The Persistence of Involuntary Memory:

Analyzing Phenomenology, Links to Mental Health, and Content

by

Ryan Christopher Yeung

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Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner	Dr. Donna Rose Addis Professor Department of Psychology, University of Toronto; Senior Scientist, Rotman Research Institute, Baycrest Health Sciences
Supervisor	Dr. Myra A. Fernandes Professor Department of Psychology University of Waterloo
Internal Members	Dr. David A. Moscovitch Professor Department of Psychology University of Waterloo
	Dr. Christine Purdon Professor Department of Psychology University of Waterloo
Internal-External Examiner	Dr. John McLevey Associate Professor Department of Knowledge Integration University of Waterloo

Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

In daily life, memories of one's personal past are often retrieved involuntarily (i.e., unintentionally and effortlessly). Termed involuntary autobiographical memories (IAMs), recent evidence suggests that these are often *recurrent* (i.e., the same event is remembered repetitively), though controversy surrounds their basic nature. Some research suggests that they are mostly positive or benign, whereas others suggest that they directly contribute to mental health disorders. Here, we show that while recurrent IAMs are common and frequent in general populations, they consistently predict symptoms of mental health disorders. In Study 1, we characterized recurrent IAMs in a large-scale survey of undergraduates. Most participants had experienced recurrent IAMs within the past year (52%), most of which were self-rated as negative in valence (52%). Experiencing negative recurrent IAMs predicted significantly more symptoms of depression, posttraumatic stress, social anxiety, and general anxiety. In Studies 2a and 2b, we examined whether age and trait emotion regulation might modulate recurrent IAMs, because older adults are well-known to have enhanced emotion regulation compared to younger adults. Results indicated that age (Study 2a) reversed the valence distribution: younger adults' recurrent IAMs were mostly negative, whereas older adults' were mostly positive. Further, trait emotion regulation (Study 2b) also modulated valence in a sample of younger adults: high emotion regulators were significantly less likely to report negative recurrent IAMs. Regardless of age or trait emotion regulation, experiencing negative recurrent IAMs again predicted greater symptoms of mental health disorders. In Study 3, we asked how analyzing content (e.g., written descriptions of recurrent IAMs) might expand our understanding of these memories, beyond self-reported valence ratings. We developed the first adaptation of computational methods (e.g., machine learning) to understand autobiographical memory content, enabling us to discover content categories ("topics") in recurrent IAMs. We found that participants experienced recurrent IAMs about a variety of events, ranging from the mundane to the extreme. In Study 4, we extended this computational approach to measure how content might predict mental health above and beyond self-reported valence ratings. Results indicated that elevated symptoms of each disorder were uniquely related to recurrent IAMs about specific topics. Our results suggest that it is imprecise to say that negative recurrent IAMs are related to increased symptoms – our current work pinpoints which specific topics in recurrent IAMs predict mental health. This dissertation

provides insight into the nature of recurrent IAMs in large samples of general populations. Importantly, this dissertation distinguishes how these memories and their relationships to mental health are modulated by individual differences. Finally, this dissertation provides a novel framework and methodology (e.g., computational text analysis) for analyzing autobiographical memory content in concert with phenomenology, opening avenues for research to be conducted at an unprecedented scope and scale.

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When I was a kid, I used to worry that I'd never say anything worthwhile, since everything meaningful had already been said better by somebody else, somewhere, at some point in history. Yeah, I know – weird thing for a child to worry about. But inexplicably, the feeling gripped me then, and it grips me today.

Despite my better judgment, I've decided to say a few things in the intervening years. In fact, this document alone is over a hundred pages of me saying things.

Have I said anything worthwhile?

I suppose that's up to you to decide.

But your own verdict notwithstanding, let me admit something: a number of people have started to change my mind. They have taught me to trust my voice, to love my craft, and to see a place for myself in the vastness of it all. And for that, I will always be grateful.

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Dedication

To the boy who felt too much,
spoke too little,
and never figured out when to give up:

This one’s for you.

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Chapter 1:
General Introduction

> I feel something start within me, something that leaves its resting-place and attempts to rise, something that has been embedded like an anchor at a great depth; I do not know yet what it is, but I can feel it mounting slowly; I can measure the resistance, I can hear the echo of great spaces traversed.
>
> —Marcel Proust, *In Search of Lost Time*

Since the dawn of memory research, scholars have acknowledged that episodes from one's personal past (autobiographical memories; AMs) can be retrieved using one of many basic modes of remembering (Ebbinghaus, 1885/2013). One of these modes involves *voluntary* retrieval: the individual makes a conscious attempt to retrieve the episode. For example, to remember where you put your keys, you might engage in a deliberate, effortful search process to reconstruct the events that occurred as you first returned home that day (Tulving, 1983). In contrast, another mode of remembering is *involuntary* retrieval: the individual makes no conscious attempt to retrieve the episode. In these cases, the episode seems to just pop into awareness; retrieval is unintentional and effortless (Berntsen, 1996). Common examples of these involuntary memories include tastes or smells suddenly evoking memories associated with those sensations. Perhaps the most well-known of these examples comes from the French author Marcel Proust's novel, *In Search of Lost Time* (1913–1927/1992). In it, Proust describes a character eating a madeleine cake dipped in tea, the taste of which immediately and unintentionally elicits a strong emotional response. As the character narrates, "an exquisite pleasure had invaded my senses, something isolated, detached, with no suggestion of its origin" (Proust, 1913–1927/1992, p. 60). This feeling soon unfolds into a rich and detailed autobiographical memory. Despite having made no attempt to retrieve any event, the character vividly relives the Sunday mornings of his childhood, when he would greet his aunt Léonie and she would give him pieces of tea-soaked madeleine cakes in return.

Termed involuntary autobiographical memories (IAMs), these experiences of spontaneously remembering the personal past exist beyond the realm of fiction – almost a century after the writings of Ebbinghaus (1885/2013) and Proust (1913–1927/1992), IAMs are now being studied empirically. Within the last few decades, researchers have found that large and diverse samples report experiencing IAMs (Ball & Little, 2006; Berntsen, 2010; Brewin, Christodoulides, & Hutchinson, 1996; Mace, 2004; Rasmussen & Berntsen, 2011; Rubin & Berntsen, 2009; Yoshizumi & Murase, 2007). In fact, some evidence suggests that IAMs outnumber voluntary AMs in everyday life (Rasmussen & Berntsen, 2011).

Based on these findings, a current model by Berntsen (2010) argues that IAMs are (1) universal to all people with intact autobiographical memory, (2) frequent in daily life, (3) reliant on the same episodic memory system as voluntary AMs, and (4) typically functional rather than dysfunctional. Indeed, this literature has grown to suggest that IAMs are related, but conceptually distinct from other forms of spontaneous thought (Berntsen, 2021) and reconstructive in nature, much like voluntary AMs (Berntsen & Nielsen, 2021).

Interestingly, IAMs are sometimes *recurrent*: that is, the IAM is subjectively experienced as being repetitive (e.g., IAMs of the same event multiple times). Seminal work from Berntsen & Rubin (2008) found that these recurrent IAMs (also known as recurrent involuntary memories or recurrent memories) were quite similar to nonrecurrent IAMs in a variety of ways. First, participants from the general public largely ascribed positive emotional valence to their recurrent IAMs (58%), prompting the conclusion that "recurrent involuntary memories typically do not favor negative material" (Berntsen & Rubin, 2008, p. 458), much akin to nonrecurrent IAMs (Berntsen, 1996; Berntsen & Rubin, 2002) and voluntary AMs (Walker et al., 2003). Second, recurrent IAMs often focused on the most emotionally arousing moments of events, echoing findings that highly emotional material is typically prominent in nonrecurrent IAMs (Berntsen, 1996) as well as voluntary AMs (McGaugh, 2013; Robinson, 1976). Third, recurrent IAMs usually shifted in terms of the exact slices of time and details remembered. In other words, although the same events were reexperienced in these recurrent IAMs, they were rarely the exact same segments of the event in question; recurrent IAMs appeared to be reconstructed, rather than duplicates of some stable, unchanging memory. This evidence again falls in line with general principles governing the overall AM system, which state that AMs are reconstructed based on complex interactions between the individual (e.g., their beliefs about themself) and their cognitive environment (e.g., the information available to them; Berntsen, 2021; Katz, 1989; Ross & Conway, 1986). Taken together, these results converge on the idea that recurrent IAMs are ordinary, run-of-the-mill memory phenomena that support our sense of self, and facilitate access to the past without taxing the limited-capacity cognitive system (Berntsen, 2021). As Proust (1913–1927/1992) might put it, recurrent IAMs appear to be "exquisite pleasure[s]" (p. 60).

Intrusive Memories

However, a parallel literature has reached very different conclusions about the nature of recurrent IAMs. Using similar definitions as the recurrent IAM literature (e.g., memories experienced unintentionally and effortlessly), other researchers have termed these phenomena as intrusive memories (Brewin, Christodoulides, & Hutchinson, 1996; Brewin, Hunter, et al., 1996; Bywaters et al., 2004; Krans et al., 2015; Williams & Moulds, 2010; Yoshizumi & Murase, 2007). While some of these authors have characterized intrusive memories as being exclusively negative in valence (Mihailova & Jobson, 2020; Newby & Moulds, 2011; Williams & Moulds, 2010) or unwanted (Cheung et al., 2015; Ehlers et al., 2004; Sündermann et al., 2013), others have explicitly stated that intrusive memories can be either pleasant or unpleasant[1] (Brewin, Christodoulides, & Hutchinson, 1996; Bywaters et al., 2004; Herz et al., 2020; Kvavilashvili, 2014; Yoshizumi & Murase, 2007).

Though scholars have not yet reached consensus on the criteria for intrusive memories, there exists a growing agreement that intrusive memories are a transdiagnostic feature of psychopathology (Brewin et al., 2010; Bryant et al., 2011; Hackmann & Holmes, 2004; Krans et al., 2009; Marks et al., 2018). For example, intrusive memories have been claimed to be a component driving the development and/or maintenance of depression (Brewin, Christodoulides, & Hutchinson, 1996; Brewin, Hunter, et al., 1996; Brewin et al., 1999; Mihailova & Jobson, 2018; Newby & Moulds, 2011), stress (Baum et al., 1993; Cheung et al., 2015; Horowitz, 1975), posttraumatic stress disorder (PTSD; Brewin, 2007; Brewin & Holmes, 2003; Ehring et al., 2011), social anxiety (Moscovitch et al., 2011; Rachman et al., 2000; Wild et al., 2007), and general anxiety (Coles & Heimberg, 2002; Hirsch & Holmes, 2007; Mathews, 1990). These cognitive models of psychopathology typically speculate that intrusive memories contribute to mental health disorders if they are intensely negative (Beckers & Kindt, 2017; Brewin et al., 2010; Mihailova & Jobson, 2018; Moulds & Holmes, 2011; Newby & Moulds, 2011), since they can evoke and/or prolong feelings of distress and other negative emotions (Cohen & Kahana, 2022; Samide & Ritchey, 2021). Indeed, evidence supports that IAMs have stronger impact on mood than voluntary AMs (Berntsen & Hall, 2004), and that individuals experiencing high symptoms of PTSD tend to have stronger emotional reactions following AMs in general (Rubin et al., 2008). From this lens, it would appear that recurrent IAMs cause or exacerbate mental health disorders – a far cry from the view that they are benign or even helpful.

How can recurrent IAMs be both adaptive and maladaptive at the same time? To reconcile these ideas, some have argued for the hypothesis that recurrent IAMs are predominantly functional (or adaptive), and only some subset of recurrent IAMs is dysfunctional (or maladaptive; Berntsen, 2010, 2021; Marks et al., 2018). This hypothesis prompts many questions, the first of which might be how we can discern between adaptive and maladaptive recurrent IAMs. Implicit in this literature is the idea that some recurrent IAMs are maladaptive in that they are accompanied by greater symptoms of mental health

[1] Note that some of these more balanced definitions of intrusive memories (i.e., can be either pleasant or unpleasant) still emphasized to participants that these memories can sometimes "interrupt day to day activity and may be difficult to control. Some of these memories may be hard to mention or even embarrassing" (Brewin, Christodoulides, & Hutchinson, 1996, p. 108). No such descriptions were provided to participants about pleasant/positive recurrent IAMs.

disorders (Berntsen et al., 2003; Brewin, Hunter, et al., 1996), whereas adaptive recurrent IAMs are, theoretically, unrelated to mental health status (Iyadurai et al., 2019). More explicit, however, are hypotheses about the phenomenology (subjective experience) of maladaptive recurrent IAMs. Some researchers have concluded that memories should be considered maladaptive when they are excessively fear-inducing and "pathologically persistent" (Vaverková et al., 2020, p. 2). Similar thoughts are described by Berntsen (2021), who suggests that dysfunctional recurrent IAMs are those that involve extreme and highly emotional events (e.g., those that are traumatic or highly stressful), fail to subside over time, are easily cued by a variety of situations. Finally, evidence supports that in clinical populations (e.g., individuals with PTSD), recurrent IAMs are more frequent and distressing compared to nonclinical samples (Berntsen et al., 2003; Brewin et al., 2010; Clark & Rhyno, 2005; Hall et al., 2018; Kleim et al., 2013; Kvavilashvili, 2014; Malaktaris & Lynn, 2019), or those with fewer symptoms (Williams & Moulds, 2007a). To summarize, the persistence of these memories (e.g., increased availability, frequent recurrence) and the negative emotional reactions they evoke (e.g., feelings of distress, loss of control) are thought to be maladaptive properties that drive the etiology of mental health disorders such as PTSD (Rubin et al., 2008; Rubin et al., 2011). It would appear, then, that the emotional quality of the recurrent IAM is consistently considered a key factor in determining whether a memory is functional or dysfunctional.

