotion states, preventing them from spilling over to the next event. As poor sleep is associated with executive control deficits (Drummond et al., 1999; Mograss et al., 2009; Nilsson et al., 2005; Qi et al., 2010; Skurvydas et al., 2020), including impaired inhibitory control (Breimhorst et al., 2008; Harrington, Ashton, Sankarasubramanian, et al., 2021; Lowe et al., 2017), it is possible that poor sleep prevents the ability to inhibit negative emotion states, leading to higher NA inertia. This idea is supported by neuroimaging work highlighting that poor sleep disrupts the functional connectivity between the medial prefrontal cortex (mPFC) and amygdala (Vandekerckhove & Wang, 2017; Walker & van der Helm, 2009; Yoo et al., 2007), potentially compromising top-down inhibitory control of emotion states (Harrington, Ashton, Sankarasubramanian, et al., 2021). Together, these findings imply that poor sleep quality makes it more difficult to downregulate NA in response to emotional events, promoting the persistence of NA over time.

It is important to note that our findings do not align with studies that found no association between sleep quality and NA inertia (Frérart et al., 2023; Minaeva et al., 2021). This discrepancy can be attributed to several factors. First, Frérart et al. (2023) only assessed affect twice in a 12-hour period (i.e. once in the morning and once in the evening). This meant that they were unable to map more subtle changes in affect across the day, when participants presumably encountered a multitude of emotional experiences. They also did not consider how individual differences in circadian rhythms may have influenced morning and evening affect. For instance, prior work has demonstrated that on work days, evening-type individuals report a delayed peak PA and lower PA compared to morning-type individuals (M. A. Miller et al., 2015). Consequently, those who are evening-types may display lower morning PA compared to those who are morning-types, suggesting that overnight inertia may be moderated by chronotype. In addition, in both studies, sleep quality was assessed using only one daily item: Minaeva et al. (2021) asked participants to rate their sleep quality the previous night from 1 (*not at all*) to 7 (*very well*), and Frérart et al. (2023) asked participants to indicate their sleep quality from 1 (*good*) to 4 (*very bad/not at all*). The use of only one item to index sleep quality may not capture sleep quality as comprehensively as the PSQI. Finally, because these studies used ESM paradigms, they were unable to control for individual differences in the intensity of the emotional events encountered (Koval, Brose, et al., 2015). This lack of experimental control may have tempered any association between sleep quality and NA inertia. Given these inconsistencies, future studies are required to corroborate the association between sleep quality and NA inertia found in this study.

An absence of sleep can reduce the effectiveness of adaptive CER strategies (Mauss et al., 2013; Zhang et al., 2019) and increase the use of maladaptive CER strategies (Latif et al., 2019). Therefore, we also investigated whether the association between greater use of adaptive CER strategies and lower persistence of NA was stronger among individuals with high sleep quality. However, we found no significant interaction between adaptive CER strategy use, sleep quality, and NA inertia when NA inertia was modelled using either raw or standardised ratings, not corroborating our hypothesis. We also found no significant interaction between maladaptive CER strategy use, sleep quality, and NA inertia for either raw or standardised ratings. The absence of a significant interaction suggests that CER strategies and sleep quality are independently associated with NA inertia. This aligns with similar work demonstrating that greater use of adaptive CER strategies, less frequent use of maladaptive CER strategies, and high sleep quality independently support resilience to depression (Sullivan et al., 2023). Furthermore, consistent with Sullivan et al. (2023), we found a significant correlation between adaptive/maladaptive CER strategy use and sleep quality, such that greater use of adaptive CER strategies was associated with higher sleep quality and greater use of maladaptive CER strategies was associated with lower sleep quality. Together, these findings suggest that sleep quality is closely tied to CER strategy use but that these variables do not have an interdependent influence on NA inertia. Therefore, it is possible that interventions targeting the improvement of adaptive CER strategies (e.g. mindfulness interventions) might be relatively safeguarded against poor sleep.

Previous studies have suggested a weak association between heightened PA inertia and lower psychological well-being (Houben et al., 2015; Koval et al., 2016) whilst other studies have linked higher PA inertia to greater well-being (Höhn et al., 2013; Poerio et al., 2016; L. N. Scott et al., 2020). In an exploratory analysis, we investigated the associations between CER strategy use, sleep quality, and PA inertia. Although PA showed significant moment-to-moment predictability, we did not find any significant relationships between adaptive or maladaptive CER strategy use and PA inertia, nor did we find a significant association between sleep quality and PA inertia, when PA inertia was modelled using either raw or standardised ratings. Therefore, CER strategy use and sleep quality may be more predictive of NA persistence than PA persistence. One reason for the lack of an association between CER strategy use and PA inertia is that the strategies assessed in the CERQ-short focus on regulating affect in response to negative rather than positive events (Heiy & Cheavens, 2014; Wenzel et al., 2022). As a result, our composite measures of adaptive and maladaptive CER strategy use may not have captured individuals who primarily focused on regulating PA in response to positive events. Because strategies that predominantly focus on up-regulating PA, such as savouring (i.e. the ability to generate, maintain, or enhance PA) and capitalising (i.e. communicating and celebrating positive events), have been associated with greater well-being (Bryant, 2003; Gable et al., 2004; Quoidbach et al., 2010), future work should examine the association between these strategies and PA inertia. It should also be noted that PA was calculated by aggregating across only two items (*relaxed* and *happy*), whereas NA was calculated by aggregating across four items. As reported above, our composite PA measure had a lower within-person reliability estimate than our composite NA measure. Consequently, we cannot rule out that the lack of association with PA inertia is due to measurement error.

We found a significant association between greater depression severity and higher NA inertia, which is consistent with the results of previous studies (Brose et al., 2015; Koval et al., 2012, 2013, 2016). Moreover, these findings are in keeping with the emotion context insensitivity account of depression (Rottenberg et al., 2005), which postulates that depression is characterised by a lack of flexible responding across NA (Bylsma et al., 2008). Our findings can be interpreted in the context of this model as they suggest that heightened depression severity is associated with NA inflexibility. Alternatively, others have suggested that the association between greater depression severity and heightened NA inertia may be underpinned by greater use of maladaptive CER strategies, such as rumination, resulting in an NA pattern that is more resistant to change over time (Bean et al., 2021; Kashdan & Rottenberg, 2010;

Kuppens, Allen, et al., 2010). However, we found no significant associations between depression severity, maladaptive CER strategy use, and NA inertia.

Greater anxiety severity was also associated with higher NA inertia. Although anxiety disorders have a higher lifetime prevalence than mood disorders, little is known about the association between NA inertia and anxiety (Kessler et al., 2005). Our findings are at odds with previous studies showing no association between anxiety and NA inertia (Bosley et al., 2019; Houben et al., 2015). However, individuals diagnosed with anxiety disorders have been shown to display higher inertia of specific components of NA, such as anger and negative thought patterns, than those without anxiety disorders (Seidl et al., 2023). Moreover, higher NA inertia has been associated with greater anxious arousal (Gilbert et al., 2019). As affective inflexibility is characteristic of internal psychopathology (Bluett et al., 2014; Gilbert et al., 2019; Kashdan & Rottenberg, 2010; McEvoy et al., 2019), heightened NA inertia may be a transdiagnostic predictor of depression and anxiety. Moreover, given that rumination is associated with greater anxiety symptomatology (McLaughlin & Nolen-Hoeksema, 2011), greater use of maladaptive CER strategies might underpin the association between heightened NA inertia and greater anxiety severity. However, consistent with our depression findings, we found no significant three-way interaction between anxiety severity, maladaptive CER strategy use, and NA inertia.

This study is the first to investigate the associations between CER strategy use, sleep quality, and NA inertia. One of the major strengths was that we validated a sample of naturalistic film clips that involved amateur recordings of real-life emotional events, as opposed to staged film clips used in previous studies (Koval et al., 2013, 2016; Zupan & Eskritt, 2020). This enabled participants to view close-to-reality experiences, thereby eliciting strong affective responses which we were able to map the trajectory of over time (Rottenberg et al., 2007; Samson et al., 2016).

Despite these strengths, this study has several limitations. First, we relied on subjective reports to index CER strategy use, sleep quality, and NA inertia. Previous research has shown that discrepancies exist between subjective and objective affective responses (Zhang et al., 2019), and self-reported sleep quality is often lower than that indicated by objective measures of sleep continuity or wake-after-sleep onset (Buysse et al., 2008; Grandner et al., 2006). Objective components of sleep, such as interrupted REM sleep, have previously been associated with higher inertia of emotional distress (Wassing et al., 2019). Therefore, subjective measures of sleep may result in different associations with NA inertia compared with objective measures of sleep (Frérart et al., 2023). Subjective measures may also be unable to capture differences in sleep quality that influence the association between CER strategy use and NA inertia. Likewise, the assessment of NA during the MIP relied on subjective ratings. Affect states also involve changes in behaviour and physiology (Koval et al., 2016), and previous studies have demonstrated that these measures are differentially associated with emotional inertia. For example, Koval, Butler, et al. (2015) found that positive reappraisal was associated with higher inertia of heart rate, but not inertia of subjective feelings. Future work can address this limitation by combining objective and subjective assessments of sleep quality and emotion regulation, potentially through the use of wearables that track sleep and physiological arousal (e.g. heart rate variability or skin conductance level). Finally, it is important to note that the MIP was delivered online, as opposed to the laboratory. This may have reduced experimental control, as we cannot be sure that the participants paid full attention to each of the videos and refrained from distractions. Therefore, future studies should replicate these findings under controlled laboratory conditions.

To examine the influence of CER strategies and sleep quality on the inertia of negative emotions more broadly, we computed a composite NA rating by combining the ratings of sadness, anger, depression, and anxiety. However, each of these NA components has been shown to have distinct associations with psychological well-being (see Consedine & Moskowitz, 2007 for a review). Moreover, previous work examining the association between sleep quality and NA inertia examined NA components separately, finding an association only with depressed affect (X. Wen et al., 2020). Relatedly, although our decision to use a composite measures of adaptive and maladaptive CER strategy use allowed us to investigate how a broad range of CER strategies were associated with NA inertia, we were unable to decipher whether a specific strategy (or a smaller combination of strategies) was particularly effective in driving this association. For example, previous studies have shown links between NA inertia and specific CER strategies, such as positive reappraisal (Koval, Butler, et al., 2015), expressive suppression (Bean et al., 2021; Koval, Butler, et al., 2015), and rumination (Blanke et al., 2022; Koval et al., 2012). Other work demonstrates that using a small combination of CER strategies predicts lower NA (Wenzel et al., 2022). Given that poor sleep impacts the use of specific CER strategies (Mauss et al., 2013; Zhang et al., 2019), it is possible that specific (or different combinations of) CER strategies and sleep quality may interact with one (or more) of the components of NA inertia. To address this, future work should examine whether there is an association between specific (or other combinations of) CER strategies and one (or more) of the components of NA inertia, and whether these associations are influenced by sleep quality.

Finally, our current analysis examined the associations between CER strategy use, sleep quality, and NA inertia in those without a mental health diagnosis. Minaeva et al. (2021) found that higher NA inertia was associated with lower sleep quality in those who were currently depressed, but not those who were previously depressed or not depressed, demonstrating different associations between sleep quality and NA inertia based on depression status. To obtain a diverse sample with regard to psychological well-being, previous studies have focused on recruiting participants using stratified sampling of depression measurements (Koval, Brose, et al., 2015). Therefore, an important endeavour for future work would be to adopt this approach and replicate the current findings in those with a mental health diagnosis, such as depression and/or anxiety.

In conclusion, using a MIP to help control for external influences on NA inertia, we found that both greater use of adaptive CER strategies and high sleep quality were associated with lower NA inertia, whereas greater use of maladaptive CER strategies was associated with higher NA inertia. However, the associations between CER strategies and NA inertia were similar at different levels of sleep quality. Building on studies using ESM paradigms, these findings highlight the importance of adaptive CER strategies and sleep quality as potential transdiagnostic targets for alleviating mental health problems by lowering NA persistence.

Chapter 5: General discussion

5.1 Overview

Sleep plays a pivotal role in our ability to process emotions (Tempesta et al., 2018). Given that difficulties with emotion regulation are a prominent feature of many psychiatric disorders, including depression and anxiety (Gross, 2014; Kring, 2010), understanding the underlying processes by which sleep supports emotion regulation is critical for learning about the development and aetiology of mental health problems. This thesis contributes to the literature by addressing key theoretical questions regarding the cognitive mechanisms by which sleep supports emotion regulation and mental health.

Across each empirical chapter, this thesis focused on three components of emotion regulation. First, Chapter 2 examined whether resilience to depression and anxiety was attributed to the association between adaptive cognitive emotion regulation (CER) strategies and sleep quality. The results demonstrated that greater use of adaptive CER strategies and high sleep quality independently supported resilience to depression, but not anxiety. However, using adaptive CER strategies to reduce depression was not contingent on high sleep quality. Next, Chapter 3 investigated whether sleep deprivation influenced the evolution of arousal responses during exposure to an environment where there was uncertainty regarding the nature of the threat. The findings demonstrated that in sleep rested individuals, physiological arousal was attenuated when exposed to prolonged ambiguous threat, whereas physiological arousal remained elevated in sleep deprived individuals. A complementary analysis also examined whether slow wave activity (SWA) was associated with affect regulation during the course of this threatening experience. However, there was no significant association between SWA and arousal regulation. Finally, Chapter 4 examined whether the association between adaptive CER strategy use and negative affect (NA) inertia was influenced by sleep quality. The findings revealed that greater (lower) use of adaptive (maladaptive) CER strategies and high sleep quality were independently associated with lower NA inertia. However, using adaptive CER strategies to lower NA inertia was not dependent on high sleep quality.

In this concluding chapter (Chapter 5), I will summarise the empirical findings before considering the key methodological and theoretical contributions of this thesis. Finally, I acknowledge the overarching limitations of this work and propose several future research avenues for further exploration.

5.2 Summary of empirical work

5.2.1 Chapter 2

Prior work supports a critical role for sleep in the success of adaptive CER strategy use (Mauss et al., 2013; Parsons et al., 2021; Tamm et al., 2019; Zhang et al., 2019), potentially due to its reliance on executive functions, such as working memory, inhibition and task switching (McRae et al., 2012; Schmeichel & Demaree, 2010; Schmeichel & Tang, 2015; Schmeichel et al., 2008). For example, working memory has shown to be important during positive reappraisal, when the alternative interpretation needs to be actively retained (Sperduti et al., 2017). As greater use of adaptive CER strategies has been associated with improved psychological well-being (Kirschbaum-Lesch et al., 2021), these findings suggest a potential mechanistic link whereby the positive benefits of using adaptive CER strategies (for reducing depression and anxiety) are dependent on good sleep quality (Mauss et al., 2013; Parsons et al., 2021; Tamm et al., 2019; Zhang et al., 2019). However, research on adaptive CER strategy use and sleep has typically been confined to laboratory contexts, where participants may be explicitly taught or encouraged to use a specific CER strategy in response to aversive images or film clips. However, in the real world, individuals need to employ CER strategies spontaneously to cope with salient emotional events. Moreover, laboratory-induced stressors often lack the enduring quality of real-world emotional events, which often necessitates continuous input from adaptive CER strategies in order for emotional responses to be modified successfully. Taken together, we know little about how individuals use adaptive CER strategies spontaneously in response to a real-world protracted stressor and whether this is influenced by sleep quality. This question was addressed by investigating whether mental health outcomes across a prolonged period of stress (i.e. the COVID-19 pandemic) were dependent on adaptive CER strategy use and sleep quality as well as the interaction between these predictors. Using self-report questionnaires, participants estimated their depression and anxiety levels, tendency to engage in adaptive CER strategies, and sleep quality levels during the initial months of the COVID-19 pandemic.

Greater use of adaptive CER strategies and higher sleep quality were significantly associated with lower levels of depression and anxiety. Such findings supported the hypothesis that greater adaptive CER strategy use and higher sleep quality would be associated with lower depression and anxiety, and aligns with previous work (Aldao & Nolen-Hoeksema, 2010; Baglioni, Spiegelhalder, et al., 2010; Domaradzka & Fajkowska, 2018; Freeman et al., 2017; Garnefski et al., 2002; Martin & Dahlen, 2005; A. J. Scott et al., 2021). However, adaptive

CER strategy use was not a significant predictor of self-reported anxiety when accounting for sleep quality in the final model. Moreover, the positive benefits of adaptive CER strategies on depression did not depend on obtaining high sleep quality. This finding did not support the hypothesis that the association between greater use of adaptive CER strategies and lower depression would be stronger in those with high quality sleep. Taken together, these findings build on a large body of laboratory-based work and highlight the potential transdiagnostic benefits of improving both adaptive CER strategy use and sleep quality when enduring periods of prolonged stress.

5.2.2 Chapter 3

A night of sleep deprivation has been shown to increase next-day state anxiety (Babson et al., 2010; Ben Simon et al., 2020; Goldstein et al., 2013), heighten physiological arousal (Franzen et al., 2008, 2009), and enhance sensitivity to perceived threat (Barber & Budnick, 2015; Goldstein-Piekarski et al., 2015; Zenses et al., 2020). However, previous studies have captured threat-related processing at only single points in time and in response to short static threats (e.g. aversive images or film clips). In the real world, emotional experiences often fluctuate in intensity (Hildebrandt et al., 2016), and the nature of threat is not always clear (McCall et al., 2022). Ambiguously threatening environments elicit states of hypervigilance, which may be adaptive in the moment, but if not appropriately regulated following the dissipation of threat, results in pathological anxiety (Grillon, 2008; McCall et al., 2022). We currently know very little about how physiological and subjective arousal unfolds during exposure to prolonged ambiguous threat, and how this might be influenced by sleep deprivation (versus a night of sleep). To address this gap in understanding, real-time physiological arousal was recorded whilst participants navigated through an immersive virtual reality (VR) environment that cycled between periods of ambiguous threat and safety following sleep deprivation or a night of sleep. Subjective arousal responses were also measured during a playback of the experience. By mapping the evolution of arousal over the course of the emotional experience, I examined whether sleep deprivation not only influenced initial reactivity to ambiguous threat but also impaired recovery following the dissipation of threat.

Physiological arousal (as indexed by skin conductance level [SCL]) increased in response to initial threat in both the sleep rested and sleep deprivation conditions. However, during prolonged exposure to threat, SCL remained elevated in sleep deprived individuals whereas SCL declined in sleep rested individuals. This finding supported the hypothesis that sleep deprivation would amplify arousal when exposed to ambiguous threat. However, there were no differences in heart rate (HR) or subjective arousal ratings in those who were sleep deprived compared to sleep rested during exposure to prolonged threat. Interestingly, there were also no differences between sleep deprived and sleep rested participants in the recovery of arousal following ambiguous threat, despite recovery being evident in both conditions. This finding did not support the hypothesis that those who were sleep deprived would show impaired recovery following the dissipation of threat.

Reciprocally, I investigated whether specific properties of sleep restore affect regulation processes. Greater amounts of SWA have been shown to support the overnight reduction of state anxiety (Ben Simon et al., 2020; Chellappa & Aeschbach, 2022) and restore the brain mechanisms critical for affect regulation (Ben Simon et al., 2020; Campbell-Sills et al., 2011). As a result, I examined whether SWA (as quantified using polysomnography [PSG]) was associated with physiological and subjective arousal when participants were exposed to prolonged ambiguous threat.

The findings revealed no associations between SWA and physiological and subjective arousal responses during exposure to prolonged ambiguous threat. This finding did not support the hypothesis that greater SWA would be associated with reduced arousal during exposure to prolonged ambiguous threat and does not align with prior work, which demonstrated an association between SWA and state anxiety (Ben Simon et al., 2020; Chellappa & Aeschbach, 2022). Nonetheless, these findings provide important insights into how a night of sleep regulates physiological arousal in response to threat, improving our understanding of how sleep (or lack of sleep) influences affect regulation when faced with ambiguity regarding the nature of threat.

5.2.3 Chapter 4

Emotional inertia refers to the persistence of an emotional state from one time point to the next. Higher emotional inertia, particularly of negative emotions, has been associated with poorer psychological well-being, including greater depressive and anxiety symptoms (Houben et al., 2015). However, we know little about the mechanisms underlying this association. Prior work suggests that CER strategies play an important role in NA inertia. Greater use of maladaptive CER strategies has been associated with higher NA inertia (Bean et al., 2021; Blanke et al., 2022; Koval et al., 2012). Conversely, frequent use of adaptive CER strategies have been associated with lower emotional inertia (Koval, Butler, et al., 2015). Sleep is another factor which may influence emotional inertia. Although recent studies have begun to examine the association between sleep and emotional inertia (Frérart et al., 2023; Minaeva et al., 2021; X. Wen et al., 2020), these studies have produced mixed findings. One explanation for this might be that studies to date have examined NA inertia using experience sampling methodology (ESM). As ESM affords limited control over the context within which emotional reactions takes place (Koval et al., 2013; Kuppens et al., 2022), we cannot rule out the possibility that individual differences in emotional inertia arise from differences in the intensity of the life events that participants encounter. To address this, I adopted a mood induction procedure (MIP) used in previous work which enabled me to expose participants to a sequence of emotional events, in a fixed order. Building on previous studies, amateur film clips depicting real-life events were used to expose participants to emotional events that they were likely to encounter in the real world. Using this MIP, I examined whether NA inertia was dependent on adaptive CER strategy use and sleep quality as well as the interaction between these predictors. To index NA inertia, participants watched the film clips in a fixed order and rated their NA following each film clip and again after a subsequent rest period following each of the film clips. Using self-report questionnaires, participants estimated their tendency to engage in CER strategies and sleep quality levels to index adaptive and maladaptive CER strategy use and sleep quality, respectively.

Greater use of adaptive CER strategies and high sleep quality were associated with lower NA inertia. Such findings supported the hypothesis that greater use of adaptive CER strategies and high sleep quality would be associated with lower NA inertia, and aligns with prior work (Kuppens, Allen, et al., 2010; X. Wen et al., 2020). Moreover, greater use of maladaptive CER strategies was associated with higher NA inertia. Again this finding supports the hypothesis that greater use of maladaptive CER strategies would be associated with higher NA inertia, and accords with previous studies (Bean et al., 2021; Blanke et al., 2022; Koval, Butler, et al., 2015; Koval et al., 2012). However, the positive benefits of adaptive CER strategies (to lower NA inertia) did not depend on obtaining good sleep quality. This finding did not support the hypothesis that the association between greater use of adaptive CER strategies and lower NA inertia would be stronger among individuals with high sleep quality. The absence of an interaction between adaptive CER strategy use and sleep quality aligns with the findings from Chapter 2. Building on prior work examining NA inertia using ESM, the findings from this study highlight the importance of greater adaptive CER strategy use and high sleep quality as potential targets for reducing the persistence of NA, an important precursor of poorer mental health.

5.3 Theoretical and methodological contributions

The empirical findings from this thesis provide important theoretical and methodological contributions to the literature on emotion regulation and sleep in a number of ways outlined below.

5.3.1 Central role for cognitive control in emotion regulation

The findings from this empirical work support theoretical models that posit a central role for cognitive control in emotion regulation (Ochsner & Gross, 2005; Ochsner et al., 2012). Cognitive control is thought to encompass three distinct executive functioning processes: updating, inhibition and switching (Friedman & Miyake, 2017; Miyake & Friedman, 2012). It can be postulated that each of these is important for the emotion regulation components investigated in this thesis. The findings from Chapter 2 demonstrated the important role of adaptive CER strategies in promoting resilience to depression and anxiety. This association is likely underpinned by the involvement of executive functions to help downregulate negative emotions when adaptive CER strategies are successfully implemented. In particular, evidence supports a role for working memory (i.e. updating) capacity when reappraising negative emotional stimuli (Schmeichel & Demaree, 2010; Schmeichel et al., 2008). This is because during positive reappraisal, individuals need to keep the alternative (less negative) interpretation in mind in order to effectively downregulate negative responses (Sperduti et al., 2017). Relatedly, the findings from Chapter 4 demonstrated an important role for adaptive CER strategies in reducing the persistence of NA over time (i.e. lower emotional inertia). Again, this association may be underpinned by executive functions. As higher NA inertia reflects a tendency for emotions to be resistant to change over time, greater use of adaptive CER strategies may promote the inhibition of negative emotion states, preventing them from spilling over into the next event (Waugh et al., 2017). Together, the findings from this work support a central role for updating and inhibition in adaptive CER strategy use.

Furthermore, the findings from Chapter 3 demonstrated that those who had a night of sleep were better able to regulate their affective response to threat, compared to those who were sleep deprived. From this, it was proposed that sleep supports affect regulation through the involvement of executive functions. Particularly in this context, switching may be important to flexibly regulate arousal when navigating between periods of ambiguous threat and safety. Switching difficulties (i.e. an exaggerated focus on threatening stimuli and a difficultly disengaging from those stimuli) are characteristic of threat bias found in anxiety (Cisler &

Koster, 2010; Hildebrandt et al., 2016). Furthermore, Hildebrandt et al. (2016) demonstrated that participants who had lower switching costs when evaluating the valence of positive stimuli showed better regulation of physiological arousal following the dissipation of threat in a VR world. Together, these findings support the idea that switching may play a pivotal role in affect regulation when responding to and disengaging from threat.

Furthermore, neuroimaging findings support the idea that sleep promotes affect regulation through the involvement of executive functions. Neuroimaging studies on affect regulation consistently report the involvement of prefrontal regions (Buhle et al., 2014; Suzuki & Tanaka, 2021). Critically, sleep deprivation, compared to a night of sleep, decreases medial prefrontal cortex (mPFC) activity, as well as the connectivity between the mPFC and amygdala when viewing negative aversive images or film clips (Ben Simon et al., 2020; van der Helm & Walker, 2012; Yoo et al., 2007). Given that the mPFC is involved in the engagement of cognitive control processes (E. K. Miller, 2000; Niendam et al., 2012; Ochsner & Gross, 2005; Ridderinkhof et al., 2004), it can be argued that sleep deprivation disrupts the prefrontal mechanisms important for cognitive control. Therefore, those who are sleep deprived may be unable to flexibly adapt when exposed to prolonged ambiguous threat.