Autobiographical Memory Content

Beyond emotionality, a further distinguishing feature between adaptive and maladaptive recurrent IAMs appears to be content (i.e., what the memory is about). Though the aforementioned arguments focus on the negative or distressing nature of dysfunctional recurrent IAMs, they also suggest that dysfunctional recurrent IAMs are typically about traumatic or very stressful events (Berntsen, 2021; Brewin, 2014; Brewin et al., 2010; Rubin et al., 2008; Rubin et al., 2011). In other words, maladaptive recurrent IAMs are thought to involve different types of events (and thus, contain different content) compared to adaptive recurrent IAMs. Naturally, memories of traumatic events are expected to be emotionally negative – however, not all traumatic memories retain their emotional charge, especially over time (Peace & Porter, 2004), and not all emotionally negative memories are of traumatic experiences. As such, an understanding of content, *independent of emotionality*, could inform the ongoing debates about the nature of recurrent IAMs. Early evidence suggests that content can indeed help delineate the maladaptive from the adaptive: recurrent memories were found to be either related or unrelated to severe depression depending on the types of events the memories were about (e.g., abuse/assault vs. illness or death; Brewin, Hunter, et al., 1996). Emotionality and content can, and should, be disentangled from each other in order to fully evaluate current hypotheses about what makes a recurrent IAM dysfunctional.

Furthermore, analyzing content might offer deeper insights into the nature of recurrent IAMs and their relationship to psychopathology. An ongoing question in both the realms of AM and psychopathology concerns whether maladaptive memories are *qualitatively* different from adaptive ones, or *quantitatively* different (Berntsen et al., 2003; Malaktaris & Lynn, 2019; Zoellner & Bittinger, 2004). In brief, qualitative differences would mean that maladaptive memories are categorically different from adaptive ones, either in terms of their cognitive (e.g., accessibility, contextual binding) or neural mechanisms (Brewin et al., 2010; Brewin, 2014). In contrast, quantitative differences would mean that maladaptive and adaptive memories exist along a continuum, with the maladaptive acting as extreme expressions of the adaptive (Rubin et al., 2008). To date, this question has largely been addressed using self-reported ratings of memory phenomenology (Berntsen et al., 2003; Malaktaris & Lynn, 2019). Much less common is the consideration of content (cf. Berntsen & Rubin, 2008), which holds qualitative information that is not always captured by ratings. Moreover, the analysis of content could answer long-standing questions about what, if anything, distinguishes recurrent IAMs across different mental health disorders (e.g., disorder-specific content; Brewin et al., 2010; Bryant et al., 2011; Gehrt et al., 2022; Reynolds & Brewin, 1999).

1.1 Overview of Current Studies

In Chapter 2, we characterized recurrent IAMs in a large sample of undergraduate students (Yeung & Fernandes, 2020). This included the memories' phenomenological (e.g., emotionality, feelings of reliving) and autobiographical properties (e.g., amount of episodic and semantic detail). Using these properties, we were able to predict how phenomenology contributes towards the strength of a recurrent IAM (i.e., its frequency of recurring) as well as these memories' relationships to mental health status (e.g., symptoms of depression, anxiety, PTSD). In Study 1, we found that a strikingly high proportion of this nonclinical sample experienced recurrent IAMs in their daily lives. Importantly, we also found that negative recurrent IAMs were related to significantly more symptoms of mental health disorders across the board (i.e., depression, stress, posttraumatic stress, general anxiety, social anxiety).

In Chapter 3, we examined how the properties of recurrent IAMs might be modulated by individual differences (Yeung & Fernandes, 2021). Based on well-known differences in emotion regulation between younger and older adults, we predicted that older age would be associated with more positive recurrent IAMs than younger age. Indeed, in Study 2a we found that the valence of recurrent IAMs reversed between younger (mostly negative) and older adults (mostly positive). In Study 2b, we asked if these differences in recurrent IAM valence could be observed based on trait emotion regulation alone (i.e., within the same age group). As in the older adult sample, younger adults with high, compared to low, emotion regulation reported significantly fewer negative recurrent IAMs. We also showed once again that valence of recurrent IAMs significantly predicted symptoms of mental health disorders.

In Chapter 4, we applied and validated computational methods to analyze the content of AM data at a much larger scale than previously possible (Yeung, Stastna, & Fernandes, 2022). Though most researchers (including our previous work) rely heavily upon self-reported ratings of memory phenomenology (e.g., valence), this only provides a limited view into the properties of a recurrent IAM. Though content is acknowledged as a valuable source of information in AM literature, it is rarely analyzed because current manual methods are prohibitively time- and labour-intensive. In Study 3, we apply computational text analysis to analyze the content of recurrent IAMs to identify content categories and quantify their prevalence across recurrent IAMs.

In Chapter 5, we used these computational methods to investigate how content in recurrent IAMs might predict symptoms of mental health disorders, above and beyond self-reported valence ratings (Yeung & Fernandes, in prep.). While we replicated our previous results that negative recurrent IAMs predicted greater symptoms of mental health disorders, we also found that content predicted additional, unique variance. Here, Study 4 revealed that symptoms of specific disorders predicted the use of specific topics, unique from symptoms of other disorders, and unique from self-reported valence ratings.

Chapter 2:
Characterizing Recurrent IAMs

2.1 Study 1

2.1.1 Introduction

Memories of one's personal past that are retrieved unintentionally and effortlessly have been termed involuntary autobiographical memories (IAMs; Barzykowski & Staugaard, 2016; Berntsen, 1996) and are reported to be experienced both universally and frequently in daily life (Berntsen, 2010; Brewin, Christodoulides, & Hutchinson, 1996; Krans et al., 2015; Mace, 2007; Rasmussen & Berntsen, 2011). Past work has also shown that some of these IAMs tend to occur recurrently – in other words, that episodes of the same event are often retrieved involuntarily and repetitively (Berntsen & Rubin, 2008). Specifically, in a large-scale telephone survey of adults in the general population, Berntsen and Rubin (2008) found that more than half of the respondents (53%) had experienced at least one recurrent IAM within the most recent year.

Despite their prevalence in the general population, recurrent IAMs have generally been characterised as dysfunctional within the clinical field. Often termed intrusive memories in this literature, a great body of evidence has framed the repetitive and involuntary reexperiencing of an event as a key component of depression (Brewin, Christodoulides, & Hutchinson, 1996; Brewin et al., 1999; Mihailova & Jobson, 2018; Newby & Moulds, 2011), stress (Baum et al., 1993; Cheung et al., 2015; Horowitz, 1975), posttraumatic stress disorder (PTSD; Brewin, 2007; Brewin & Holmes, 2003; Ehring et al., 2011), social anxiety (Moscovitch et al., 2011; Rachman et al., 2000; Wild et al., 2007), and general anxiety (Coles & Heimberg, 2002; Hirsch & Holmes, 2007; Mathews, 1990). Given this diversity of conditions involving recurrent IAMs, there has been increasing support for models suggesting that intrusive cognitions such as recurrent IAMs are a transdiagnostic feature of disorders across psychopathology (Brewin et al., 2010; Holmes et al., 2015; Krans, 2011; Marks et al., 2018). In these models, recurrent IAMs are proposed to have a strong impact on emotional state, such that the unwanted or uncontrollable reexperiencing of an event may prolong negative moods or induce high levels of stress. Indeed, past work has shown that involuntary memories more strongly influence mood and rouse physical, bodily reactions in comparison to voluntary memories (Berntsen & Hall, 2004). Taken together, this evidence seems to converge on the idea that recurrent IAMs play a central role in mental health status.

Given this, it is surprising that few studies have explored the relation between mental health and recurrent IAMs in nonclinical populations. How is it that recurrent IAMs could be both an important component of mental illness as well as an everyday phenomenon in the general population? One potential distinction between these pathological, intrusive memories and functional, involuntary memories might be the emotionality of the memory. In clinical contexts where recurrent IAMs are characterised as abnormal or pathological, the memories are also classified as emotionally negative or distressing to the individual experiencing them (Clark & Rhyno, 2005; Krans et al., 2015; Mihailova & Jobson, 2018). In stark contrast, Berntsen and Rubin (2008) found that the majority of recurrent IAMs reported by the general population were self-rated as emotionally positive. This discrepancy in reported valence of memories could therefore play a potential role in whether or not a recurrent IAM is related to mental health status. However, it remains worth noting that nonclinical adults do still report experiencing negative IAMs, recurrent or otherwise (Bywaters et al., 2004; Krans et al., 2015; Moulds & Holmes, 2011). In other words, negative emotionality alone seems insufficient to explain why certain recurrent IAMs are linked to poor mental health while others are not. Rather than just any negativity, many authors suggest that clinical manifestations of intrusive memories are extreme expressions of everyday negative IAMs (Moulds & Holmes, 2011; Newby & Moulds, 2011). In a review by Brewin et al. (2010), it is reported that recurrent IAMs are more frequent and more distressing in individuals with clinical disorders compared to nonclinical controls. Careful assessment of these memories' autobiographical features such as emotional intensity and vividness, as we have done in the current study, could reveal key factors in the relation between recurrent IAMs and mental health. Moreover, investigating recurrent IAMs in general populations would answer open questions about whether these memories have detectable associations with mental health, even at the subclinical level.

Beyond potential insights into mental health status, more closely examining the autobiographical properties of recurrent IAMs in the general population may also build our understanding of why certain memories tend to become recurrent while others fade away. A major goal in the study of intrusive memory has been the identification of factors that predict the development of a recurrent IAM (for a review, see Marks et al., 2018). Past research has generally focused on how individual differences (e.g., personality traits or ability to suppress retrieval; Davies & Clark, 1998; Meyer et al., 2013; Streb et al., 2016) or information processing strategies (e.g., verbal or visual encoding; Holmes & Bourne, 2008; Krans et al., 2009) might lead a memory to become recurrent or intrusive. For instance, factors related to an individual's executive functioning have been of particular interest as potential vulnerabilities predisposing certain people to developing recurrent IAMs (Levy & Anderson, 2008; Verwoerd et al., 2009). In contrast to these individual differences, an alternative area of inquiry that remains relatively unstudied in the context of recurrent IAMs are subjective properties of the memory itself.

Properties of Autobiographical Memories

To examine how subjective qualities of a given memory might predict how frequently it recurs, we looked towards the literature on autobiographical memory. To date, there exists a wealth of evidence in this field to suggest that many phenomenological qualities of a memory can influence its strength (Rubin, 2005; Sutin & Robins, 2007; Talarico et al., 2004). For instance, subjective experiences such as a memory's emotionality, the perspective from which it is remembered (i.e., as if from one's own view versus from an outside observer's view), and feelings of reliving have all been recognised as defining features of autobiographical memory (Boyacioglu & Akfirat, 2015). By measuring some of these dimensions in studies of involuntary memory, authors have begun to identify a number of characteristics distinguishing between involuntary and voluntary memories (Hall & Berntsen, 2008; Rubin et al., 2011). As an example, one such study found that IAMs were self-rated to have significantly greater emotional intensity and less centrality (i.e., the degree to which a memory is considered a part of an individual's life story) than their voluntary counterparts (Rubin et al., 2008). Additional memory qualities have also been identified in clinical literature as important features promoting the development of intrusive memories, such as feelings of shame (Robinaugh & McNally, 2010) or social evaluation (Moscovitch et al., 2011). Given that these phenomenological characteristics play a role in the involuntary or intrusive nature of a memory, we investigated whether these qualities could predict the strength of a recurrent IAM (e.g., the frequency with which it recurs). As such, in the current study, we carefully measured recurrent IAMs' subjective characteristics.

Perhaps one of the most fundamental of these characteristics is the extent to which an autobiographical memory's narrative is rooted in a specific time and space. While some autobiographical memories feel richly reexperienced with access to information such as contextual details, many autobiographical memories require no such reliving. For example, an elaborate retelling of an event in one's childhood home seems quite different from recalling the address of that house, despite both memories being classified as autobiographical. To distinguish between these memories, a continuum has been proposed using the well-established episodic-semantic distinction (Levine, 2004; Tulving, 1972, 2002). Under this framework, recollecting information from an event as it was originally experienced (e.g., one's own thoughts and feelings during the event) reflects episodic autobiographical memory. It is thought that these contextualised details, specific to a time and a place, demonstrate "mental time travel" and an awareness that the event is part of one's personal past (Levine, 2004), which are defining features of episodic memory. In contrast, remembering factual knowledge from one's past (e.g., general characteristics of oneself) reflects semantic autobiographical memory, which can be retrieved without necessarily reliving a specific time or place (Levine, 2004). This degree of episodic versus semantic content in autobiographical memory is thought to be related to mental health status, having been connected to wide variety of clinical disorders (Brown et al., 2014; King et al., 2010; Moscovitch et al., 2018). For example, disruptions in one's capacity to produce episodic detail in one's memories (i.e., overgeneralisation) predicts the diagnosis of mood disorders such as major depressive disorder (King et al., 2010; Williams et al., 2007). Furthermore, emotionality – a key component in models of both involuntary and intrusive memory – has been shown to influence the amount of episodic and semantic content in voluntary autobiographical memories. Specifically, emotion (regardless of valence) was found to significantly increase the level of episodic detail used (St. Jacques & Levine, 2007). Despite these theoretical links between episodic/semantic content, mental health, and emotionality, the dimension of episodic and semantic detail has yet to be investigated in recurrent IAMs.

In the current study, we investigated whether and how recurrent IAMs might be linked to symptoms of poor mental health despite also being experienced by large proportions of the general population. Further, we explored how autobiographical features of a given recurrent IAM might be related to an individual's long-term mental health status, and the frequency with which the IAM recurs. To address these questions, we administered a battery of online questionnaires to a large sample of undergraduate students. While one of these questionnaires probed for the presence and subjective characteristics of any recurrent IAMs, other questionnaires measured current symptoms of mental health issues. Of particular interest were participants' self-ratings of the memory's emotionality, given theoretical relevance to models of intrusive memory (Clark & Rhyno, 2005). Rather than instructing participants to retrieve a specific type of recurrent IAM (e.g., neutral or negative), we allowed participants to report any recurrent IAM, and then investigated if recurrent IAMs with certain qualities (e.g., negative in valence) were related to poorer mental health status. We would therefore expect that both benign and maladaptive recurrent IAMs were reported – if these categories exist – and that our current design would be able to distinguish the two empirically. Finally, we asked participants to provide text descriptions of their recurrent IAMs and coded these descriptions using the Autobiographical Interview (AI; Levine et al., 2002) in order to assess relations between emotionality and episodic/semantic content in recurrent IAMs.

2.1.2 Methods

Participants

Over two months, 2,184 undergraduate students who were enrolled in at least one psychology course at the University of Waterloo responded to an online battery of questionnaires in return for partial course credit. Of the respondents, 73% identified as women, 26% identified as men, and 1% identified as genderqueer, gender nonconforming, or nonbinary. The mean age was 19.8 (*SD* = 2.7).

Materials

Recurrent Memory Scale. The Recurrent Memory Scale was developed for use in the current study to measure autobiographical properties of participants' recurrent IAMs. First, participants were asked if they had experienced at least one recurrent IAM within the past year, not within the past year, or never (adapted from the procedure used in Berntsen & Rubin, 2008). If they indicated that they had experienced at least one within the past year, they were asked to write out a brief description of their one most frequently recurring IAM (in approximately three to five sentences). Following this description, they reported how long ago the original event occurred (age of the memory), and self-rated that same memory on a series of 5-point Likert scales. These scales assessed the recurrent IAM on the following autobiographical properties: level of completeness/detail (Reisberg et al., 1988), clarity of visual imagery (Bywaters et al., 2004; Sutin & Robins, 2007), amount of reliving (Hall & Berntsen, 2008), vantage perspective (Siedlecki, 2015; Williams & Moulds, 2007b), valence (Berntsen & Rubin, 2008; Rozin & Royzman, 2001), emotional intensity (Talarico et al., 2004), centrality (Newby & Moulds, 2011; Rubin et al., 2008), social evaluation (Moscovitch et al., 2011), and shame (Robinaugh & McNally, 2010). Similar to past work, if a participant had not experienced a recurrent IAM within the past year or ever, they were not asked to write a text description or provide any self-ratings (Berntsen & Rubin, 2008). Items in this scale are listed in Appendix A (Table A1).

Depression Anxiety Stress Scales. The DASS-21 (Lovibond & Lovibond, 1995) consists of 21 items, each falling under one of three subscales: depression (DASS-D; e.g., "I felt that I had nothing to look forward to"), anxiety (DASS-A; e.g., "I felt I was close to panic"), or stress (DASSS; e.g., "I found it hard to wind down"). Participants indicated how much each statement applied to them over the past week on a 4-point Likert scale (0 = *did not apply to me at all*, 3 = *applied to me very much, or most of the time*). The DASS-21 has been found to have excellent internal consistency and adequate concurrent validity (Antony et al., 1998). Internal consistency was high in the current sample for the full scale ($\alpha = .94$), as well as the subscales for depression (α =. 91), anxiety (α =. 85), and stress ($\alpha = .86$).

Posttraumatic Stress Disorder Checklist for DSM-5. The PCL-5 (Weathers et al., 2013) consists of 20 items assessing for symptoms of PTSD. Participants indicated how much a series of problems (e.g., "Repeated, disturbing, and unwanted memories of the stressful experience") bothered them within the past month on a 5-point Likert scale (0 = *not at all*, 4 = *extremely*). The PCL-5 has been found to have strong internal consistency, test-retest reliability, and convergent and discriminant validity (Blevins et al., 2015). Internal consistency was high in the current sample ($\alpha = .95$).

Social Phobia Inventory. The SPIN (Connor et al., 2000) consists of 17 items assessing fear, anxiety, and physical discomfort experienced during social situations. Participants indicated how much a series of problems (e.g., “Being embarrassed or looking stupid are among my worst fears”) tended to bother them in a typical week on a 5-point Likert scale (0 = not at all, 4 = extremely). Although the established cutoff score of 19 is thought to have some ability to distinguish between individuals with and without SAD (Connor et al., 2000), formal diagnoses of SAD or any other psychopathology were not confirmed by a clinician. The SPIN has been found to have good test-retest reliability, internal consistency, convergent and divergent validity, and construct validity (Connor et al., 2000). Internal consistency was high in the current sample (α = .93).

State-Trait Inventory of Cognitive and Somatic Anxiety. The STICSA (Grös et al., 2007) assessed participants’ levels of general anxiety. The STICSA consists of 21 items that represent both cognitive (e.g., “I feel agonised over my problems”) and somatic (e.g., “My heart beats fast”) aspects of anxiety. Participants indicated how much each statement described them on a 4-point Likert scale (1 = not at all, 4 = very much so). Participants only reported the degree to which the statements described them in general (trait anxiety; STICSA-T), and were not administered the version assessing state anxiety. The STICSA has been found to have excellent internal consistency, and good convergent and divergent validity (Grös et al., 2007). Internal consistency was high in the current sample (α = .93).

Procedure

Undergraduate students enrolled in at least one psychology course at the University of Waterloo had the opportunity to participate in an online battery of questionnaires. After providing informed consent, participants completed a series of computerised scales in a randomised order. Embedded within this battery were the key scales of interest: the Recurrent Memory Scale, DASS-21, PCL-5, SPIN, and STICSA-T. Other questionnaires in the battery were used by researchers at the University of Waterloo for work unrelated to the current study. The full battery took approximately 60 minutes to complete. All study procedures were approved by the Office of Research Ethics at the University of Waterloo (Protocol #40049).

2.1.3 Results

Prevalence of Recurrent IAMs

Of the 2,184 respondents, 14 were missing responses for the item asking if they had experienced a recurrent IAM and were removed from all further analyses. Of the remaining 2,170 respondents, 1,132 respondents (52% of the sample) reported having experienced at least one recurrent IAM within the past year. As well, 565 respondents (26% of the sample) also reported having experienced at least one recurrent IAM, but not within the past year. Finally, 473 respondents (22% of the sample) reported having never experienced a recurrent IAM. Participants who had experienced at least one recurrent IAM within the past year also tended to report experiencing multiple recurrent IAMs (M = 7.30, SD = 12.35).

Valence of Recurrent IAMs

Of the 1,132 respondents who reported experiencing at least one recurrent IAM within the past year, 37 were missing responses for self-rated valence of the memory and were removed from the current analysis. Of the remaining 1,095 recurrent IAMs (one per respondent who experienced at least one recurrent IAM within the past year) with valid self-ratings of valence, 568 (52%) were self-rated as negative or very negative. In contrast, 321 (19%) were self-rated as positive or very positive, and 206 (29%) were self-rated as neutral. A chi-square test revealed that this distribution was significantly different from an even distribution across valences, $\chi^2(2, N = 1{,}095) = 187.47, p < .001$.

Further, frequency of recurring was examined across levels of valence. Of the 1095 recurrent IAMs with valid self-ratings of valence, one was missing a response for self-rated frequency of recurring and was removed from the current analysis. A chi-square test of independence revealed that the proportions of frequency were significantly different across levels of valence, χ^2 (8, N = 1,094) = 61.17, p < .001. Further examination of the adjusted Pearson residuals showed that IAMs that recurred only once within the past year were disproportionately more neutral (adjusted Pearson residual = 5.1) and less negative than expected (adjusted Pearson residual = −6.2). In contrast, IAMs that recurred several times a day or several times a week were disproportionately more negative than expected (adjusted Pearson $\text{residual}_{\text{several/day}}$ = 3.1, adjusted Pearson $\text{residual}_{\text{several/week}}$ = 3.3; Bonferroni corrected α = .003, critical value = 2.93).

Recurrent IAM Valence and Mental Health

To examine the potential link between recurrent IAM valence and mental health, participants were randomly sampled such that equal group sizes were obtained for each of four bins: participants who reported a self-rated neutral IAM as the most frequently recurring, a negative IAM as the most frequently recurring, a positive IAM as the most frequently recurring, or having not recently experienced a recurrent IAM (i.e., either never or not within the past year). Because the bin for neutral IAMs was originally the smallest (206 participants), participants were randomly selected until each bin contained 206 participants. A series of between-subjects one-way analyses of variance (ANOVAs) were then run to compare symptoms of mental health issues across these four groups (IAM type: neutral, negative, positive, no recent recurrent IAM). For each analysis, all participants missing any responses on the mental health-related scale of interest were removed from each analysis separately.

For DASS-D (depression) score, Levene's test showed that the variances were not equal across groups, $F(3, 812) = 4.66$, $p = .003$. As such, a Welch's ANOVA was conducted, which revealed a significant main effect of IAM type, Welch's $F(3, 449.97) = 6.78$, $p < .001$. Post hoc Games-Howell tests showed that participants who reported a negative recurrent IAM also reported significantly more depressive symptoms ($M = 7.04$, ps < .002) than all other groups. No other differences were significant (ps > .98).

For DASS-S (stress) score, Levene's test showed that the variances were not equal across groups, $F(3, 812) = 3.88$, $p = .009$. As such, a Welch's ANOVA was conducted, which revealed a significant main effect of IAM type, Welch's $F(3, 450.38) = 7.65$, $p < .001$. Post hoc Games-Howell tests showed that participants who reported a negative recurrent IAM also reported significantly more stress symptoms ($M = 7.91$, ps < .006) than all other groups. No other differences were significant (ps > .41).

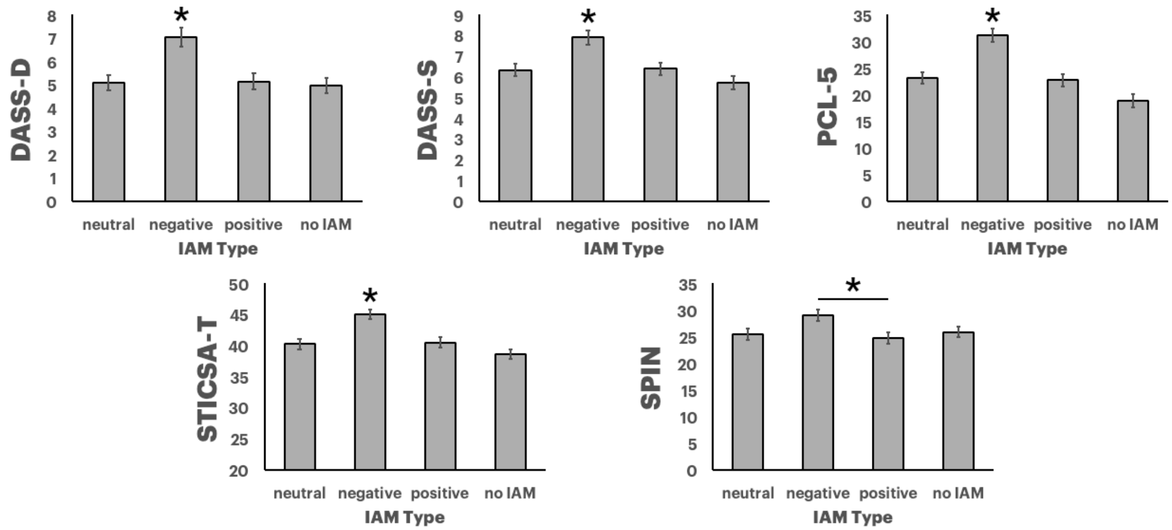
For PCL-5 score, Levene's test showed that the variances were not equal across groups, $F(3, 802) = 2.76$, $p = .04$. As such, a Welch's ANOVA was conducted, which revealed a significant main effect of IAM type, Welch's $F(3, 444.84) = 16.28$, $p < .001$. Post hoc Games-Howell tests showed that participants who reported a negative recurrent IAM also reported significantly more posttraumatic stress symptoms ($M = 31.17$, ps < .001) than all other groups. Participants who reported no recent recurrent IAM also reported nominally fewer posttraumatic stress symptoms ($M = 18.94$) than those reporting a neutral recurrent IAM ($M = 23.15$, $p = .056$), though this difference was not significant. No other differences were significant (ps > .12).