Given that sleep loss is widely associated with executive control deficits (Drummond et al., 1999; Mograss et al., 2009; Nilsson et al., 2005; Qi et al., 2010; Skurvydas et al., 2020), I expected that the same theoretical framework would underlie the association between sleep and adaptive CER strategy use in Chapters 2 and 4. However, there was no synergistic association between these two predictors in relation to mental health outcomes (Chapter 2) or NA inertia (Chapter 4). Therefore, the positive benefits of adaptive CER strategies were not continent on obtaining good sleep quality. These discrepancies may result from examining the influence of sleep quality rather than sleep deprivation. Prior work has primarily focused on the effects of acute sleep deprivation on executive function performance, with little work supporting a link between poorer sleep quality and impaired executive functioning in neurotypical adults (Minkel et al., 2012). Therefore, sleep quality may have a more nuanced association with emotion regulation compared to sleep deprivation. Alternatively, self-report measures were used to index sleep quality and emotion regulation, rather than objective measures, such as PSG and psychophysiology. The use of objective measures is thought to capture implicit components of emotion regulation, which may be more sensitive to the effects of sleep loss (e.g. physiological arousal) than subjective measures. Nonetheless, the importance of using both subjective and objective measures is discussed in detail in the "Multimethod assessment of emotion regulation and sleep" section.

5.3.2 Cognitive emotion regulation and sleep quality as transdiagnostic predictors of mental health

The findings of this thesis also shed light on the independent influence of adaptive CER strategies and sleep quality on mental health outcomes and NA inertia. Chapter 2 demonstrated that despite greater use of adaptive CER strategies being significantly correlated with higher sleep quality, these predictors independently promoted resilience to depression when enduring prolonged stress. Likewise, the findings from Chapter 4 revealed a significant correlation between greater use of adaptive CER strategy and higher sleep quality; however, these predictors independently contributed to lower NA inertia. Theorists have proposed that sleep disturbance and emotion dysregulation might be reciprocally related factors (Fairholme et al., 2013). On the one hand, sleep disturbance increases negative mood, blunts positive mood and impairs ones' ability to use adaptive CER strategies effectively. Conversely, impaired adaptive CER strategy use and heightened negative mood may increase sleep disturbance (Harvey et al., 2011). This proposal aligns with the mutual maintenance hypothesis, which argues that sleep disturbance and emotion dysregulation might be mutually maintaining factors, with each contributing uniquely to the aetiology and maintenance of psychopathology (Fairholme et al., 2013; Harvey et al., 2011).

Practically, these findings encourage the development of prevention and intervention programmes focussed on improving adaptive CER strategy use and sleep quality. For example, techniques such as cognitive behavioural therapy (CBT) and cognitive behavioural therapy for insomnia (CBT-I) may be potential therapeutic avenues for promoting both adaptive CER strategy use (Hayes, 2008; S. G. Hofmann & Asmundson, 2008) and sleep quality (Muench et al., 2022). Importantly, these treatment programmes have potentially broad diagnostic applicability given the relevance of these factors across a range of psychopathology symptoms.

5.3.3 Multimethod assessment of emotion regulation and sleep

A multimethod approach was adopted in this thesis, using subjective and objective measures to index both emotion regulation and sleep. Previous studies have found only weak-to-moderate associations between subjective experiences and physiological responses to emotion-eliciting stimuli (Hollenstein & Lanteigne, 2014; Mauss & Robinson, 2009). Moreover, Mauss and Robinson (2009) stated that both subjective and objective measures are important for understanding emotional responding and cannot be assumed to be interchangeable. Subjective reports of emotion regulation are important for capturing individual differences outside of the laboratory. However, they may require an element of cognitive introspection if retrospective (Mauss & Robinson, 2009). On the other hand, objective measures tend to capture fine-grained implicit emotion regulation processes in response to laboratory based stimuli (Bradley & Lang, 2007; Cunningham et al., 2014; Franzen et al., 2009; Tempesta et al., 2020). Therefore, these measures likely tap into different constructs and have different levels of sensitivity. In Chapter 2, emotion regulation was indexed using a self-report questionnaire (CERQ-short). This allowed me to examine whether individual differences in self-reported adaptive CER strategy use in daily life were associated with sleep quality and mental health outcomes. In Chapter 3, emotion regulation was indexed by measuring real-time physiological and subjective arousal responses, allowing the assessment of implicit and retrospective reports of arousal, respectively, in response to prolonged threat. The findings from this study suggested that physiological arousal was more sensitive to the effects of sleep deprivation than subjective arousal. Finally, in Chapter 4, emotion regulation was measured using in-the-moment self-report ratings of affect to index NA inertia. From this, I examined whether individual differences in NA inertia in response to naturalistic film clips were associated with adaptive CER strategies and sleep quality. Overall, the use of multiple measures to assess emotion regulation has advanced our knowledge of how individual differences in emotion regulation and implicit emotion regulation processes are influenced by sleep.

With regard to sleep measures, prior work has demonstrated that self-reported sleep quality is often lower than that indicated by objective measures of sleep continuity or wake-after-sleep onset (Baker et al., 1999; Buysse et al., 2008; Grandner et al., 2006). However, long periods of sustained wakefulness are rare in real-world settings; therefore, measuring subjective sleep quality helps capture individual differences in sleep that are commonly experienced day-to-day (Minkel et al., 2012). Nonetheless, sleep deprivation paradigms can uncover various aspects of sleep function per se as well as provide valuable insights into the influence of sleep loss on emotion regulation. In Chapters 2 and 4, self-report questionnaires were used to index sleep quality (PSQI). This enabled me to examine whether the associations between adaptive CER strategies and mental health outcomes (Chapter 2) and NA inertia (Chapter 4) were influenced by individual differences in naturally varying levels of sleep quality. In Chapter 3, PSG was employed to measure SWA. From this, I was able to examine the impact of acute sleep loss on affect regulation as well as the mechanistic role of SWA in regulatory control. Therefore, the inclusion of multiple methods to measure sleep has led to a broader understanding of how individual differences in sleep quality, certain properties of sleep, and acute sleep loss influence emotion regulation and mental health.

5.3.4 Capturing the dynamic nature of emotion regulation

Emotion dynamics involves studying how the physiological, subjective, and behavioural components of emotion fluctuate over time (Kuppens & Verduyn, 2015). Despite the dynamic nature of emotions, studies have largely assessed emotion regulation at single points in time (Kuppens & Verduyn, 2015, 2017). However, in this thesis I examined how emotional responses unfold over time, as outlined below.

In Chapter 2, I examined adaptive CER strategy use over several months in response to a protracted stressor. It was expected that this stressor would require continuous input from adaptive CER strategies in order for emotional responses to be modified successfully. The findings revealed that the associations between greater adaptive CER strategy use, high sleep quality and lower depression and anxiety remained stable during the initial months of the COVID-19 pandemic. Such findings demonstrate the robust positive impacts of adaptive CER strategies and sleep quality on mental health outcomes when dealing with sustained emotional hardship.

In Chapter 3, real-time measurements of physiological and subjective arousal were collected whilst participants were exposed to a prolonged threatening experience that cycled between periods of ambiguous threat and safety. From this, I examined not only initial arousal responses to prolonged threat but also arousal responses once the initial threat has dissipated. I found that a night of sleep (versus sleep deprivation) promotes the regulation of physiological arousal when exposed to prolonged threat but does not influence the recovery of arousal following the dissipation of threat. The findings from this study provide important insights into the regulation of arousal over the course of an emotional experience.

Finally, in Chapter 4, I examined one of the key features of the emotion trajectory, emotional inertia. This study assessed the degree to which an emotion state carried over from one time point to the next when participants were exposed to a standardised sequence of emotional events. The findings demonstrated that greater use of adaptive CER strategies and high sleep quality were associated with lower NA inertia. This study highlights the importance of adaptive CER strategies and sleep quality when predicting the persistence of negative emotion states over time. Collectively, the findings from this thesis have advanced our understanding of the mechanisms by which sleep supports emotion regulation as it unfolds over time.

5.4 Limitations and future directions

Although each chapter acknowledges the limitations of the associated work, several general limitations should be noted. Nonetheless, these limitations highlight interesting avenues for future research.

5.4.1 Dichotomisation of adaptive and maladaptive CER strategies

Throughout this thesis, CER strategies were dichotomised as putatively adaptive or maladaptive using composite scores. Whilst this provided a useful framework for examining how sleep is associated with CER strategy use, there are situations in which what is considered adaptive or maladaptive may vary.

According to the strategy-situation-fit hypothesis, CER strategies are adaptive only when used in appropriate contexts (Aldao et al., 2015; Bonanno & Burton, 2013; McRae, 2016). For instance, the effectiveness of positive reappraisal (an adaptive CER strategy) may depend on the controllability of the situation (Haines et al., 2016; Troy et al., 2013, 2017). Troy et al. (2013) demonstrated that positive reappraisal success was associated with lower levels of depression when participants' recent life stressors were relatively uncontrollable (e.g. a loved one's illness). However, when recent life stressors were relatively controllable (e.g. potential job loss due to poor performance), positive reappraisal success was associated with higher levels of depression (Troy et al., 2013). These findings suggest that positive reappraisal may only be adaptive when modifying emotional responses to an uncontrollable stressor.

In relation to this thesis, in Chapter 2, adaptive CER strategy use was examined within the context of the COVID-19 pandemic. The initial months of the COVID-19 pandemic were characterised by both uncontrollable (e.g. being made redundant, contracting the virus) and controllable (e.g. staying connected to family and friends, exposure to media coverage of the virus) stressors (Coiro et al., 2021). If participants were using adaptive CER strategies, including positive reappraisal, following controllable stressors this may have increased depression and anxiety levels, relative to if they were using adaptive CER strategies in response to uncontrollable stressors. Although the results showed that greater adaptive CER strategy use was associated with lower depression and anxiety, this association was not contingent on high sleep quality. As the 'adaptiveness' of emotion regulation was not fully captured, as I did not account for the controllability of stressors, this may have tempered any association with sleep quality.

The effectiveness of CER strategies may also depend on the nature of the emotion to be regulated. For example, positive reappraisal tends to be less effective when dealing with high-intensity emotional situations (Sheppes & Levin, 2013; Sheppes & Meiran, 2007; Sheppes et al., 2014). Sheppes and Meiran (2007) found that positive reappraisal is less effective at downregulating negative emotions in highly intense emotional situations. In addition, Sheppes et al. (2014) revealed that in high (versus low) intensity negative situations, participants preferred to use distraction over positive reappraisal. Accordingly, it has been suggested that during positive reappraisal, conflict arises between the initial (often negative) appraisal and the new less negative appraisal. Therefore, as the intensity of an emotional situation increases, it becomes more difficult to override the initial appraisal of the situation (Ortner et al., 2016). Together, these findings suggest that positive reappraisal may only be adaptive in response to low-intensity stressors.

In the context of this work, in Chapter 3, arousal responses were measured as participants navigated through threatening and non-threatening environments following a night of sleep or sleep deprivation. It is possible that sleep deprived participants found the threatening parts more emotionally intense than the non-threatening parts. As adaptive CER strategy use is less effective when dealing with high-intensity emotional situations, this may explain why there was no influence of adaptive CER strategy use on arousal regulation during the threatening parts of the VR world but there was a buffering effect of adaptive CER strategy use on arousal responses in the non-threatening parts. Moreover, in Chapter 4, participants were exposed to a mixture of negative, positive and neutral film clips. It is possible that the use of adaptive CER strategies was less effective at reducing NA in response to the highly negative film clips compared to the positive and neutral film clips as they were more emotionally intense. Similar to the findings from Chapter 2, although there was as association between greater adaptive CER strategy use and lower NA inertia, this association was not contingent on high sleep quality, again suggesting that this association may have been tempered.

To address these issues, future research could examine how sleep supports the flexibility of adaptive CER strategy use (i.e. the ability to implement and adjust CER strategies based on context; Aldao et al., 2015; Bonanno & Burton, 2013). For example, Battaglini et al. (2022) found that greater context sensitivity and greater responsivity to feedback in the selection of adaptive CER strategies was associated with adaptive affective outcomes such as reduced NA. The flexibility of adaptive CER strategy use could be examined using daily diaries where participants are not only asked about the CER strategies they use in response to a negative event, but also about the type of events they experience, the controllability of the perceived events and the intensity of the events encountered. These could then be used as moderators when examining the associations between adaptive CER strategy use, sleep and mental health. For example, it could be hypothesised that in Chapter 2, controllability of a stressor would moderate the association between adaptive CER strategy use and depression and anxiety and that this association would be stronger among those with high levels of sleep quality.

In addition, the categorisation of adaptive and maladaptive CER strategies prevented us from determining whether a specific strategy (or a smaller combination of strategies) influenced mental health outcomes (Chapter 2), arousal regulation (Chapter 3), and/or NA inertia (Chapter 4). As such, future work should examine naturally occurring combinations of CER strategies (i.e. CER repertoires). For example, in each of my studies, statistical analysis methods, such as hierarchical K-means clustering could be used to identify the most common CER strategy combinations, which could be added as predictors to the linear mixed models (LMMs). From this, it could be established whether certain cluster profiles are more strongly associated with mental health outcomes, as in previous work (Waterschoot et al., 2022), arousal regulation, and NA inertia, and whether these predictors are influenced by sleep. This analysis allows us to consider the interplay between different CER strategies, beyond the constraints of classifying them as putatively adaptive or maladaptive.

5.4.2 Reciprocal mechanisms by which emotion regulation supports sleep

This thesis has focused on the mechanisms by which sleep supports emotion regulation and mental health. Nonetheless, evidence suggests a bidirectional association between sleep and emotion regulation, with poor sleep impairing emotion regulation ability and emotion dysregulation leading to disrupted sleep (R. Gruber & Cassoff, 2014).

Some studies have demonstrated that CER strategy use influences subsequent sleep (Guastella & Moulds, 2007; Thomsen et al., 2003; Vandekerckhove et al., 2012). For instance, Thomsen et al. (2003) found that greater use of habitual rumination was significantly associated with poorer sleep quality. Importantly, this association remained significant after controlling for negative mood. Guastella and Moulds (2007) advanced on this work by instructing participants to ruminate about a negative event prior to sleep. They found that individuals in the rumination condition, who also had high levels of trait rumination, reported poorer sleep quality than low-trait ruminators. Furthermore, Vandekerckhove et al. (2012) used PSG to compare the effects of using an experiential CER strategy (focusing on downregulating the feelings associated with the emotional experience) versus an analytical CER strategy (focusing on cognitive thinking instead of the feelings associated with an emotional experience) following negative feedback prior to a night of sleep. Although participants in the experiential CER strategy condition had a longer sleep latency, they had fewer awakenings, longer sleep duration, and higher sleep efficiency compared to those in the analytical CER strategy condition. Together, these findings suggest that using maladaptive CER strategies, such as an analytic CER strategy, negatively impacts sleep quality, whereas using adaptive CER strategies, such as an experiential CER strategy, increases sleep latency but reduces subsequent sleep disturbance.

Heightened emotional reactivity can also negatively influence sleep (Fairholme & Manber, 2015). Evidence for this comes from research examining responses to stressful events that elicit negative valence and high arousal. Stress has been shown to increase sleep latency and night awakenings, decrease sleep efficiency, and decrease SWS and rapid eye movement (REM) sleep duration (Fairholme & Manber, 2015; E. J. Kim & Dimsdale, 2007). Furthermore, the induction of pre-sleep arousal results in longer sleep latency and shorter sleep duration following a nap period (Tang & Harvey, 2004). Collectively, these findings suggest that heightened emotional reactivity contributes to poor sleep quality and duration.

No studies have directly examined the influence of emotional inertia on sleep. However, evening mood has been shown to influence overnight sleep (Takano et al., 2012, 2014; Vandekerckhove et al., 2011). Vandekerckhove et al. (2011) found that induced negative mood was associated with increased sleep fragmentation and decreased sleep efficiency. Moreover, higher levels of repetitive thoughts in the evening have been associated with reduced sleep quality (Takano et al., 2012, 2014). In light of these findings, we would expect higher NA inertia to negatively impact sleep.

As the influence of emotion regulation on sleep has received much less attention than vice versa, it would be fruitful to examine these pathways concurrently in future work. Given the significant correlations between adaptive CER strategy use and sleep quality reported in Chapters 2 and 4, there is clear motivation to explore these associations. Moving beyond examining unidirectional associations in LMMs, a more complex methodology, such as structural equation modelling (SEM), would allow us to simultaneously estimate the relationships between emotion regulation and sleep, as well as bidirectional associations. For example, in Chapter 4, the use of SEM would help establish whether there is a unidirectional or bidirectional association between NA inertia and sleep quality.

5.4.3 Individual differences as critical moderators of the association between sleep and emotion regulation

Individual differences can influence how sleep supports emotion regulation. Below, I discuss how age and sex are likely to serve as critical moderators in this relationship.

First, age may moderate the association between sleep and emotion regulation. Older age has been associated with poorer sleep quality (Buysse et al., 1991; Madrid-Valero et al., 2017). Nonetheless, older adults tend to use adaptive CER strategies, such as positive reappraisal, more frequently compared to younger adults (Gross & John, 2003). McRae et al. (2012) also found improvements in emotion regulation ability with age. Alongside this, they also demonstrated age-related increases in activation of the left ventrolateral PFC and left inferior frontal gyrus during a positive reappraisal task. These results imply that the ability to implement positive reappraisal improves with age due to increased activation of prefrontal brain regions during emotion regulation (Schmeichel & Tang, 2015). In addition, D. P. Smith et al. (2005) found that older adults, compared to younger adults, subjectively rated images as more arousing and had an increased startle blink in response to negative images. However, physiological reactivity to these images (i.e. electromyography [EMG] activity and heart rate deceleration [HRD]) was lower than that of younger adults. It is possible that older adults experienced heightened subjective arousal and startle-blink responses as they found negative images (e.g. images of threat and grief) to be more personally relevant, whereas lower physiological responses may reflect a decline in cardiovascular physiology (D. P. Smith et al., 2005). Older adults have also been shown to display lower NA inertia but higher positive affect (PA) inertia than younger adults in a study which assessed the day-to-day persistence of self-reported affect (Hamaker et al., 2018). Taken together, age seems to influence not only sleep but also the components of emotion regulation investigated in this thesis. In Chapter 2, the participant sample encompassed a broad age range (18–90 years). However, the participant samples in Chapters 3 and 4 only included young adults (aged 18–30 years). Therefore, further research is needed establish the moderating influence of age when examining associations between sleep, emotional reactivity, and NA inertia.

Sex is another factor which may moderate the association between sleep and emotion regulation. Sleep problems are more prevalent in females compared to males (Buysse et al., 1991; Middelkoop et al., 1996). It has also been demonstrated that females use adaptive CER strategies, such as positive reframing, less frequently than males do (Costa Martins et al., 2016; Kelly et al., 2008). With regard to emotional reactivity, females have been shown to display higher levels of subjective arousal, greater HRD, and larger startle responses to unpleasant stimuli compared to males (Bianchin & Angrilli, 2012). This heightened emotional reactivity in females is thought to reflect greater susceptibility to negative life events and lower mood (Bianchin & Angrilli, 2012). Sex was also found to moderate the association between depression and PA inertia, such that the persistence of PA over time (i.e. higher PA inertia) was higher among depressed compared to non-depressed females, whereas there was no difference in PA inertia between depressed and non-depressed males (Nelson et al., 2020). However, sex did not significantly influence the inertia of NA. These sex differences may be explained by differences in brain activation in emotion-related limbic and prefrontal regions, which are critical for affect regulation. For example, Domes et al. (2010) showed greater amygdala activity in response to aversive stimuli along with increased activity in small clusters of the prefrontal cortex (PFC) and temporal cortex in females than in males. Moreover, females demonstrate lower activation than males in the orbitofrontal cortex, anterior cingulate cortex (ACC), and dorsolateral PFC when instructed to decrease emotional reactions (Domes et al., 2010). As sleep deprivation has been shown to increase amygdala activity and reduce PFC activity when viewing aversive images and film clips (Ben Simon et al., 2020; van der Helm & Walker, 2012; Yoo et al., 2007), it is possible that females are more sensitive to the effects of poor sleep than males, resulting in a greater loss of regulatory control in response to emotional events. Although sex was added as a covariate to the LMMs in Chapter 2, the sample was highly skewed towards female participants (80%), meaning that we were unlikely to find any effects if they did exist. Therefore, as females appear to have poorer sleep quality and greater difficulties with emotion regulation, it would be fruitful for future work to examine possible sex influences on the association between sleep and emotion regulation.

5.4.4 Influence of sleep on other emotion dynamics

It is important to note that Dejonckheere et al. (2019) identified 16 different indicators of emotion dynamics; however, only emotional inertia was examined in this thesis. Two of the most common indices of emotion dynamics, which are often contrasted with emotional inertia, are the standard deviation (SD) and the mean squared successive difference (MSSD). The SD is considered a measure of variability and reflects the extent to which an individual's emotion state fluctuates from its emotional baseline over a given period of time (Koval et al., 2021). In contrast, the MSSD assesses the average magnitude of moment-to-moment fluctuations in an individual's emotion state and is considered a measure of instability (Koval et al., 2021). Although the interrelations between these emotion dynamics are relatively complex, higher levels of instability seem to result from a combination of high variability and low inertia (Jahng et al., 2008).

Several studies have examined the association between sleep and emotional variability, and, as with the literature on emotional inertia, they have produced mixed findings (Leger et al., 2019; Song et al., 2023; X. Wen et al., 2020). For example, Leger et al. (2019) found that both greater NA and PA variability were associated with poorer sleep. However, when adjusting for mean NA levels, NA variability was no longer significantly associated with poorer sleep. Similarly, X. Wen et al. (2020) demonstrated no significant association between NA variability and sleep duration. However, Song et al. (2023) found that higher NA variability was associated with poor sleep quality beyond daily levels of NA. These discrepant findings may be due to use of ESM to measure emotional inertia. As discussed in Chapter 4, ESM does not consider the emotional events that participants encounter day-to-day which may contribute to individual differences in NA inertia. Interestingly, no studies have yet examined the association between emotional instability and sleep. Based on prior work and the findings from Chapter 4, it is likely that higher NA instability is associated with poor sleep. Nonetheless, this highlights an important gap that should be addressed in future research. The association between sleep and other emotion dynamics, such as NA instability, could be examined using the same MIP employed in Chapter 4 to help control for the emotional events that participants encounter.

Furthermore, different measures of affect dynamics often tend to be studied in isolation, as emotional inertia was in Chapter 4. It has been argued that this may lead to inconsistent conclusions regarding what aspects of emotion dynamics contribute to psychological maladjustment (Dejonckheere et al., 2019); is it higher emotional inertia, greater emotional variability or higher emotional instability? These measures were independently associated with lower mental health outcomes in a previous meta-analysis (Houben et al., 2015). In a similar vein, future work should examine which indicators of emotion dynamics are more strongly associated with sleep by using techniques such as multilevel meta-analysis, which compares the predictive accuracy of various multilevel models (Dejonckheere et al., 2019).

5.5 Conclusion

Across each empirical chapter, this thesis explored the cognitive mechanisms by which sleep supports emotion regulation and mental health. First, I investigated whether sleep supports mental health through adaptive CER strategy use, finding that greater use of adaptive CER strategies and high sleep quality independently promoted resilience to depression, but not anxiety (Chapter 2). However, the positive benefits of adaptive CER strategy use on depression was not contingent on high sleep quality. Second, I examined whether sleep supports emotion regulation through emotional reactivity, demonstrating that sleep promotes the regulation of physiological arousal during exposure to prolonged ambiguous threat (Chapter 3). However, SWA was not associated with this regulatory control. Finally, I examined whether sleep supports emotion regulation through emotional inertia, finding that greater use of adaptive CER strategies and high sleep quality independently predicted lower NA inertia (Chapter 4). However, the positive benefits of adaptive CER strategy use on NA inertia was not contingent on high sleep quality. The theoretical and methodological contributions discussed in this chapter offer new insights into the underlying processes by which sleep contributes to successful emotion regulation and optimum mental health, and conversely, how poor sleep contributes to emotion dysregulation and mental ill-health. The limitations discussed outline key issues that can be addressed in future research. Other interesting avenues for future research were also discussed. Given the links between sleep, emotion regulation, and mental health, the findings from this thesis point towards modifiable mechanisms, such as promoting the use of adaptive CER strategies and improving sleep quality, which can help alleviate poorer mental health outcomes, particularly in relation to depression and anxiety.

Appendices

Supplementary Materials: Chapter 2

Table A.1. Additional demographic characteristics of the depression and anxiety samples.

	Depression sample	Anxiety sample
N	**551**	**590**
Age		
Mean	39.12	38.49
Standard deviation	17.07	16.89
Biological sex		
Female	457	489
Male	94	101
Gender		
Female	449	481
Male	89	96
Non-binary/third-gender	2	2
Prefer to self-describe	4	4
Prefer not to say	1	1
Unknown	6	6
Race		
African American	9	11
Asian	37	45
White	458	487
Hispanic/Latinx	10	10
More than one race/Prefer to self-describe	31	32
Prefer not to say	4	3
Unknown	2	2
Ethnicity		
Hispanic	24	27
Not Hispanic	519	554

Prefer not to say	7	7
Unknown	1	2
Mental Health Disorder*		
Yes	119	126
No	432	464
Serious Medical Problems		
Yes	49	50
No	502	540
Highest Education Level		
Some high school	1	1
High school diploma/GED	10	10
Some college	64	72
Bachelor’s degree	148	160
Some post-bachelor education	54	56
Graduate, medical or professional degree	274	291
Marital Status		
Single	154	172
In a relationship	138	149
Married	217	225
Divorced/separated	28	30
Widowed	14	14
Student		
Yes	111	124
No	440	466
Currently employed (if not student)		
Yes	342	363
No	98	103
Household Income		
$0-$25,000	30	33
$25,001-$50,000	89	92

$50,001-$75,000	99	107
$75,001-$100,000	89	101
$100,001-$150,000	106	112
$150,001-$250,000	80	88
$250,000+	58	57

*Mental health disorder is not limited to depression and anxiety.