For STICSA-T score, the ANOVA revealed a significant main effect of IAM type, $F(3, 803) = 11.93$, $MSE = 129.33$, $p < .001$, $\eta_p^2 = .04$. Post hoc Tukey tests showed that participants who reported a negative recurrent IAM also reported significantly more general anxiety symptoms ($M = 45.02$, ps < .001) than all other groups. No other differences were significant (ps > .33).

For SPIN score, the ANOVA revealed a significant main effect of IAM type, $F(3, 810) = 3.35$, $MSE = 217.90$, $p = .02$, $\eta_p^2 = .01$. Post hoc Tukey tests showed that participants who reported a negative recurrent IAM also reported significantly more social anxiety symptoms ($M = 29.04$, $p = .02$) than those who reported a positive recurrent IAM ($M = 24.79$). No other differences were significant (ps > .08; see Figure 1).

Figure 1

Symptoms of Mental Health Issues by Recurrent IAM Type



Note. Error bars represent ±1 standard error of the mean, and asterisks represent significance of *p* <. 05.

Predicting Frequency of Recurrent IAMs

In the current work, we operationalised strength of a recurrent IAM using participants' self-reported ratings of their IAMs' frequency of recurring. To predict the self-rated frequency of a recurrent IAM, a regression model was run using participants' self-ratings of their recurrent IAM's autobiographical features as predictors. Four variables were found to be significant predictors: age of the memory, completeness/detail, emotional intensity, and centrality (*p*s < .001; see Table 1). Age of the memory was a significant negative predictor, indicating that older IAMs recurred less frequently. In contrast, completeness/detail, emotional intensity, and centrality were all significant positive predictors, indicating that more complete/detailed IAMs, more emotionally intense IAMs, and more central IAMs recurred more frequently. No other predictors were significant (*p*s > .11). Variance inflation factors were less than 2.03 and tolerance values were greater than .49, indicating no issues related to multicollinearity.

Table 1

Regression Analysis with Self-Rated Autobiographical Features Predicting Frequency of Recurring

Variable	**B**	***SE* B**	**ß**
Model 1			
age of memory	-0.03	0.01	-0.14***
completeness/detail	0.15	0.04	0.15***
clarity of visual imagery	0.03	0.04	0.03
reliving	0.02	0.04	0.02
vantage perspective	-0.01	0.03	-0.01
valence	0.02	0.03	0.03
emotional intensity	0.15	0.03	0.18***
centrality	0.11	0.03	0.14***
social evaluation	-0.01	0.03	-0.01
shame	0.05	0.03	0.06

Note. Model 1 R^2 = .21, adjusted R^2 = .20, p < .001, Cohen's f^2 = 0.25. *** p < .001.

Text Descriptions of Recurrent IAMs

To examine how emotionality might be associated with the level of episodic and semantic detail in recurrent IAMs, we coded participants' written descriptions of their recurrent IAMs. We then analyzed whether recurrent IAMs would differ in the degree of detail based on emotional valence.

Coding and Reliability Analyses. Four research assistants were trained by author RY to independently code text descriptions by identifying the number of internal (episodic) and external (semantic) details in each text following the Autobiographical Interview (Levine et al., 2002). The raw number of internal details was averaged across coders and then converted to an internal-to-total ratio score (number of internal details divided by total number of internal and external details combined) in order to control for total verbal output (Levine et al., 2002; Miloyan et al., 2019). This process was repeated for external details to create an external-to-total ratio score.

Coders were blind to the groups and hypotheses of the study, and only saw the text descriptions of the recurrent IAMs; none of the coders saw any of the self-ratings. Out of the 1,132 participants who reported having experienced a recurrent IAM within the past year, 183 were missing responses for text description of the memory and were removed from all analyses on text descriptions. One of the coders

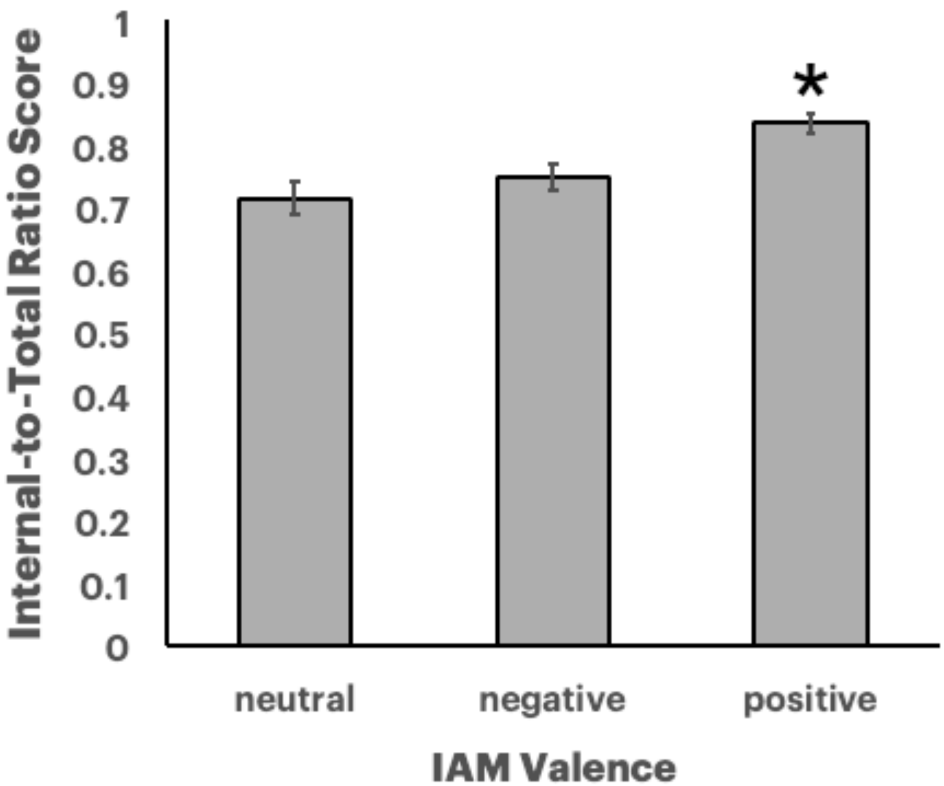
(C1) coded all of the remaining 949 texts, whereas the other three coders (C2, C3, C4) all coded approximately 316 texts each (33% of the texts). Each text was therefore coded by two individuals separately (once by C1, and once by one of C2, C3, or C4). Of the 949 recurrent IAMs with text descriptions, 132 of the texts were identified as noncompliant by at least one coder (e.g., participant wrote that they are declining to describe their recurrent IAM in text) and were also removed from all analyses on text descriptions. For the remaining 817 recurrent IAMs with valid text descriptions, interrater reliability between coders was calculated using intraclass correlation (ICC) based on a mean-rating (k = 2), absolute agreement, one-way random effects model (Koo & Li, 2016). For raw number of internal details, the average measures ICC between C1 and C2, C3, or C4 was .76, indicating good reliability, $F(816, 817) = 4.23$, $p < .001$, 95% CI [.73, .79]. For raw number of external details, the average measures ICC between C1 and C2, C3, or C4 was .51, indicating moderate reliability, $F(816, 817) = 2.05$, $p < .001$, 95% CI [.44, .58].

To compare interrater reliability across coders, ICCs were also calculated between C1 and each of C2, C3, and C4 separately. These ICCs were based on a mean-rating (k = 2), consistency, two-way random effects model. For raw number of internal details, the average measures ICC was .75 (95% CI [.69, .81]) for C1-C2, .77 (95% CI [.71, .82]) for C1-C3, and .81 (95% CI [.76, .85]) for C1-C4 (ps < .001). Confidence intervals were overlapping across each coder pair, indicating that they did not significantly differ from each other. For raw number of external details, the average measures ICC was .08 (95% CI [-.17, .28]) for C1-C2 (p = .24). In contrast, the average measures ICC was .61 (95% CI [.50, .69]) for C1-C3, and .40 (95% CI [.24, .53]) for C1-C4 (ps < .001). Because confidence intervals did not overlap for C1-C2 compared to C1-C3 and C1-C4, another ICC between C1 and C2, C3, or C4 (one-way random effects model) was calculated for raw number of external details, except with C2's ratings removed. The average measures ICC across all coder pairs with C2 excluded was .56, $F(545, 546) = 2.26$, $p < .001$, 95% CI [.48, .63], which was not significantly different from the average measures ICC across all coder pairs with C2 included (.51, 95% CI [.44, .58]). As such, C2's coding was retained in the following analyses.

Episodic and Semantic Details. Amount of episodic detail, as indexed by the internal-to-total ratio score, was then compared across levels of valence. Using the same method of randomly sampling bins with equal group sizes (see prior analyses on symptoms of mental health issues), three bins were included in the current analysis because they had text descriptions: participants who reported a self-rated neutral IAM as the most frequently recurring, a negative IAM as the most frequently recurring, or a positive IAM as the most frequently recurring. Because the bin for neutral IAMs was the smallest following exclusions (120 participants), participants were randomly selected until each bin contained 120 participants. When comparing internal-to-total ratio score across levels of self-rated valence, Levene's test showed that the variances for internal-to-total ratio score were not equal across groups, $F(2, 357) = 10.48$, $p < .001$. As such, a Welch's ANOVA was conducted, which revealed a significant main effect of valence, Welch's $F(2, 231.65) = 9.56$, $p < .001$. Post hoc Games-Howell tests showed that positive recurrent IAMs were described using significantly more internal details ($M = .84$) than both neutral recurrent IAMs ($M = .72$; $p < .001$) and negative recurrent IAMs ($M = .75$; $p = .005$), which were not significantly different from each other ($p = .56$; see Figure 2).

Figure 2

Internal-to-Total Ratio Score by Recurrent IAM Valence



Note. Error bars represent ±1 standard error of the mean, and asterisks represent significance of $p < .05$.

Word Count. To examine the potential link between valence and word count of the description, mean word count was compared across levels of self-rated valence using the same method of randomly sampling bins with equal group sizes (see prior analyses on symptoms of mental health issues or internal/external details). The same randomly sampled bins from the prior analysis on internal/external details were retained for the current analysis (120 participants each).

When comparing word count across levels of self-rated valence, Levene's test showed that the variances for word count were not equal across groups, $F(2, 357) = 5.37$, $p = .005$. As such, a Welch's ANOVA was conducted, and revealed a nonsignificant main effect of valence, Welch's $F(2, 234.64) = 1.32$, $p = .27$.

2.1.4 Discussion

In the current study, we investigated how recurrent IAMs and their autobiographical properties might be linked to mental health. To do so, we administered a series of online questionnaires to a large sample of undergraduate students. Of these questionnaires, one probed for the presence and characteristics of any recurrent IAMs. If a participant indicated that they had experienced a recurrent IAM recently (i.e., within the past year), we also asked them to write a brief text description of their most frequently recurring IAM. Using these text descriptions, we were able to quantify the amount of episodic and semantic detail in the IAMs using the AI coding scheme (Levine et al., 2002). Finally, the remaining questionnaires measured current symptoms of mental health issues, such as depression and PTSD, to explore whether recurrent IAMs might be linked to mental health status.

Prevalence and Valence of Recurrent IAMs

Our results replicate key findings about prevalence from past work on recurrent IAMs. Specifically, we found that the majority of our sample (52%, $N = 2{,}184$) had experienced at least one recurrent IAM within the past year. This very closely replicates findings from Berntsen and Rubin (2008), who also found that the majority of their participants had recurrent IAMs within the past year (53%, $N = 1{,}504$). The current evidence therefore supports prior ideas that recurrent IAMs are a common experience in everyday life.