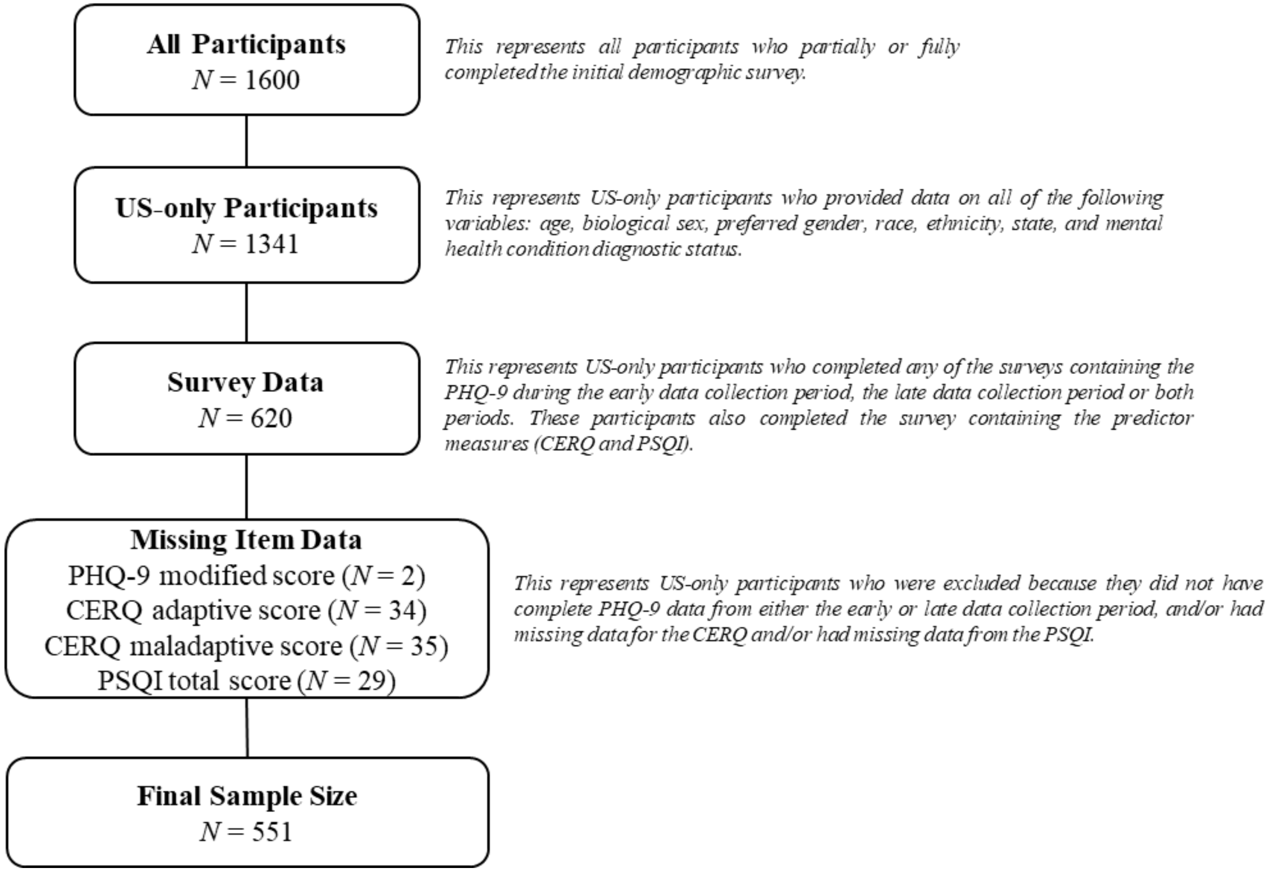

Figure A.1. Flow chart outlining participant exclusions for the depression sample.

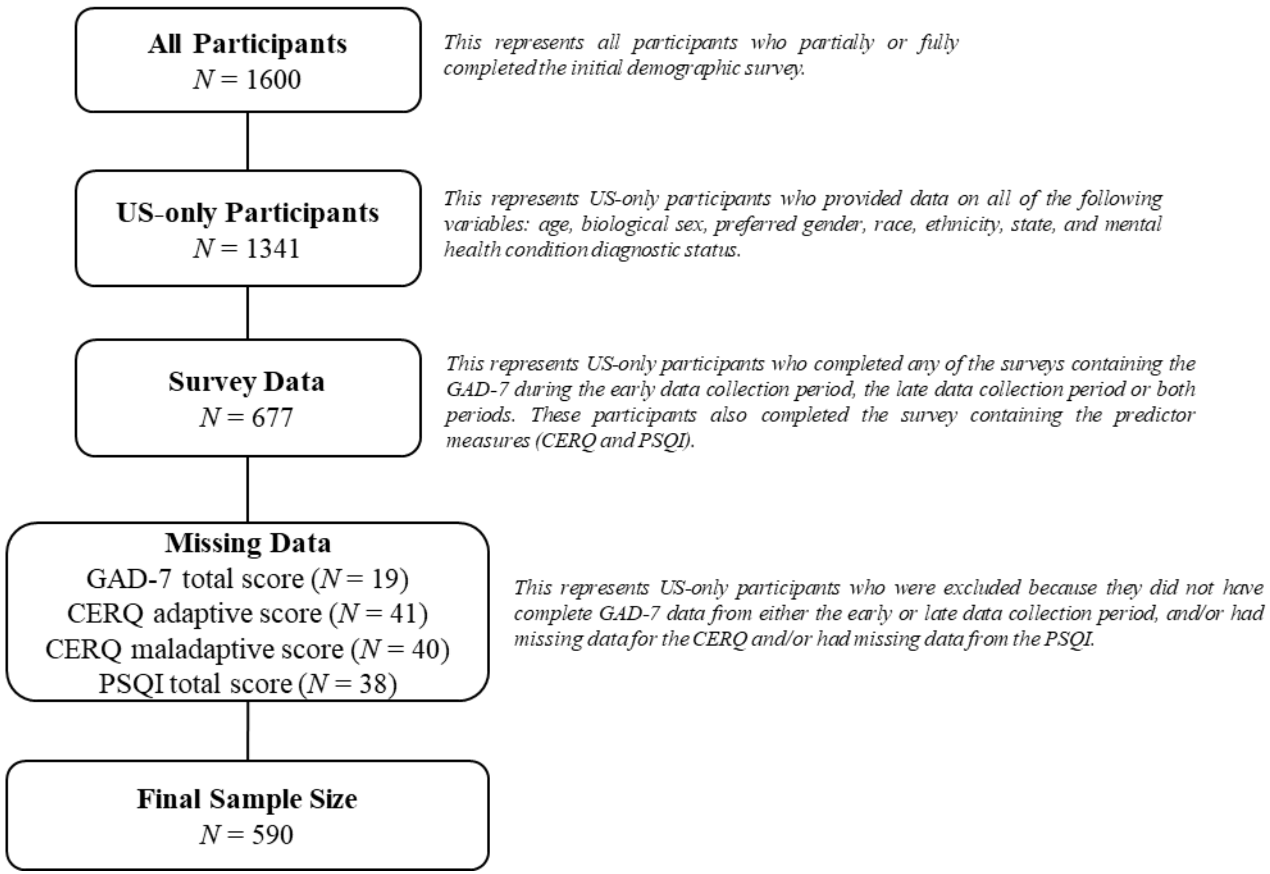

Figure A.2. Flow chart outlining participant exclusions for the anxiety sample.

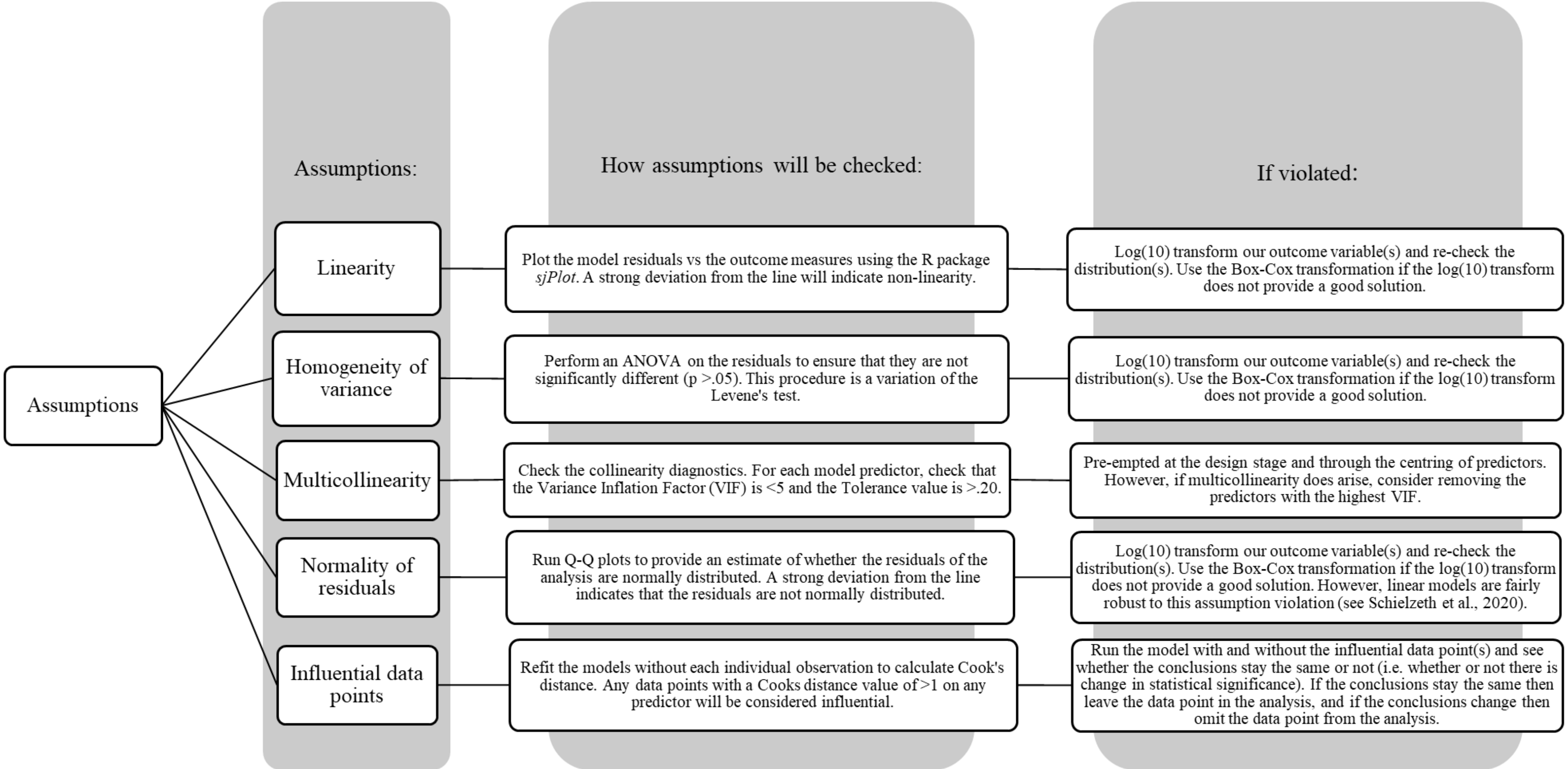

Figure A.3. Flowchart of how each assumption of linear mixed models was investigated and which transformation was applied if an assumption was violated.

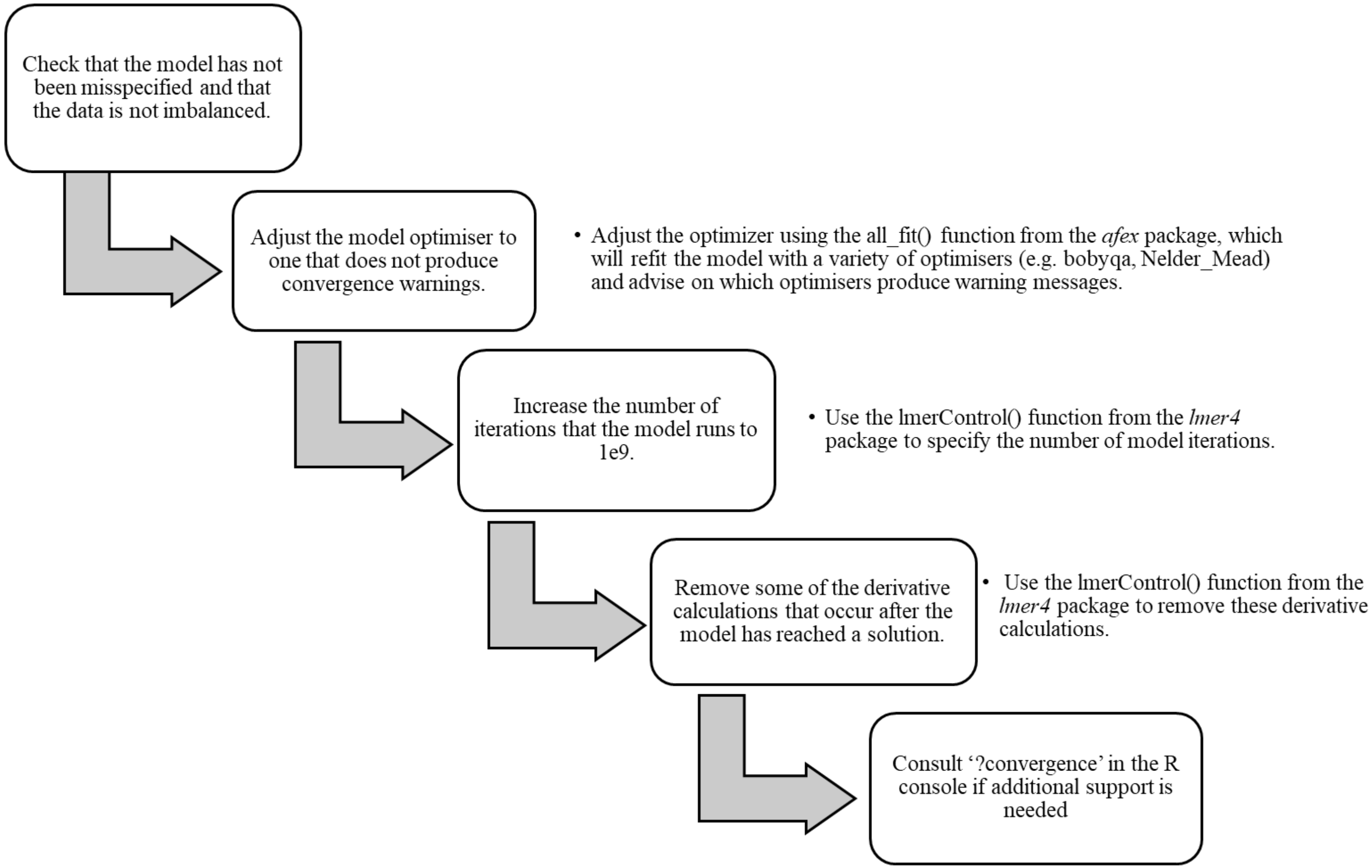

Figure A.4. Workflow for non-convergence. This is ordered hierarchically such that if one step did not solve the convergence problem, we moved on to the next.