However, findings regarding valence were not replicated in the current study. We found that the recurrent IAMs reported by our participants were disproportionately negative (52%), as opposed to positive (19%) or neutral (29%). In contrast, Berntsen and Rubin (2008) found that recurrent IAMs from their sample were mostly positive (58%), and that few were rated as neutral (22%) or negative (20%). This discrepancy could potentially stem from a methodological difference between studies: while participants in the current study completed the measures online, the past procedure used by Berntsen and Rubin (2008) involved a telephone survey. Given the sensitive or personal nature of some recurrent IAMs, participants may have felt uncomfortable disclosing some information about these memories over the phone – especially for negative recurrent IAMs. Alternatively, another difference between studies that could have led to the dissimilar valence distributions is the population sampled. In our study, participants were all undergraduate students, who were mostly young adults (M_{age} = 19.8, range = 17–46). Conversely, Berntsen and Rubin (2008) recruited community-dwelling adults, including middle-aged and older adults (M_{age} = 45.2, range = 18–96). This age disparity could be responsible for the reversal in recurrent IAM valence given that older adults commonly show enhanced memory for positive information (relative to neutral or negative information), including autobiographical memories (Kennedy et al., 2004; Mather & Carstensen, 2005). In contrast, young adults tend to show a memory bias towards negative information (Carstensen & DeLiema, 2018; Reed et al., 2014; Rozin & Royzman, 2001). Indeed, data from Berntsen and Rubin (2008) seem to support this hypothesis, such that mean valence ratings of recurrent IAMs grew significantly more positive with age. Although more work is needed to specify the mechanism underlying the observed reversal in valence distribution, our data show that recurrent IAMs are not necessarily mostly positive, even in a large sample of nonclinical adults.

Recurrent IAMs and Mental Health Status

The current findings also provide novel evidence that valence plays an important role in the relation between recurrent IAMs and mental health. While it has been claimed that only some IAMs are indicative of poor mental health (Berntsen, 2010), past work has not been able to conclude as to what aspects of a recurrent IAM make one benign as opposed to maladaptive. Our results here show that the valence of one's most frequently recurring IAM is linked to mental health status, such that those reporting a negative recurrent IAM showed significantly more symptoms of depression, general anxiety, social anxiety, stress, and posttraumatic stress. This finding aligns with past models of psychopathology that define intrusive, or clinically relevant, memories as negative in valence (Clark & Rhyno, 2005).

However, authors have suggested that recurrent IAMs need to be not only negative, but also highly disturbing or vivid in order to be a component of clinical disorders (Moulds & Holmes, 2011). For instance, in one study by Newby and Moulds (2011), the authors assessed the presence and properties of any intrusive memories in participants that were either currently depressed, recovering from depression, or never depressed. Results showed that a large proportion of all three groups reported having experienced negative recurrent IAMs recently, including 73% of the participants who were never depressed. Although the prevalence of negative recurrent IAMs was not significantly different across severity of mental health issues, specific autobiographical features did significantly differ: participants with current depression self-rated their recurrent IAMs as more negative, more distressing, and more vivid than participants who had never been depressed.

In contrast, the present data argue that negative valence is indeed sufficient to determine whether a recurrent IAM is indicative of poor mental health, but at the subclinical level. In other words, even without including feelings of distress or vividness, simply reporting a negative IAM as one's most frequently recurring is still associated with significantly more mental health issues. By assessing both recurrent IAMs and subclinical symptoms of mental health problems in a large sample of young adults, the current evidence extends prior work to show that the valence of recurrent IAMs can reflect mental health status.

Predicting Frequency of Recurrent IAMs

Past claims that memory characteristics such as vividness play a key role in recurrent IAMs remain valid – however, instead of dictating whether a recurrent IAM is maladaptive, the current analyses suggest that phenomenological characteristics predict an IAM's frequency of recurring. Specifically, through multiple regression analysis we identified four characteristics that were significant predictors of frequency: age of the memory, emotional intensity, centrality, and level of completeness/detail. These features map well onto extant models of involuntary memory. For instance, age of the memory has been previously linked to frequency of recurring, such that Berntsen and Rubin (2008) reported that recurrent IAMs are more likely to be about more recent events (within the past few decades) as opposed to more remote events (within earlier decades). As well, the Autobiographical Memory Theory of PTSD developed by Rubin et al. (2011) proposes that greater emotional intensity and centrality of an autobiographical memory increases the likelihood that it will spring to mind involuntarily. Notably, emotional intensity (but not valence) has also been found to be a significant positive predictor of whether or not an IAM would be experienced as a "flashback" (i.e., high vividness, high mood impact, and associated with a physical reaction; Berntsen, 2001).

Of particular interest is the final memory characteristic that significantly predicted frequency: level of completeness/detail. Specifically, this finding has novel implications for how vividness factors into frequency of recurring. Although past research has agreed that vividness is critical component of autobiographical memory (Brewer, 1996), it has been conceptualised in various ways, including level of completeness/detail (Reisberg et al., 1988) as well as clarity of visual imagery (Bywaters et al., 2004; Sutin & Robins, 2007). To compare how these components contribute to frequency of recurring, we measured both qualities separately and used each score as individual predictors in a multiple regression model. Results showed that only completeness/detail was a significant positive predictor of frequency, whereas clarity of visual imagery did not reach significance. Because clarity of visual imagery was not a significant predictor, the data suggest that the frequency of a recurrent IAM may be less reliant on specifically visual aspects of vividness as opposed to general level of completeness/detail. While some work has previously shown that visual cues are less effective at evoking IAMs relative to verbal cues

(Mace, 2004; Mazzoni et al., 2014), the present findings further suggest that the visual quality of the memory itself is a less important factor in how frequently an IAM recurs.

Episodic and Semantic Detail in Recurrent IAMs

Finally, by applying the AI coding scheme (Levine et al., 2002) to our participants' text descriptions of their recurrent IAMs, we also identified a novel feature distinguishing involuntary from voluntary autobiographical memory: the ratio of episodic to semantic content across emotional memories. Although episodic and semantic details are well-known as a core feature of autobiographical memory (Levine, 2004; Tulving, 1972, 2002), they have only since been applied to voluntary autobiographical memories. For example, multiple studies have found that emotional (i.e., either positive or negative) memories were described using greater episodic detail than neutral memories (Comblain et al., 2005; St. Jacques & Levine, 2007). In contrast, the current results showed that only positive recurrent IAMs were described using greater episodic detail than neutral recurrent IAMs; negative recurrent IAMs were not significantly different from neutral. As such, our data show that negative recurrent IAMs fail to receive the same emotional enhancement as seen in their voluntary counterparts.

Why might negative recurrent IAMs have less episodic detail than positive ones, and why does this pattern differ from voluntary autobiographical memories? One potential explanation links back to our finding that these negative recurrent IAMs were also indicative of poorer mental health: the relative deficit in episodic detail could reflect overgeneralised autobiographical memory. Characterised by greater semantic detail and less episodic detail, overgeneralising has been noted as a feature of mental health issues such as depression (Williams et al., 2007) and PTSD (Brown et al., 2014; Ono et al., 2016). Although the current sample was from a nonclinical population, it remains possible that the increased symptoms of mental illness reported by the negative recurrent IAM group could be driving the observed decrement in episodic specificity. Conversely, another interpretation of this link between mental health status and reduced episodic detail relates to emotion regulation. Specifically, models have argued that it is adaptive to strategically recall autobiographical memories with less specificity in order to minimise aversive emotions (Williams et al., 2007). For instance, authors have found that less specificity in negative autobiographical memories can offer short-term benefits such as preventing rumination or immediate feelings of reliving (Hermans et al., 2008; Raes et al., 2003). However, these same short-term benefits are also accompanied by long-term consequences like greater symptoms of depression at a later follow-up (Gibbs & Rude, 2004), much like the increase in mental health issues observed in the current study. In other words, reducing episodic detail could be a strategic goal engaged during retrieval, either voluntary or involuntary (Lemogne et al., 2009), leading to increased mental health issues as opposed to an outcome of the mental health issues. These ideas further imply that negative voluntary autobiographical memories are not indicative of mental health status in the same way as recurrent IAMs; future work comparing recurrent IAMs to voluntary autobiographical memories will be needed to test this hypothesis.

An alternative account is that the experience of a negative recurrent IAM could be evoking different feelings than a negative voluntary autobiographical memory. Past evidence shows that involuntary memories are associated with stronger mood impact than voluntary memories (Berntsen, 2010; Berntsen & Hall, 2004; Rubin et al., 2008), so it is possible that retrieving a negative recurrent IAM could have provoked a more negative mood than that of past work on negative voluntary memories. Given that inducing negative mood reduces specificity in autobiographical memory (Sutherland & Bryant, 2007; Yeung et al., 2006), we may have observed less episodic detail in negative recurrent IAMs due to their characteristically high impact on mood state. Assessing participants' emotional states before and/or after retrieving the recurrent IAM could be an important next step to identifying the mechanism driving the effect of valence on episodic detail.

Limitations

Although participants' text descriptions were of memories they had experienced both recurrently and involuntarily, we asked our participants to recall them voluntarily for the purposes of the survey (i.e., in order to make a series of judgments about the memory). As such, these descriptions may not have fully captured the natural experience of an IAM springing to mind. For instance, voluntarily recounting a recurrent IAM might not evoke any feelings of uncontrollability or intrusiveness that might typically accompany the memory, and colour its phenomenology and subsequent description. However, our procedure closely follows past studies on recurrent IAMs, where involuntary memories were retrieved voluntarily during the study (Berntsen & Rubin, 2008). Future studies could compare these voluntary accounts to descriptions soon after an IAM's recurrence, perhaps through a diary method in which participants record IAMs immediately, as they occur in daily life (Berntsen, 1996).

An additional limitation related to participants' text descriptions stems from our coding of episodic and semantic details (Levine et al., 2002), and the reliability of this coding scheme. Specifically, one coder pair (C1-C2) produced very little agreement across their judgments of texts' semantic details (ICC = .08). Although it is possible that this disagreement could reflect low reliability in the coding scheme, evidence suggests that it is much more likely related to specific coders' understanding and/or execution of the coding task itself. If the coding scheme itself were unreliable, we would expect to see widespread issues with agreement across multiple coder pairs and dependent variables. On the contrary, the disagreement seemed specific to C2: reliability for semantic details was moderate across our other coder pairs (C1-C3 ICC = .61; C1-C4 ICC = .40). Moreover, disagreement between the C1-C2 coder pair was limited to semantic details, and not episodic details (C1-C2 ICC = .75). The present data therefore suggest that additional protocols may be necessary to confirm or supplement coders' abilities to apply the current coding scheme.

A further limitation of our current study is that although participants may have reported experiencing multiple recurrent IAMs recently, we did not assess the properties of any recurrent IAMs beyond their single most frequent one. This was done for numerous reasons, first of which was to maintain comparability with prior work, which also examined participants' one most frequently recurring IAM (Berntsen & Rubin, 2008). Second, because there were few previous studies of recurrent IAMs in the general population, we had little a priori evidence to suggest that participants would experience multiple recurrent IAMs. Because we did not have strong predictions about participants' less-frequently recurring IAMs, we focused on the memories they were most likely to describe and rate with confidence (i.e., their most frequently recurrent IAM). Our study revealed that participants who had recently experienced at least one recurrent IAM often reported experiencing multiple recurrent IAMs (M = 7.30, SD = 12.35). Further research seems warranted to investigate how one's less-frequently recurring IAMs may influence current conclusions about recurrent IAMs.

Finally, it is worth noting that in our study, the significant differences in mental health status across recurrent IAM valence were observed using clinical measures of mental health problems. This is remarkable because our current sample was nonclinical – that is, ability to detect differences in symptom severity of mental health disorders could have been limited since participants were nonclinical. As such, it remains possible that the current work is a conservative estimate of the link between recurrent IAM valence and mental health status. Future work can consider measuring constructs more closely oriented towards nonclinical young adults (such as wellbeing or thriving) in order to potentially capture mental health status with more granularity in the general population.

2.1.5 Conclusions

In the current study, we assessed the qualities of recurrent IAMs experienced by a large sample of nonclinical young adults and asked how those qualities might relate to mental health. We found that recurrent IAMs were experienced by the majority of our sample, and that they were mostly negative in valence. This aspect of valence was indicative of one's mental health status: participants who reported a negative IAM as their most frequently recurring memory also had significantly worse symptoms of mental health issues including depression, anxiety, and stress. Although negativity was related to poorer mental health, valence did not account for the intrusive nature of IAMs. The frequency with which an IAM recurred was instead predicted by the memory's age, level of completeness/detail, emotional intensity, and centrality to one's life story. As well, to our knowledge, our study is the first to show that recurrent IAMs that are positive in valence are described using significantly greater episodic detail relative to both neutral and negative recurrent IAMs. This suggests that the type of details used, and nature of how they are recounted, may reflect emotional regulation strategies: positive recurrent IAMs were better rooted in space and time, perhaps to elevate or maintain mood. Our findings reveal important characteristics of recurrent IAMs and specify their link to mental health status.

Chapter 3:
Individual Differences Modulate Recurrent IAMs

3.1 Study 2a

3.1.1 Introduction

Although they are common, many questions about recurrent IAMs' properties remain unanswered. In particular, a discrepancy exists regarding their valence. A notable finding from Berntsen and Rubin (2008) was that most participants reported positive recurrent IAMs (58%). This led to the suggestion that recurrent IAMs "typically do not favor negative material" (Berntsen & Rubin, 2008, p. 458), much like autobiographical memory in general (Walker et al., 2003). However, valence was dramatically different in recent work by Yeung and Fernandes (2020): Most participants reported negative recurrent IAMs (52%). Despite similar methods and large sample sizes, valence distributions were nearly reversed between these studies. In this study (Yeung & Fernandes, 2021), we examined whether age is related to recurrent IAMs, and whether these memories reflect mental health in both younger and older age groups.