Table A.2. Non-standardised and standardised parameter estimates entered into the power analysis simulations (obtained from the pilot sample).

	Depression		Anxiety	
	B *[SE]*	**β** *[SE]*	**B** *[SE]*	**β** *[SE]*
Model 2				
Intercept	8.15 *[0.72]*	0.17 *[0.13]*	7.78 *[0.74]*	0.18 *[0.13]*
Age	−0.10 *[0.04]*	−0.25 *[0.09]*	−0.08 *[0.04]*	−0.18 *[0.09]*
Sex	−0.39 *[1.19]*	−0.07 *[0.22]*	0.74 *[1.25]*	0.14 *[0.23]*
Mental Health Diagnosis	−3.70 *[1.23]*	−0.69 *[0.23]*	−2.94 *[1.22]*	−0.54 *[0.22]*
Time	−1.80 *[0.54]*	−0.33 *[0.10]*	−1.49 *[0.73]*	−0.27 *[0.13]*
Adaptive CER Strategy Use	−0.09 *[0.14]*	−0.11 *[0.16]*	0.06 *[0.14]*	0.07 *[0.16]*
Time × Adaptive CER Strategy Use	−0.04 *[0.06]*	−0.04 *[0.07]*	0.01 *[0.08]*	0.01 *[0.09]*
Model 3				
Intercept	7.65 *[0.69]*	0.08 *[0.13]*	8.11 *[0.72]*	0.24 *[0.13]*
Age	−0.03 *[0.03]*	−0.08 *[0.09]*	0.01 *[0.04]*	0.03 *[0.09]*
Sex	−0.42 *[1.03]*	−0.08 *[0.19]*	0.11 *[1.14]*	0.02 *[0.21]*
Mental Health Diagnosis	−1.68 *[1.20]*	−0.31 *[0.22]*	−1.28 *[1.19]*	−0.23 *[0.22]*
Time	−1.62 *[0.67]*	−0.30 *[0.12]*	−1.17 *[0.85]*	−0.21 *[0.15]*
Adaptive CER Strategy Use	−0.05 *[0.15]*	−0.06 *[0.17]*	−0.05 *[0.16]*	−0.06 *[0.18]*
Sleep Quality	1.15 *[0.24]*	0.65 *[0.14]*	1.08 *[0.26]*	0.63 *[0.15]*
Time × Adaptive CER Strategy Use	−0.18 *[0.12]*	−0.21 *[0.13]*	−0.15 *[0.18]*	−0.17 *[0.20]*

Time × Sleep Quality	0.02 *[0.25]*	0.01 *[0.14]*	−0.09 *[0.31]*	−0.05 *[0.18]*
Adaptive CER Strategy Use × Sleep Quality	−0.09 *[0.06]*	−0.33 *[0.19]*	−0.13 *[0.06]*	−0.48 *[0.20]*
Time × Adaptive CER Strategy Use × Sleep Quality	−0.05 *[.03]*	−0.16 *[0.09]*	−0.06 *[0.03]*	−0.20 *[0.11]*

B = Non-standardised ES, β = Standardised ES.

Table A.3. Proportion and 95% confidence interval of the number of times that the Model 3 simulation analysis produced a false positive when excluding the effect sizes of interest. Values are shown for both the non-standardised and standardised models.

	Depression		**Anxiety**	
Proportion of false positives	**Non-standardised** *[CIs]*	**Standardised** *[CIs]*	**Non-standardised** *[CIs]*	**Standardised** *[CIs]*
Model 3				
Time	0.02 *[0.01–0.03]*	0.02 *[0.01–0.03]*	0.01 *[0.01–0.02]*	0.02 *[0.01–0.03]*
Adaptive CER Strategy Use	0.02 *[0.01–0.02]*	0.02 *[0.01–0.03]*	0.01 *[0.01–0.02]*	0.02 *[0.01–0.03]*
Sleep Quality	0.02 *[0.01–0.03]*	0.02 *[0.01–0.02]*	0.03 *[0.02–0.04]*	0.02 *[0.01–0.03]*
Time × Adaptive CER Strategy Use	0.02 *[0.01–0.03]*	0.02 *[0.01–0.03]*	0.02 *[0.01–0.03]*	0.02 *[0.01–0.02]*
Time × Sleep Quality	0.03 *[0.02–0.04]*	0.02 *[0.01–0.03]*	0.02 *[0.01–0.03]*	0.02 *[0.01–0.02]*
Adaptive CER Strategy Use × Sleep Quality	0.02 *[0.01–0.03]*	0.01 *[0.01–0.02]*	0.07 *[0.05–0.08]*	0.03 *[0.02–0.04]*
Time × Adaptive CER Strategy Use × Sleep Quality	0.02 *[0.01–0.02]*	0.02 *[0.01–0.03]*	0.01 *[0.01–0.02]*	0.01 *[0.01–0.02]*

Maladaptive CER strategies

In this exploratory analysis, we included maladaptive CER strategy use and sleep quality as predictors of depression and anxiety. The statistical analysis was identical to our main analysis except that maladaptive CER strategy use was entered as a predictor in Models 2 and 3 instead of adaptive CER strategy use. Correlational analyses indicated no significant relationship between the frequency of adaptive CER strategy use and maladaptive CER strategy use in either the depression (r_s = .06, p = 1) or anxiety datasets (r_s = .06, p = 1; see Figure A.5). However, there was a significant association between maladaptive CER strategy use and sleep quality in both the depression and anxiety datasets (r_s = .14, p = .001; r_s = .17, p < .001, respectively), such that greater use of maladaptive CER strategies was associated with poorer sleep quality (higher scores on the PSQI).

Model 1, effect of time: There was a main effect of time on depression (B = −0.25 [−0.37, −0.14], p < .001, d = 0.46), such that depression decreased from Spring to Autumn 2020. However, there was no main effect of time on anxiety (B = 0.04 [−0.08, 0.16], p = .706, d = 0.07). Age significantly predicted both depression (B = −0.01 [−0.01, 0.00], p = .045, d = 0.22) and anxiety (B = −0.01 [−0.02, −0.01], p = .001, d = 0.31), such that increased age was associated with lower depression and anxiety symptoms. There was no main effect of biological sex (female/male) on either depression (B = −0.03 [−0.33, 0.27], p = .898, d = 0.02) or anxiety (B = −0.24 [−0.54, 0.06], p = .331, d = 0.13). For both depression and anxiety, there was a main effect of current mental health diagnosis (yes/no; B = −0.76 [−1.03, −0.49], p < .001, d = 0.45; B = −0.74 [−1.01, −0.46], p < .001, d = 0.42, respectively): those with a diagnosed mental health condition had significantly higher depression and anxiety compared to those without diagnosed mental illness.

Model 2, effect of time and maladaptive CER strategy use: The outcomes for Model 2 are illustrated in Figure A.6. For depression, there was a main effect of maladaptive CER strategy use (B = 0.08 [0.05, 0.10], p < .001, d = 0.55, BF_{10} > 100), but no significant interaction between maladaptive CER strategy use and time (B = −0.01 [−0.03, 0.02], p = .752, d = 0.05, BF_{10} = 0.23). Therefore, greater use of maladaptive CER strategies was associated with higher depression, irrespective of time. For anxiety, there was also a main effect of maladaptive CER strategy use (B = 0.08 [0.16, 0.10], p < .001, d = 0.59, BF_{10} > 100) and a significant interaction between maladaptive CER strategy use and time (B = −0.04 [−0.06, −0.01], p = .014, d = 0.30, BF_{10} = 16.95), such that greater use of maladaptive CER strategies was associated with higher anxiety, and this relationship was most pronounced in the initial stages of the pandemic (Spring 2020). These findings are consistent with previous work demonstrating a link between greater use of maladaptive CER strategies and higher levels of depression and anxiety (Aldao & Nolen-Hoeksema, 2012b; Aldao et al., 2010; Domaradzka & Fajkowska, 2018; Garnefski et al., 2002; McLaughlin & Nolen-Hoeksema, 2011; Nolen-Hoeksema et al., 2008).

Model 3, effect of time, maladaptive CER strategy use and sleep quality: The outcomes for Model 3 are illustrated in Figure A.7. The effect of maladaptive CER strategy use on depression and anxiety reported in Model 2 remained significant (B = 0.05 [0.03, 0.07], p < .001, d = 0.39; B = 0.06 [0.04, 0.08], p < .001, d = 0.43, respectively). There was a main effect of sleep quality on both depression (B = 0.21 [0.18, 0.24], p < .001, d = 1.13, BF > 100) and anxiety (B = 0.17 [0.14, 0.21], p < .001, d = 0.87, BF_{10} > 100), such that higher sleep quality was associated with lower depression and anxiety. There was no interaction between sleep quality and time or sleep quality and maladaptive CER strategy use on either depression (B = −0.02 [−0.06, 0.02], p =.571, d = 0.11, BF_{10} = 0.15; B = 0.00 [−0.01, 0.00], p = .635, d = 0.07, BF_{10} = 0.18, respectively) or anxiety (B = −0.04 [−0.07, 0.00], p = .255, d = 0.18, BF_{10} = 2.12; B = 0.00 [−0.01, 0.01], p = .889, d = 0.02, BF_{10} = 0.14, respectively). In addition, there was no significant three-way interaction between time, maladaptive CER strategy use and sleep quality on depression (B = 0.00 [−0.01, 0.01], p = .740, d = 0.06, BF_{10} < .01) or anxiety (B = 0.00 [−0.01, 0.00], p = .430, d = 0.12, BF_{10} = 0.87). These results complement our main study findings and suggest that both adaptive and maladaptive CER strategies contribute to depression and anxiety symptoms. However, the association between emotion regulation strategy use and mental health outcomes (depression and anxiety) does not appear to be influenced by naturally varying levels of sleep quality.

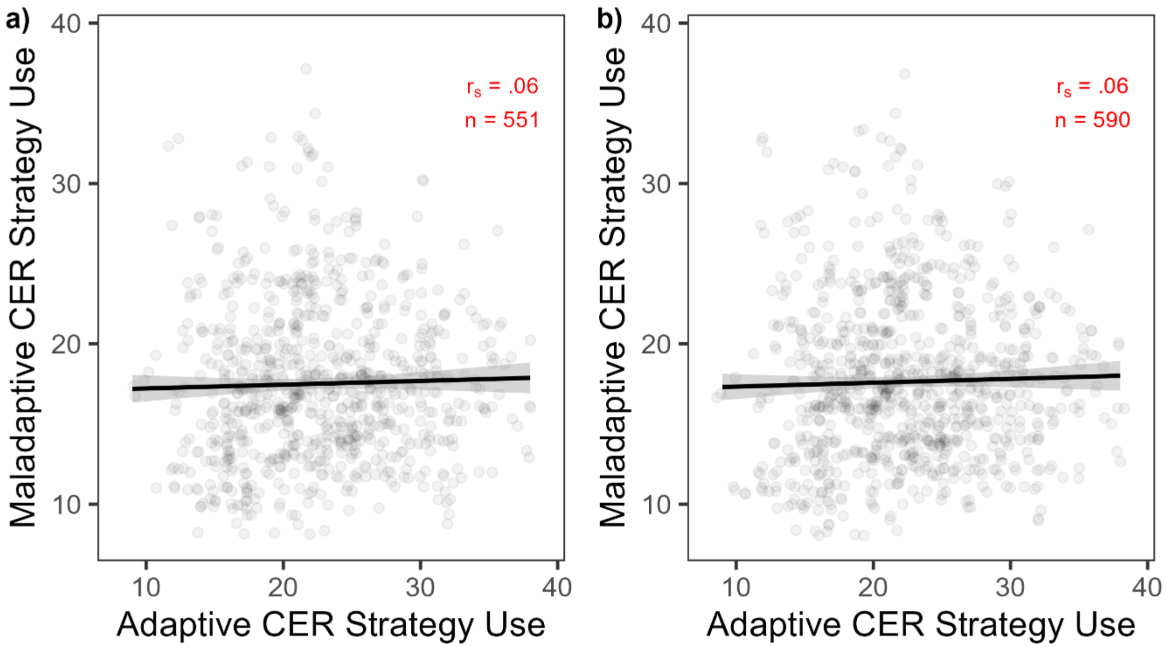

Figure A.5. There was no significant association between adaptive CER strategy use and maladaptive CER strategy use in either a) the depression or b) anxiety dataset. Grey areas represent 95% confidence intervals. Multiple comparisons correction was applied using Holm's method (Hochberg, 1988).