Are the Properties of Recurrent IAMs Modulated by Age?

What might be responsible for the discrepancy in valence across studies? One potential explanation is participant age ($M \approx 43$ in Berntsen & Rubin, 2008; $M \approx 20$ in Yeung & Fernandes, 2020). This difference is relevant given the well-documented effects of aging on both memory for emotional information (Mather & Carstensen, 2005) and emotion regulation (ER), or the ability to change the magnitude/duration of emotional states (Gross, 2013). In one account, Socioemotional Selectivity Theory (SST; Carstensen, 1995; Carstensen et al., 1999) claims that older adults prioritize ER more than younger adults. As time left in life becomes perceived as limited, motivations and behaviors shift to maximize positive and minimize negative emotion. A complementary account comes from Strength and Vulnerability Integration (SAVI; Charles & Luong, 2013), which argues that older adults show specific advantages in enacting effective ER strategies. For example, SAVI claims that older adults often avoid exposure to negative emotions by avoiding situations that might provoke unpleasant feelings.

Critically, these preferences for positivity (and away from negativity) extend to autobiographical memory. Older adults have been shown to remember life events more positively compared to the ratings they originally gave those same events over a decade earlier (Kennedy et al., 2004). Similarly, older adults report significantly fewer negative IAMs than younger adults and sometimes ascribe neutral or positive valence to these memories (Schlagman et al., 2006). Taken together, both SST and SAVI suggest that age could modulate recurrent IAM valence by motivating older adults to make current experiences positive (Carstensen et al., 1999) or reappraise past ones positively (Charles & Luong, 2013). Thus, we hypothesized that older adults' recurrent IAMs would be more positive, whereas younger adults' would be more negative, explaining valence discrepancies across prior studies.

In addition to valence, aging could relate to the frequency of recurrent IAMs (i.e., how often they recur). Older age is characterized by episodic memory decline (Nilsson, 2003) and less frequent voluntary autobiographical memories, whereas IAM frequency is relatively spared (Berntsen et al., 2017). Multiple studies have reported nonsignificant age effects on IAM frequency (Berntsen et al., 2017; Warden et al., 2019), including recurrent IAMs (Berntsen & Rubin, 2008), though this may be limited to retrospective measures (e.g., questionnaires; Maillet & Schacter, 2016). Finding nonsignificant age differences in prevalence and frequency would support the idea that IAMs do not typically decline with age.

Are Recurrent IAMs Linked to Mental Health in Younger and Older Adults?

Another goal of our study was to examine relationships between aging, recurrent IAMs, and mental health. In the literature, there is debate regarding the degree to which IAMs reflect mental health. Clinical perspectives largely agree that recurrent IAMs are often distressing and contribute to psychopathology (Brewin et al., 2010; Clark & Rhyno, 2005; Marks et al., 2018; Mihailova & Jobson, 2018). In contrast, cognitive perspectives conceptualize these memories as typically benign or pleasant (Berntsen & Rubin, 2008), only a subset of which are dysfunctional (Berntsen, 2010). Indeed, recurrent IAMs seem too common to be a solely clinical phenomenon (Yeung & Fernandes, 2020). However, recurrent IAMs have been shown to be related to mental health at the subclinical level: Those reporting negative recurrent IAMs had significantly worse mental health (e.g., more symptoms of depression, anxiety, posttraumatic stress) compared to those reporting neutral, positive, or no recurrent IAMs (Yeung & Fernandes, 2020).

Importantly, it is unknown whether these relationships between recurrent IAMs and mental health generalize to older adults. In younger adults, negative recurrent IAMs may maintain poor mental health by evoking intense feelings of distress (Brewin et al., 2010; Mihailova & Jobson, 2018; Samide & Ritchey, 2021) and having strong impact on mood (Berntsen & Hall, 2004). According to SST, aging could disrupt this process since older adults show greater ability to dissipate negative emotions (Carstensen et al., 2000). If distress elicited by negative recurrent IAMs is better dissipated by older adults, these memories may be unrelated to mental health in older age, despite being predictive of younger adults' mental health (i.e., a significant interaction with age). Conversely, SAVI suggests that although older adults tend to successfully avoid negative emotions in daily life, benefits to ER are attenuated when distress is unavoidable (Charles & Carstensen, 2010; Charles & Luong, 2013). As such, an alternative prediction based on SAVI is that relationships between recurrent IAMs and mental health are similar across younger and older adults (i.e., a nonsignificant interaction with age), since distress evoked by negative IAMs may represent situations where individuals have already failed to avoid negative emotion.

To test our hypotheses, we administered online surveys probing for recurrent IAMs, their properties (e.g., frequency, valence), and participants' symptoms of mental health issues (e.g., depression, anxiety, posttraumatic stress). We compared the frequency and valence of recurrent IAMs between younger and older adults to examine age differences in recurrent IAMs. Finally, we investigated whether recurrent IAMs predicted mental health similarly or differently across age groups.

3.1.2 Method

Participants

Community-dwelling older adults were recruited from the Waterloo Research in Aging Pool (WRAP) database, consisting of people aged 60+. Of the 95 older adults who participated, 72% were women, 27% were men, and 1% preferred not to answer. Mean age was 75.6 (SD = 6.2, range = 64–91, with 54% aged 75+). In terms of education, 18% completed high school or lower, 24% completed some postsecondary education, 42% completed bachelor's degrees, and 16% completed graduate degrees.

Younger adults were recruited from the University of Waterloo. To equate sample sizes across age groups, 95 younger adults were randomly selected from a pool of participants (n = 2,184). Of these 95 younger adults, 74% were women, 25% were men, and 1% were nonbinary. Mean age was 19.7 (SD = 1.8, range = 18–26). In terms of education, 44% were first year, 16% were second year, 24% were third year, 14% were fourth year, and 2% were fifth year or above.

Materials

For summaries of each measure, see Study 1 and Appendix A. For descriptives, correlations between measures, and example text descriptions of recurrent IAMs, see online supplemental materials (https://osf.io/mznuw).

Recurrent Memory Scale. The Recurrent Memory Scale (Yeung & Fernandes, 2020; Table A1) measured autobiographical properties of recurrent IAMs. Participants indicated if they had experienced at least one recurrent IAM within the past year, not within the past year, or never (Berntsen & Rubin, 2008). Those who experienced at least one within the past year wrote a brief description of their one most frequently recurring IAM and rated it on twelve 5-point Likert scales, including frequency (i.e., how often it recurred) and valence, which were the focus of the present study.

Depression Anxiety Stress Scales. The Depression Anxiety Stress Scales (DASS-21; Lovibond & Lovibond, 1995) consist of 21 items with 3 subscales: depression (DASS-D), anxiety (DASS-A), and stress (DASS-S). Internal consistency was high in the current sample for the full scale ($\alpha = .95$) and the subscales for depression ($\alpha = .91$), anxiety ($\alpha = .87$), and stress ($\alpha = .89$).

Posttraumatic Stress Disorder Checklist for DSM-5. The Posttraumatic Stress Disorder Checklist for DSM-5 (PCL-5; Weathers et al., 2013) consists of 20 items assessing symptoms of posttraumatic stress disorder. Internal consistency was high in the current sample ($\alpha = .96$).

Social Phobia Inventory. The Social Phobia Inventory (SPIN; Connor et al., 2000) consists of 17 items assessing fear, anxiety, and physical discomfort experienced during social situations. Internal consistency was high in the current sample ($\alpha = .95$).

State-Trait Inventory of Cognitive and Somatic Anxiety. The State-Trait Inventory of Cognitive and Somatic Anxiety (STICSA; Grös et al., 2007) consists of 21 items assessing cognitive and somatic aspects of anxiety. Only the version assessing trait anxiety (STICSA-T) was administered. Internal consistency was high in the current sample ($\alpha = .94$).

Procedure

A 30-min online survey was emailed to all older adults in the WRAP database with valid email addresses ($n = 288$), 95 of whom responded. After providing informed consent, participants completed the scales of interest (see Materials) in a randomized order. Following participation, older adults received gift cards valued at $5.00 CAD.

Undergraduate students enrolled in at least one psychology course at the University of Waterloo self-registered for the 60-min online study in return for course credit. After providing informed consent, participants completed the same scales, embedded in a randomized order within a battery of questionnaires; all other measures were unrelated to the present study. All procedures were approved by the University of Waterloo's Office of Research Ethics (Protocol #40049).

3.1.3 Results

Participants were excluded pairwise (analysis-by-analysis) if they provided no response for at least one item in an analysis.

Prevalence and Frequency of Recurrent IAMs Across Age Groups

Of the 95 younger adults, 52 (55%) experienced at least one recurrent IAM within the past year, whereas 22 (23%) experienced recurrent IAMs within prior years, and 21 (22%) never experienced any.

Of the 95 older adults, 3 provided no response for the presence of recurrent IAMs. Among the remaining 92 older adults, 50 (54%) experienced at least one recurrent IAM within the past year, whereas 21 (23%) experienced recurrent IAMs within prior years, and 21 (23%) never experienced any.

A chi-square test of homogeneity indicated that prevalence distributions were not significantly different between age groups, $\chi^2(2, N = 187) = .01$, $p = .99$. A Bayes factor (BF) for contingency tables was calculated using an independent multinomial prior (Gunel & Dickey, 1974; Jamil et al., 2017; Morey & Rouder, 2018), which indicated strong evidence favoring the null hypothesis ($BF_{01} = 20.61$).

The frequency of recurring was also compared across younger and older adults. An independent samples *t*-test found that frequency was not significantly different across age groups, $t(91) = 1.35$, $SE = 0.24$, $p = .18$. A BF was calculated using a Jeffreys–Zellner–Siow prior (JZS; Morey & Rouder, 2018; Rouder et al., 2009), which indicated anecdotal evidence favoring the null hypothesis ($BF_{01} = 2.06$).

Valence of Recurrent IAMs Across Age Groups

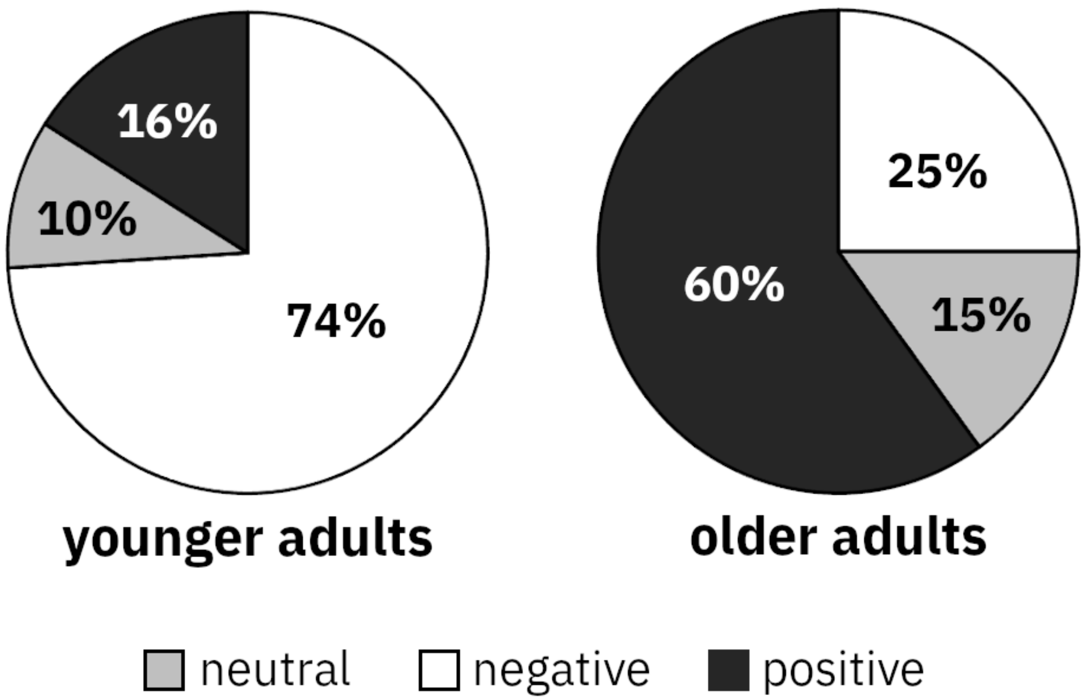
Of the 52 younger adults who experienced recurrent IAMs within the past year, 2 provided no response for valence. Among the remaining 50 younger adults, 37 (74%) reported negative or very negative recurrent IAMs, whereas 8 (16%) reported positive or very positive ones, and 5 (10%) reported neutral ones. A chi-square test showed that this distribution was significantly uneven across valences, $\chi^2(2, N = 50) = 37.5$, $p < .001$.

Of the 50 older adults who experienced recurrent IAMs within the past year, 10 provided no response for valence. Among the remaining 40 older adults, 24 (60%) reported positive or very positive recurrent IAMs, whereas 10 (25%) reported negative or very negative ones, and 6 (15%) reported neutral ones. A chi-square test showed that this distribution was significantly uneven across valences, $\chi^2(2, N = 40) = 13.4$, $p = .001$.

A chi-square test of homogeneity indicated that valence distributions were significantly different between age groups, $\chi^2(2, N = 90) = 22.8$, $p < .001$ (Figure 3). To determine which cells motivated the rejection of the null hypothesis, an analysis of contingency tables (ACT) was conducted using a one-stage bootstrap approach (30,000 replicates; García-Pérez et al., 2015). The ACT indicated that older adults were significantly less likely to report negative recurrent IAMs (residual = −4.62), and significantly more likely to report positive ones (residual = 4.33; familywise critical value = 2.31) than younger adults. No other differences were significant (residual = 0.72).

Figure 3

Distributions of Self-Reported Valence for Recurrent IAMs, Compared Between Younger and Older Adults (ns = 95)



Recurrent IAM Presence and Mental Health Across Age Groups

To assess whether the presence of recurrent IAMs (present = at least one recurrent IAM within the past year, absent = none within the past year or never) predicted mental health, separate hierarchical regressions were conducted for each mental health measure. Age differences in this relationship were assessed via Presence × Age group (younger, older) interactions. Variance inflation factors (VIFs) indicated no multicollinearity issues (VIFs < 3.34).

Model 1 revealed that recurrent IAM presence was a significant positive predictor for symptoms of all mental health measures (*p*s < .02). The addition of age group in Model 2 significantly improved all analyses (ΔR^2s > .09, *p*s < .001). Age group was a significant negative predictor, such that older age predicted fewer symptoms across all measures (*p*s < .001), replicating many studies (Bijl et al., 1998; Karlin et al., 2008; Westerhof & Keyes, 2010). However, Presence × Age group interactions in Model 3 were nonsignificant (*p*s > .11), indicating that relationships between presence and mental health were not significantly different between age groups (Table 2). BFs were calculated for the nonsignificant interactions using JZS priors (Morey & Rouder, 2018; Rouder et al., 2009), which indicated anecdotal to moderate evidence favoring Model 2 (BF_{01}s = 1.95–6.03).

Table 2

Hierarchical Multiple Regression Analyses with Recurrent IAM Presence, Age Group, and Their Interaction Predicting Mental Health Status (Symptoms of Depression, Stress, Posttraumatic Stress, General Anxiety, and Social Anxiety; ns = 174–178)

Variable	DASS-D			DASS-S			PCL-5			STICSA-T			SPIN		
	B	*SE* B	ß	B	*SE* B	ß	B	*SE* B	ß	B	*SE* B	ß	B	*SE* B	ß
Model 1															
Recurrent IAM Presence[a]	2.96	0.64	0.33***	2.33	0.62	0.27***	12.85	2.37	0.38***	7.75	1.70	0.33***	4.96	2.15	0.17*
Model 2															
Recurrent IAM Presence	2.84	0.61	0.31***	2.17	0.56	0.25***	11.99	2.05	0.36***	7.29	1.54	0.31***	4.15	1.73	0.14*
Age Group[b]	-2.70	0.61	-0.30***	-3.41	0.56	-0.40***	-15.80	2.04	-0.47***	-9.72	1.54	-0.41***	-17.08	1.73	-0.59***
Model 3															
Recurrent IAM Presence	3.32	0.85	0.32***	2.47	0.78	0.26***	15.16	2.83	0.36***	9.13	2.12	0.31***	5.07	2.39	0.14*
Age Group[b]	-2.18	0.90	-0.30*	-3.07	0.83	-0.40***	-12.29	2.97	-0.47***	-7.66	2.25	-0.41**	-16.05	2.52	-0.59***
Recurrent IAM Presence × Age Group	-0.99	1.23	-0.06	-0.63	1.13	-0.04	-6.60	4.08	-0.10	-3.86	3.07	-0.08	-1.95	3.47	-0.03
Model 1 R^2	0.11***			0.08***			0.15***			0.11***			0.03*		
Model 2 ΔR^2	0.09***			0.16***			0.22***			0.17***			0.35***		
Model 3 ΔR^2	0.003			0.001			0.01			0.006			0.001		
Model 3 BF_{01}[c]	3.72			4.69			1.95			2.76			6.03		

Note. [a] 0 = absent, 1 = present. [b] 0 = younger, 1 = older. [c] Model 3 Bayes factors were calculated relative to Model 2. * $p < .05$; ** $p < .01$; *** $p < .001$.

Recurrent IAM Valence and Mental Health Across Age Groups

To assess whether recurrent IAM valence predicted mental health, separate hierarchical regressions were conducted for each mental health measure. Age differences in this relationship were assessed via Valence × Age group (younger, older) interactions. Valence was mean centered (Iacobucci et al., 2016), after which VIFs indicated no multicollinearity issues (VIFs < 2.73).

Model 1 revealed that recurrent IAM valence was a significant negative predictor for symptoms of all mental health measures (ps < .01), such that positive valence predicted fewer symptoms. The addition of age group in Model 2 significantly improved almost all analyses (ΔR^2s > .10, *p*s < .001), except for depression ($\Delta R^2 = .03$, $p = .09$). As expected, age group was a significant negative predictor, such that older age predicted fewer symptoms (*p*s < .01; Bijl et al., 1998; Karlin et al., 2008; Westerhof & Keyes, 2010), excluding depression ($p = .09$). However, Valence × Age group interactions in Model 3 were nonsignificant (*p*s > .67), indicating that relationships between valence and mental health were not significantly different between age groups (Table 3). BFs were calculated for the nonsignificant interactions using JZS priors (Morey & Rouder, 2018; Rouder et al., 2009), which indicated moderate evidence favoring Model 2 (BF_{01}s = 2.97–4.93).

Table 3

Hierarchical Multiple Regression Analyses with Recurrent IAM Valence, Age Group, and Their Interaction Predicting Mental Health Status (Symptoms of Depression, Stress, Posttraumatic Stress, General Anxiety, and Social Anxiety; ns = 87–89)

Variable	DASS-D			DASS-S			PCL-5			STICSA-T			SPIN		
	B	*SE* B	ß	B	*SE* B	ß	B	*SE* B	ß	B	*SE* B	ß	B	*SE* B	ß
Model 1															
Recurrent IAM Valence[a]	-0.97	0.35	-0.29**	-0.95	0.31	-0.32**	-3.96	1.25	-0.33**	-3.32	0.83	-0.39***	-4.60	0.95	-0.46**
Model 2															
Recurrent IAM Valence	-0.65	0.39	-0.19	-0.38	0.32	-0.13	-1.30	1.26	-0.11	-1.85	0.90	-0.22*	-2.15	0.98	-0.22*
Age Group[b]	-2.00	1.17	-0.20	-3.63	0.97	-0.40***	-17.27	3.77	-0.48***	-9.22	2.71	-0.36**	-14.52	2.97	-0.48***
Model 3															
Recurrent IAM Valence	-0.75	0.54	-0.20	-0.25	0.45	-0.12	-1.00	1.74	-0.10	-2.21	1.25	-0.22	-2.06	1.34	-0.22
Age Group[b]	-2.01	1.18	-0.20	-3.61	0.97	-0.40***	-17.22	3.80	-0.47***	-9.29	2.72	-0.37**	-14.49	3.01	-0.48***
Recurrent IAM Valence × Age Group	0.21	0.79	0.03	-0.28	0.65	-0.05	-0.64	2.55	-0.03	0.75	1.80	0.04	-0.19	1.98	-0.01
Model 1 R^2		0.08**			0.10**			0.11**			0.16***			0.21***	
Model 2 ΔR^2		0.03			0.13***			0.18***			0.10***			0.17***	
Model 3 ΔR^2		0.001			0.001			<0.001			0.002			<0.001	
Model 3 BF_{01}[c]		2.97			3.47			4.01			3.66			4.93	

Note. [a] Valence was mean centered. [b] 0 = younger, 1 = older. [c] Model 3 Bayes factors were calculated relative to Model 2. * $p < .05$, ** $p < .01$, *** $p < .001$.

3.1.4 Discussion

Recurrent IAMs are surprisingly common in daily life (Berntsen & Rubin, 2008; Yeung & Fernandes, 2020). Despite their prevalence, little is known about how properties of recurrent IAMs (e.g., frequency, valence) might vary across age groups, and how these memories relate to mental health in both younger and older age. In our study, we reasoned that older adults would report fewer negative recurrent IAMs than younger adults (Carstensen, 1995; Carstensen et al., 1999; Charles & Carstensen, 2010; Charles & Luong, 2013). Further, we compared recurrent IAMs' ability to predict mental health across age groups to contrast the predictions of SST (Carstensen, 1995; Carstensen et al., 1999) and SAVI (Charles & Luong, 2013).

First, we addressed discrepancies in recurrent IAM valence seen across past studies. Although recurrent IAMs were mostly positive in earlier research (Berntsen & Rubin, 2008), recent work found the opposite pattern (i.e., mostly negative; Yeung & Fernandes, 2020). We identified participant age as a potentially important difference between these studies. Extensive work supports that older adults show preferences toward positive information (Carstensen et al., 1999; Mather & Carstensen, 2005; Reed & Carstensen, 2012) and enhanced ER (Giromini et al., 2017; Orgeta, 2009; Prakash et al., 2017). Consistent with the significant increases in recurrent IAM valence over the lifespan reported by Berntsen & Rubin (2008), we found that age was related to recurrent IAM valence: While younger adults' recurrent IAMs were disproportionately negative (74%), older adults' recurrent IAMs were disproportionately positive (60%).

From a theoretical standpoint, this age difference in recurrent IAM valence is interesting because both SST and SAVI highlight goal-directed processes that result in positivity preferences (Carstensen, 1995; Carstensen et al., 1999; Charles & Luong, 2013). These strategic processes may seem incompatible with recurrent IAMs, given that these memories are involuntary; however, IAMs are readily affected by the current situation or cues available (Berntsen, 2010). For example, individuals can avoid certain cues (e.g., the smell of gasoline) if they know that those cues tend to provide access to negative IAMs (e.g., having been in a car crash). According to SST, older adults likely prioritize avoiding such cues given their focus on emotional goals (Charles & Carstensen, 2010). Further, SAVI suggests that this proactive avoidance is precisely what older adults excel at in daily life (Charles & Luong, 2013). Older adults might be modulating recurrent IAM valence by selecting situations that provoke positive IAMs and avoiding situations that provoke negative IAMs.

SST and SAVI also illustrate how age might modulate relationships between recurrent IAMs and mental health. While recurrent IAMs can predict symptoms of mental health issues in younger adults (Yeung & Fernandes, 2020), models of aging question whether this relationship persists into older age.

Specifically, SST suggests that aging could change this relationship because older adults may dampen the distress evoked by negative recurrent IAMs (Berntsen & Hall, 2004; Brewin et al., 2010; Samide & Ritchey, 2021), thanks to enhanced ER (Carstensen, 1995; Carstensen et al., 1999). Conversely, SAVI predicts that the distress associated with negative recurrent IAMs would prevent older adults from engaging their enhanced ER strategies, attenuating age differences (Charles & Luong, 2013).

In line with SAVI, we found nonsignificant interactions between recurrent IAMs and age group when predicting mental health (BF_{01}s = 2–6; moderate evidence for the null hypothesis). Instead, main effects of recurrent IAM presence and valence significantly predicted mental health, regardless of age. Our work suggests that despite fewer negative recurrent IAMs in older age, recurrent IAMs reflect mental health similarly across age groups. These associations between recurrent IAMs and mental health have been theorized to be driven by distress (Brewin et al., 2010; Marks et al., 2018; Mihailova & Jobson, 2018), such that negative recurrent IAMs induce distress, which in turn contributes to psychopathology. It follows that these associations may be sensitive to individuals' abilities to regulate distress: for those who are able to dissipate distress evoked by negative recurrent IAMs, these memories should be unrelated to mental health. However, recurrent IAM presence and valence significantly predicted mental health in both age groups, suggesting that neither age group sufficiently dissipated this distress – a pattern supported by SAVI (i.e., attenuated age differences), since distress evoked by negative recurrent IAMs might represent situations where one has already failed to avoid a stressor. Although our results align more closely to SAVI than SST, further replication seems warranted to adjudicate between these models.