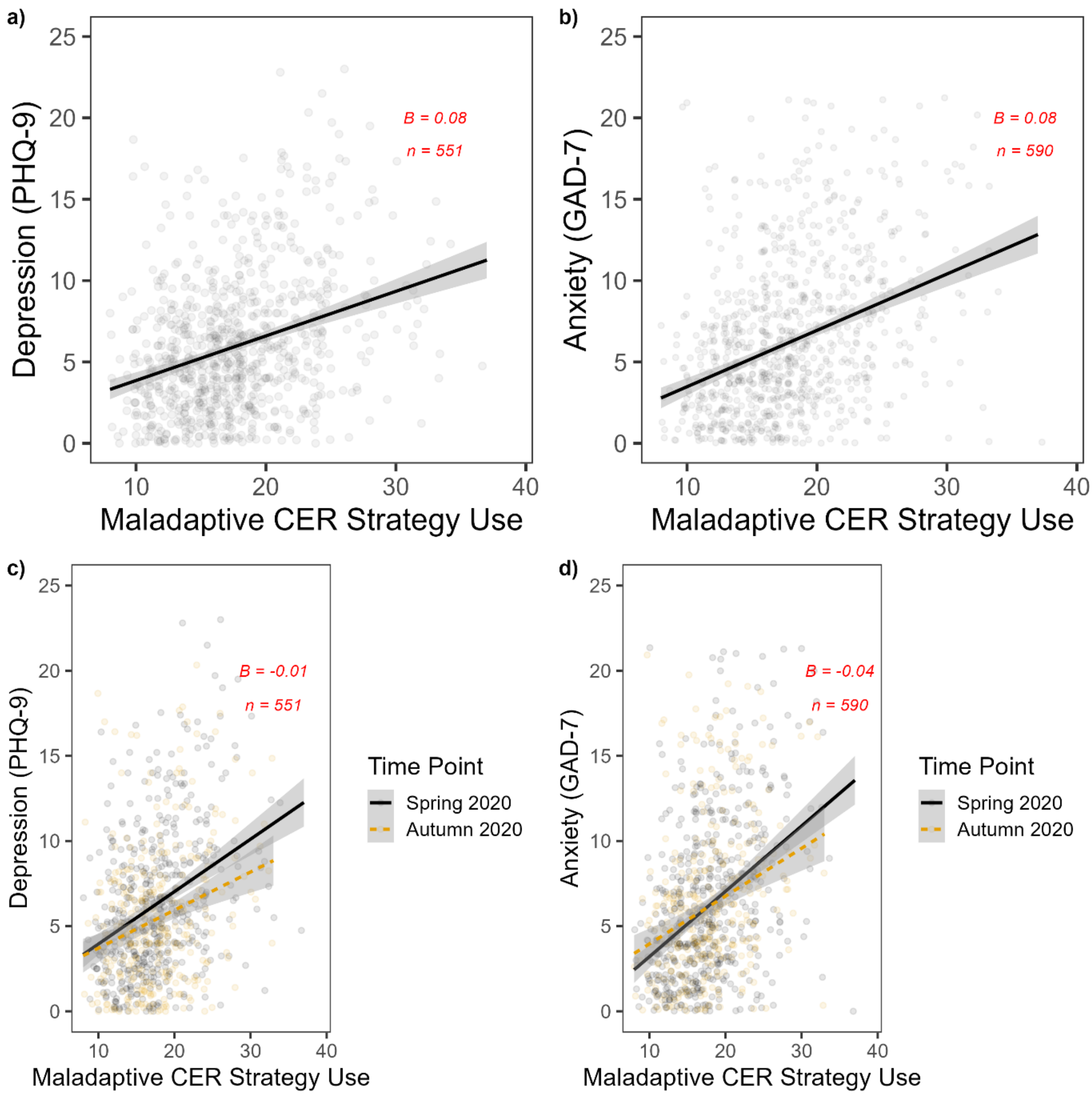

Figure A.6. Greater use of maladaptive CER strategies was significantly associated with a) higher depression and b) anxiety across both timepoints (Spring and Autumn 2020). There was no significant interaction between maladaptive CER strategy use and time on c) depression, but a significant interaction between maladaptive CER strategy use and time did emerge for d) anxiety (black line = Spring 2020; dashed line = Autumn 2020). The relationship between maladaptive CER strategy use and anxiety was more pronounced in the initial stages of the pandemic (Spring 2020), as compared to the later stages (Autumn 2020). Grey areas represent 95% confidence intervals. Non-transformed outcomes are shown for visualisation purposes.

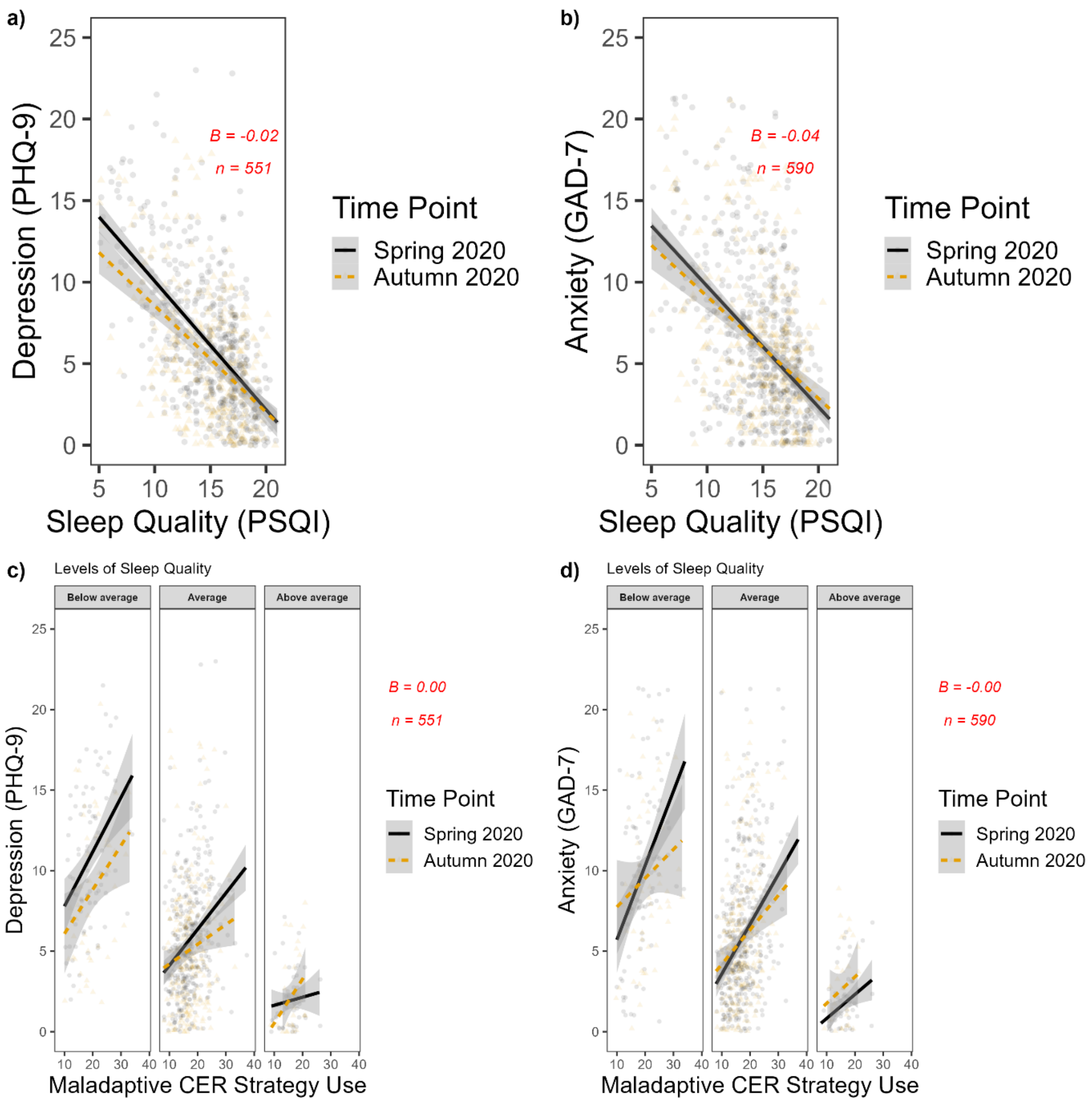

Figure A.7. Higher sleep quality was significantly associated with a) lower depression and b) anxiety over time (black line = Spring 2020; dashed line = Autumn 2020). Sleep quality scores have been inverted for visualisation purposes such that higher scores represent higher sleep quality. There was no significant interaction between maladaptive CER strategy use, sleep quality and time on c) self-reported depression or d) anxiety. Data are plotted at different levels of sleep quality (mean and at $\pm$ 1 SD). Grey areas represent 95% confidence intervals. Non-transformed outcomes are shown for visualisation purposes.

Race

Given the influence of race on mental health outcomes during the COVID-19 pandemic (Czeisler et al., 2020; Wu et al., 2021), we re-ran our models but included race as a covariate. Because there were a low number of participants from different racial minorities, race was dichotomised into white and non-white. For our depression dataset, 16.9% were non-white (83.1% white) and for our anxiety dataset 17.5% were non-white (82.5% white).

Model 1, effect of time: There was a main effect of time on depression (B = −0.25 [−0.37, −0.13], p < .001, d = 0.46), such that depression decreased from Spring to Autumn 2020. However, there was no main effect of time on anxiety (B = 0.04 [−0.08, 0.16], p = .785, d = 0.07). Age did not significantly predict depression (B = −0.01 [−0.02, 0.00], p = .078, d = 0.21) but was a significant predictor of anxiety (B = −0.01 [−0.02, −0.01], p = .001, d = 0.33), such that increased age was associated with lower anxiety symptoms. There was no main effect of biological sex (female/male) on either depression (B = −0.03 [−0.33, 0.27], p = .987, d = 0.02) or anxiety (B = −0.24 [−0.53, 0.06], p = .524, d = 0.12). For both depression and anxiety, there was a main effect of current mental health diagnosis (yes/no; B = −0.76 [−1.04, −0.49], p < .001, d = 0.45; B = −0.73 [−1.01, −0.46], p < .001, d = 0.42, respectively): those with a diagnosed mental health condition had significantly higher depression and anxiety than individuals without diagnosed mental illness. There was no main effect of race (white/non-white) on depression or anxiety (B = 0.01 [−0.30, 0.32], p = .987, d < 0.01; B = −0.14 [−0.45, 0.17], p = .785, d = 0.07, respectively).

Model 2, effect of time and adaptive CER strategy use: For depression, there was a main effect of adaptive CER strategy use (B = −0.05 [−0.07, −0.03], p < .001, d = 0.47, BF_{10} > 100) but no significant interaction between adaptive CER strategy use and time (B = −0.01 [−0.03, 0.01], p = .518, d = 0.12, BF_{10} = 0.16). For anxiety, there was also a main effect of adaptive CER strategy use (B = −0.03 [−0.05, −0.02], p = .003, d = 0.29, BF_{10} > 100) but, again, no significant interaction between adaptive CER strategy use and time (B = 0.00 [−0.02, 0.02], p = .911, d = 0.02, BF_{10} = 0.14). Therefore, greater use of adaptive CER strategies was associated with lower depression and anxiety, irrespective of time. Race was not a significant predictor of depression (B = 0.04 [−0.27, 0.34], p = .987, d = 0.02) or anxiety (B = −0.11 [−0.42, 0.19], p = .785, d = 0.06).

Model 3, effect of time, adaptive CER strategy use and sleep quality: For depression, the effect of adaptive CER strategy use reported in Model 2 remained significant in this expanded model ($B = -0.03$ [−0.05, −0.01], $p = .004$, d = 0.29). However, for anxiety, the effect of adaptive CER strategy use was no longer significant ($B = -0.02$ [−0.03, 0.00], $p = .366$, d = 0.15). There was a main effect of sleep quality on both depression ($B = 0.21$ [0.18, 0.24], $p < .001$, d = 1.18, $BF_{10} > 100$) and anxiety ($B = 0.19$ [0.16, 0.22], $p < .001$, d = 0.93, $BF_{10} > 100$), such that higher sleep quality was associated with lower depression and anxiety. There was no interaction between sleep quality and time or sleep quality and adaptive CER strategy use on either depression ($B = -0.03$ [−0.07, 0.01], $p = .332$, d = 0.17, $BF_{10} = 0.14$; $B = 0.00$ [−0.01, 0.00], $p = .809$, d = 0.05, $BF_{10} = 0.13$, respectively) or anxiety ($B = -0.05$ [−0.08, −0.01], $p = .112$, d = 0.23, $BF_{10} = 2.05$; $B = 0.00$ [−0.01, 0.01], $p = .912$, d = 0.01, $BF_{10} = 0.18$, respectively). In addition, there was no significant three-way interaction between time, adaptive CER strategy use and sleep quality on either depression ($B = -0.01$ [−0.01, 0.00], $p = .332$, d = 0.16, $BF_{10} < 0.01$) or anxiety ($B = 0.00$ [−0.01, 0.01], $p = .862$, d = 0.04, $BF_{10} < 0.01$). In sum, our models were not influenced by participant race. However, as our sample was predominantly white (83.1% for depression and 82.5% for anxiety), we are limited in the extent to which we were able to capture the experiences of individuals from racial minorities.

Mental health diagnosis

We ran an exploratory analysis excluding individuals who reported having a diagnosed mental health condition. Our models were identical to those performed in the main analysis, with the exception that current mental health diagnosis was removed as a covariate. The sample sizes for the depression and anxiety datasets were $N = 432$ and $N = 464$, respectively.

Model 1, effect of time: For depression, there was a main effect of time ($B = -0.19$ [−0.31, −0.07], $p = .012$, d = 0.38), such that depression decreased from Spring to Autumn 2020. However, for anxiety, there was no main effect of time ($B = 0.06$ [−0.06, 0.18], $p = .695$, d = 0.11). Age significantly predicted both depression ($B = -0.01$ [−0.02, 0.00], $p = .037$, d = 0.26) and anxiety ($B = -0.01$ [−0.02, −0.01], $p = .001$, d = 0.37), such that increased age was associated with lower depression and anxiety. There was no main effect of biological sex (female/male) on either depression ($B = -0.04$ [−0.33, 0.26], $p = .942$, d = 0.02) or anxiety ($B = -0.21$ [−0.50, 0.08], $p = .455$, d = 0.13).

Model 2, effect of time and adaptive CER strategy use: For depression, there was a main effect of adaptive CER strategy use ($B = -0.06$ [−0.08, −0.04], $p < .001$, d = 0.56, $BF_{10} > 100$) but no significant interaction between adaptive CER strategy use and time ($B = -0.02$ [−0.04, 0.00], $p = .274$, d = 0.20, $BF_{10} = 0.38$). For anxiety, there was also a main effect of adaptive CER strategy use (B = −0.04 [−0.06, −0.02], p = .001, d = 0.35, BF_{10} > 100) but, again, no significant interaction between adaptive CER strategy use and time (B = 0.00 [−0.02, 0.02], p = .899, d = 0.02, BF_{10} = 0.13). Thus, greater use of adaptive CER strategies was associated with lower depression and anxiety over time when not accounting for mental health diagnosis.

Model 3, effect of time, adaptive CER strategy use and sleep quality: The effect of adaptive CER strategy use on depression reported in Model 2 remained significant (B = −0.04 [−0.05 −0.02], p < .001, d = 0.41). However, the effect of adaptive CER strategy use on anxiety was no longer significant in this expanded model (B = −0.02 [−0.04, 0.00], p = .103, d = 0.22). There was a main effect of sleep quality on both depression (B = 0.19 [0.16, 0.22], p < .001, d = 1.16, BF_{10} > 100) and anxiety (B = 0.17 [0.14, 0.20], p < .001, d = 0.94, BF_{10} > 100), such that higher sleep quality was associated with lower depression and anxiety. There was no interaction between sleep quality and time or sleep quality and adaptive CER strategy use on either depression (B = −0.02 [−0.06, 0.01], p =.487, d = 0.14, BF_{10} = 0.10; B = 0.00 [0.01, 0.00], p = .942, d = 0.03, BF_{10} = 0.13, respectively) or anxiety (B = −0.03 [−0.07, 0.00], p = .288, d = 0.20, BF_{10} = 0.28; B = 0.00 [−0.01, 0.00], p = .899, d = 0.03, BF_{10} = 0.15, respectively). In addition, there was no significant three-way interaction between time, adaptive CER strategy use and sleep quality on either depression (B = 0.00 [−0.01, 0.00], p = .487, d = 0.13, BF_{10} < 0.01) or anxiety (B = 0.00 [−0.01, 0.00], p = .772, d = 0.10, BF_{10} < 0.01). In sum, these results demonstrate that our study findings did not differ when those with a current mental health diagnosis were excluded from the analyses.

Negative experience of the pandemic

We also conducted an exploratory analysis on only participants who reported having a negative experience of the pandemic. This information was collected from a one-time survey administered between 26th February 2021 and the 7th April 2021. Participants were asked to rate their experience during the COVID-19 pandemic from 1 [*Entirely Negative*] to 7 [*Entirely Positive*]. Only participants with scores of $\leq$ 3 on this item were included in our analyses. Our sample sizes were N = 156 (20.5% reported a current diagnosed mental health condition) for the depression dataset and N = 155 (20.6% reported a current diagnosed mental health condition) for the anxiety dataset. We ran the same models as in our main analysis with this subset of participants.

Model 1, effect of time: There was no main effect of time on depression (*B* = −0.20 [−0.39, −0.01], p = .286, d = 0.37) or anxiety (*B* = −0.01 [−0.27, 0.25], p = .987, d = 0.01). Age was not a significant predictor of depression (*B* = −0.01 [−0.02, 0.00], p = .472, d = 0.20) or anxiety (*B* = −0.01 [−0.03, 0.00], p = .514, d = 0.25). There was no main effect of biological sex (female/male) on depression (*B* = 0.32 [−0.24, 0.87], p = .543, d = 0.18) or anxiety (*B* = −0.31 [−0.99, 0.37], p = .657, d = 0.14). For the depression, there was a main effect of current mental health diagnosis (yes/no; *B* = −0.90 [−1.40, −0.41], p = .008, d = 0.57). Those with a diagnosed mental health condition had significantly higher depression compared to those with no mental illness. However, there was no main effect of current mental health diagnosis on anxiety (*B* = −0.87 [−1.48, −0.26], p = .095, d = 0.46).

Model 2, effect of time and adaptive CER strategy use: For depression, there was no significant effect of adaptive CER strategy use (*B* = −0.04 [−0.08, 0.00], p = .297, d = 0.31, BF_{10} = 1.59) and no significant interaction between adaptive CER strategy use and time (*B* = −0.01 [−0.05, 0.03], p = .953, d = 0.08, BF_{10} = 0.21). For anxiety, there was no significant effect of adaptive CER strategy use (*B* = −0.03 [−0.08, 0.02], p = .596, d = 0.20, BF_{10} = 0.70) and, again, there was no significant interaction between adaptive CER strategy use and time (*B* = −0.02 [−0.07, 0.03], p = .657, d = 0.15, BF_{10} = 0.29). Therefore, frequency of adaptive CER strategy use was no longer a significant predictor of depression and anxiety, unlike our main analysis.

Model 3, Effect of time, adaptive CER strategy use and sleep quality: For depression and anxiety, the effect of adaptive CER strategy use remained non-significant (*B* = −0.03 [−0.07, 0.00], p = .297, d = 0.32; *B* = −0.03 [−0.07, 0.01], p = .596, d = 0.22, respectively). There was a main effect of sleep quality on both depression (*B* = 0.21 [0.17, 0.26], p < .001, d = 1.44, BF_{10} > 100) and anxiety (*B* = 0.23 [0.16, 0.29], p < .001, d = 1.10, BF_{10} > 100), such that higher sleep quality was associated with lower depression and anxiety. There was no interaction between sleep quality and time or sleep quality and adaptive CER strategy use on either depression (*B* = 0.00 [−0.05, 0.06], p =.953, d = 0.02, BF_{10} = 0.12; *B* = 0.00 [−0.01, 0.01], p = .905, d = 0.08, BF_{10} = 0.22, respectively) or anxiety (*B* = −0.08 [−0.15, 0.00], p = .415, d = 0.32, BF_{10} = 1.08; *B* = 0.00 [−0.02, 0.01], p = .907, d = 0.06, BF_{10} = 0.27, respectively). In addition, there was no significant three-way interaction between time, adaptive CER strategy use and sleep quality on either depression (*B* = 0.00 [−0.01, 0.01], p = .953, d = 0.01, BF_{10} < 0.01) or anxiety (*B* = −0.01 [−0.03, 0.01], p = .625, d = 0.19, BF_{10} = 0.03).

Supplementary Materials: Chapter 4

Table A.4. Description of amateur film clips used in the mood induction procedure.

Selected film clip	**Novel or existing database**	**Film duration (in seconds)**	**One sentence film description**	**Mean valence (1-9)**	**Mean arousal (1-9)**	**Mean familiarity (prop)**	**YouTube link**
San Francisco sidewalk (practice trial - *neutral*)	Novel	31	Footage walking down a sidewalk in San Francisco.	5.13	3.88	0.00	https://youtu.be/hXCzAAYl6zo
1. School boy recounting bullying (*negative*)	Novel	44	Tearful son recounting being bullied at middle school.	2.00	6.13	0.07	https://youtu.be/kz1xzBYppW8?si=pSziNSh9BM-yV5BQ
2. Nepal earthquake (*negative*)	Novel	43	Multiple perspectives from the moment the devastating earthquake hit Nepal.	2.40	6.00	0.00	https://youtu.be/pfMMWzv89m0
3. BART train (*neutral*)	Novel	17	San Francisco Bay Area Rapid Transit (BART) pulling in to a station.	4.73	4.27	0.00	https://youtu.be/nMqUQdHzIy8
4. Baby evil eye (*positive*)	Existing	18	Baby in high chair makes evil look at everyone and starts laughing only to do it again.	7.40	3.87	0.07	https://youtu.be/MLVfBYwnXq4

5. London underground (*neutral*)	Novel	32	Doors closing and the tube departing from Embankment station.	4.80	4.33	0.00	https://youtu.be/d2g9HlwoC-s
6. Starving children Yemen (*negative*)	Novel	26	BBC news report on starving children in Yemen.	1.87	6.07	0.00	https://youtu.be/J_6fDCo1REI?si=-ckOXFNUkchixXlh
7. Thirsty baby drinks (*positive*)	Existing	22	Baby tries to drink from a garden hose.	7.33	4.40	0.07	https://youtu.be/a5lKucggtuI
8. Singing dog (*positive*)	Existing	28	Dog is singing to melody from iPad.	7.13	4.40	0.00	https://youtu.be/Mk4bmK-acEM
9. Tsunami Indonesia (*negative*)	Novel	44	Footage of a tsunami slamming into the Indonesian city of Palu on Sulawesi island after a major earthquake.	2.60	6.00	0.00	https://youtu.be/T7r6ex4WnkQ
10. Boy fails hula hoop (*positive*)	Existing	19	Baby tries to hula hoop without the hula hoop - just wiggles hips around while everyone laughs.	6.80	4.33	0.00	https://youtu.be/bK1EKdDCOX0

The database for the existing film clips can be found here: Samson, A. C., Kreibig, S. D., Soderstrom, B., Wade, A. A., & Gross, J. J. (2016). Eliciting positive, negative and mixed emotional states: A film library for affective scientists. *Cognition and emotion*, *30*(5), 827-856. https://doi.org/10.1080/02699931.2015.1031089

Table A.5. Coefficients and 95% confidence intervals from the raw multilevel models for which the random slope was removed due to non-convergence.

	Fixed effect		
Model	**Estimate *(SE)***	**95% CI**	***p***
Preliminary			
NA Inertia (Raw)	**0.24 (*0.01*)**	**0.21–0.27**	**< .001**
Adaptive CER Strategy Use			
NA Inertia (Raw)	**−0.04 (*0.01*)**	**−0.07–−0.01**	**.010**
Maladaptive CER Strategy Use			
NA Inertia (Raw)	*NA*	*NA*	*NA*
Sleep Quality			
NA Inertia (Raw)	*NA*	*NA*	*NA*
Adaptive CER Strategy Use × Sleep Quality			
NA Inertia (Raw)	−0.03 (*0.01*)	−0.05–0.00	.101
Maladaptive CER Strategy Use × Sleep Quality			
NA Inertia (Raw)	*NA*	*NA*	*NA*

NA indicates model converged with the inclusion of random slopes. Statistically significant coefficients are shown in bold.

Table A.6. Coefficients and 95% confidence intervals from the standardised multilevel models for which the random slope was removed due to non-convergence.

	Fixed effect		
Model	**Estimate *(SE)***	**95% CI**	***p***
Preliminary			
NA Inertia (Standardised)	**0.16 (*0.01*)**	**0.14–0.19**	**< .001**
Adaptive CER Strategy Use			
NA Inertia (Standardised)	−0.02 (*0.01*)	−0.05–0.01	.197
Maladaptive CER Strategy Use			
NA Inertia (Standardised)	0.03 (*0.01*)	0.00–0.05	.149
Sleep Quality			
NA Inertia (Standardised)	**0.04 (*0.01*)**	**0.01–0.07**	**.007**
Adaptive CER Strategy Use × Sleep Quality			
NA Inertia (Standardised)	−0.02 (*0.01*)	−0.05−0.00	.230
Maladaptive CER Strategy Use × Sleep Quality			
NA Inertia (Standardised)	0.01 (*0.01*)	−0.02–0.04	.783

Note. For each of our standardised models, a random effects structure encompassing both the random slope and intercept yielded a singular fit. Removal of the random slope still resulted in a singular fit due to the random intercept exhibiting negligible variance, implying a lack of participant-specific variability. Despite this, we retained the random intercept to align with the within-person design, acknowledging that it did not affect model estimates. This inclusion of the random intercept ensures that the model appropriately reflects the study design without compromising estimation accuracy and ensures that the same model was used for both the raw and standardised models. Statistically significant coefficients are shown in bold.

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