Finally, our findings show that recurrent IAMs are common and frequent across age groups. In our study, most younger adults (55%) experienced at least one recurrent IAM within the past year, closely replicating prior estimates (52%–53%; Berntsen & Rubin, 2008; Yeung & Fernandes, 2020). Interestingly, prevalence was similarly high in our older adults (54%), suggesting that prevalence may not decline with age. Failing to observe age effects replicates many studies on IAMs (Berntsen et al., 2017; Schlagman et al., 2009; Warden et al., 2019), though Berntsen and Rubin (2008) found a slight (but significant) reduction in recurrent IAM prevalence with age. Although the BF strongly favored the null hypothesis in our study (21:1), we may have failed to detect age differences due to our smaller sample size or different administration method (online vs. telephone; Berntsen & Rubin, 2008). Consistent with prevalence, we found no significant age difference in recurrent IAM frequency (i.e., how often they recur), and a BF favoring the null hypothesis (2:1), replicating past studies (Berntsen et al., 2017; Berntsen & Rubin, 2008).

Limitations

Although enhanced ER is well documented in older adults (Carstensen, 1995; Giromini et al., 2017; Mather & Carstensen, 2005; Orgeta, 2009; Prakash et al., 2017), we did not directly measure ER in our study. As such, we cannot be certain that age differences in recurrent IAM valence were driven by ER. For instance, cohort effects could have colored participants' recurrent IAMs in divergent ways. In Study 2b, we investigate relationships between ER and recurrent IAMs, isolated from aging.

The current work also relied on self-report, scale-based measures of recurrent IAM valence. Although this approach is consistent with past studies (Berntsen & Rubin, 2008; Yeung & Fernandes, 2020), scales may not fully capture the emotional experiences of recurrent IAMs. Participants may have wished to ascribe mixed or discrete emotions to recurrent IAMs, especially older adults, who tend to have complex emotional experiences (Carstensen et al., 1999). To incorporate these more nuanced expressions of emotion in AMs, in Studies 3 and 4, we examined content in recurrent IAMs (participants' written descriptions) to further refine our understanding of the relationships between IAMs and mental health.

3.1.5 Conclusions

Recurrent IAMs are common and frequent in daily life. Our work suggests that the proportion of people experiencing recurrent IAMs, and the rate at which they recur, are stable across younger and older adults in the general population. Conversely, the valence of recurrent IAMs was nearly reversed across age groups. Perhaps most noteworthy, the presence and valence of recurrent IAMs reflected mental health similarly across age groups, despite the involuntary nature of these memories. That is, properties of recurrent IAMs significantly predicted mental health (e.g., symptoms of depression, anxiety, posttraumatic stress), regardless of whether one was a younger or older adult. Results suggest that recurrent IAMs offer insight into mental health for both younger and older adults.

3.2 Study 2b

3.2.1 Introduction

Emotion regulation, or the activation of a goal to modify one's emotional state (e.g., changing its magnitude or duration; Gross, 2013), is known to vary across age: older adults show increased motivation and ability to elevate and maintain mood relative to younger adults (Carstensen, 1995; Carstensen et al., 1999; Charles & Carstensen, 2010; Mather & Carstensen, 2005). Moreover, older adults consistently report fewer difficulties in ER than younger adults (i.e., enhanced ER; Giromini et al., 2017; Orgeta, 2009; Prakash et al., 2017). This age-related benefit to ER has well-documented effects on many cognitive processes, including memory, wherein positive information becomes preferred over negative information (Reed & Carstensen, 2012).

In line with this age-related positivity effect, our findings from Study 2a replicate and extend past work to show that aging is related to the valence distribution of recurrent IAMs: while younger adults' recurrent IAMs were disproportionately negative, older adults' were disproportionately positive. However, ER was only inferred based on participants' age groups. As well, it was not possible to rule out the potential influence of cohort, since younger and older adults were born in different eras (e.g., the 1940s vs. the 2000s). It stands to reason that ER, disentangled from aging, could similarly modulate recurrent IAMs' properties.

Existing work indicates that how one regulates one's emotions following an event impacts memory for that event (Hayes et al., 2010; Richards & Gross, 2000, 2006). For instance, regulating emotion by using cognitive reappraisal (e.g., changing the meaning of an event) or expressive suppression (e.g., not displaying emotional reactions outwardly) has been shown to improve or impair explicit memory, respectively (Hayes et al., 2010). Recent work has extended these findings to IAMs, suggesting that IAMs can elicit different ER strategies, in the moment, compared to voluntary autobiographical memories (del Palacio-Gonzalez et al., 2017). These differences in ER could, in turn, influence the retention and phenomenology of recurrent IAMs, independent from the additional factor of aging.

There is also reason to believe that ER could modulate relationships between recurrent IAMs and mental health indices, independent from aging. ER is well-known as playing an important role in the etiology and maintenance of psychopathology, with recent literature converging on the idea that ER processes are transdiagnostic: altered ER processes can be observed across a wide variety of disorders, and evidence suggests that these changes in ER *cause* changes in mental health (Aldao et al., 2010; Cludius et al., 2020; Fernandez et al., 2016; Sloan et al., 2017). In these models, those who tend to use certain ER strategies (e.g., ruminating on negative information) are at greater risk of developing or exacerbating mental health disorders (Cludius et al., 2020), since these ER processes can prolong negative mood and feelings of distress. Importantly, one's ability to carry out ER strategies in response to voluntary autobiographical memories has been linked to symptoms of mental health disorders (del Palacio-Gonzalez & Berntsen, 2020). Indeed, emotions evoked by memories have been acknowledged as important antecedents to ER in daily life (Samide & Ritchey, 2021), suggesting that those who have difficulties regulating emotions evoked by negative memories may be more susceptible to mental health disorders.

To investigate the relationship between ER and recurrent IAMs, isolated from the factor of aging, we conducted Study 2b, comparing recurrent IAMs between younger adults with either low or high trait ER scores. In this way, we addressed the limitation of potential cohort effects from Study 2a and examined a potential mechanism by which valence of recurrent IAMs may be influenced. Further, we investigated whether enhanced ER, independent from aging, could disrupt associations between negative recurrent IAMs and symptoms of mental health disorders.

3.2.2 Method

Participants

Undergraduate students were recruited from the University of Waterloo, all of whom were enrolled in at least one psychology course. Participants self-registered for the current study in return for partial course credit. Of the 870 participants, 73% were women, 25% were men, 1% preferred not to answer, and 1% were nonbinary. Mean age was 20.9 (*SD* = 3.6, range = 18–48).

From this sample, groups of high and low trait ER were formed based on upper and lower quartiles for scores on the Difficulties in Emotion Regulation Scale (DERS-16; Bjureberg et al., 2016). Higher scores on the DERS-16 reflect more difficulties with regulating emotions (i.e., lower ER), whereas lower scores reflect fewer difficulties (i.e., higher ER). Using the cumulative distribution function method (Langford, 2006) to calculate quartiles, 215 participants scored in the lower quartile (*M* = 22.8, *SD* = 3.9, range = 16–29) and 215 participants scored in the upper quartile (*M* = 60.3, *SD* = 7.4, range = 51–80) on the DERS-16. This lower quartile is henceforth referred to as the high ER group, and the upper quartile is referred to as the low ER group.

Materials

All materials were identical to Study 2a, except for the addition of the DERS-16. Internal consistency was high for the DASS-D (α = .90), DASS-S (α = .85), PCL-5 (α = .95), STICSA (α = .93), and SPIN (α = .93) in the current sample.

Difficulties in Emotion Regulation Scale. The DERS-16 (Bjureberg et al., 2016) consists of 16 items assessing difficulty with regulating emotion. Participants indicated how often each statement applied to them (e.g., "When I am upset, my emotions feel overwhelming") on a 5-point Likert scale (1 = *almost never*, 5 = *almost always*). Higher scores indicate more difficulty regulating one's emotions. The DERS-16 has been found to have excellent internal consistency, good test-retest reliability, and good convergent and divergent validity (Bjureberg et al., 2016). Internal consistency was high in the current sample ($\alpha = .95$).

Procedure

All procedures were identical to that of the younger adult sample in Study 2a, except for the addition of the DERS-16 (Bjureberg et al., 2016) as one of the scales of interest. All study procedures were approved by the Office of Research Ethics at the University of Waterloo (Protocol #40049).

3.2.3 Results

As in Study 2a, participants were excluded pairwise (analysis-by-analysis) if they were missing responses for at least one item in any of the measures included in a given analysis.

Prevalence and Frequency of Recurrent IAMs Across ER Groups

Of the 215 participants in the low ER group, one was missing a response on the item assessing presence of recurrent IAMs. Among the remaining 214 participants, 119 participants (56%) reported having experienced at least one recurrent IAM within the past year. In addition, 50 participants (23%) reported having experienced at least one recurrent IAM, but not within the past year. Finally, 45 participants (21%) reported having never experienced a recurrent IAM.

Of the 215 participants in the high ER group, 82 participants (38%) reported having experienced at least one recurrent IAM within the past year. In addition, 57 participants (27%) reported having experienced at least one recurrent IAM, but not within the past year. Finally, 76 participants (35%) reported having never experienced a recurrent IAM.

To compare the prevalence of recurrent IAMs between low and high ER groups, a chi-square test of homogeneity was conducted. Distributions of prevalence were significantly different between low and high ER groups, χ^2 $(2, N = 429) = 15.2$, $p < .001$. To determine which cells motivated the rejection of the omnibus null hypothesis, an ACT was conducted using a one-stage bootstrap approach (García-Pérez et al., 2015). Using 30,000 replicates, the ACT indicated that the high ER group was significantly less likely to experience recurrent IAMs within the past year (residual = -3.63), and significantly more likely to have never experienced them (residual = 3.30; familywise critical value = 2.36) compared to the low ER group. No other differences were significant (residual = 0.75).

Frequency of recurring was also compared across low and high ER groups. An independent samples *t*-test found that recurrent IAMs were rated as recurring significantly more frequently by the low ER group ($M = 2.85$) relative to the high ER group ($M = 2.37$; $t(198) = 3.36$, $SE = 0.14$, $p < .001$, $d = 0.48$).

Valence of Recurrent IAMs Across ER Groups

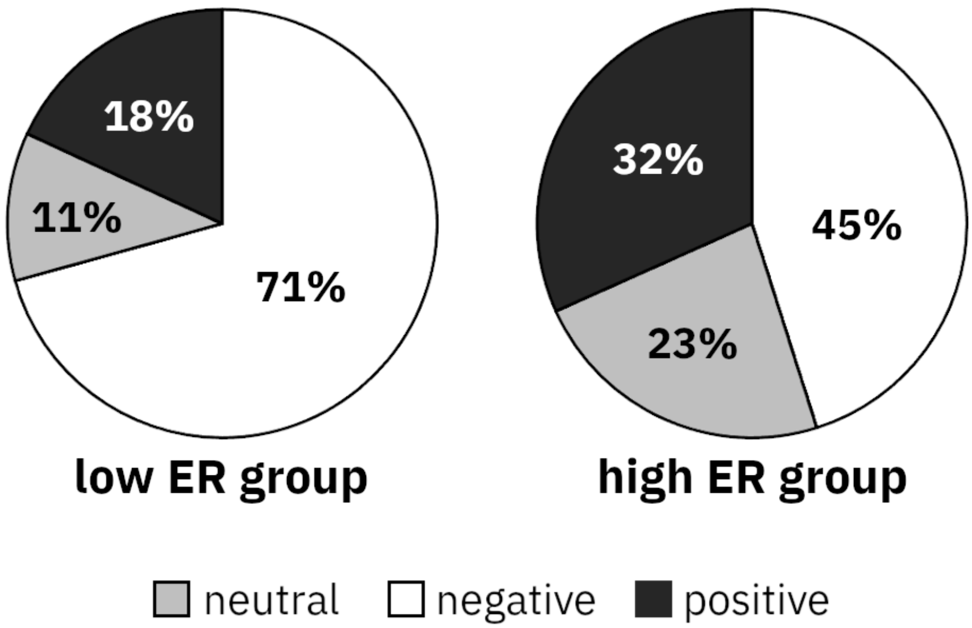
Of the 119 participants in the low ER group who reported experiencing at least one recurrent IAM within the past year, three were missing responses for self-rated valence of the memory. Among the remaining 116 participants, 82 participants (71%) rated their most frequently recurring IAM as negative or very negative. Conversely, 21 participants (18%) rated them as positive or very positive, and 13 participants (11%) rated them as neutral. A chi-square test showed that this distribution was significantly different from an even distribution across valences, χ^2 (2, $N = 116$) = 73.7, $p < .001$.

Of the 82 participants in the high ER group who reported experiencing at least one recurrent IAM within the past year, 26 participants (32%) rated their most frequently recurring IAM as positive or very positive. Conversely, 37 participants (45%) rated them as negative or very negative, and 19 participants (23%) rated them as neutral. A chi-square test showed that this distribution was significantly different from an even distribution across valences, χ^2 (2, $N = 82$) = 6.0, $p = .049$.

To compare the valence of recurrent IAMs between low and high ER groups, a chi-square test of homogeneity was conducted (see Figure 4, comparing valence by ER group). Distributions of valence were significantly different between low and high ER groups, χ^2 (2, $N = 198$) = 13.2, $p = .001$. To determine which cells motivated the rejection of the omnibus null hypothesis, an ACT was conducted using a one-stage bootstrap approach (García-Pérez et al., 2015). Using 30,000 replicates, the ACT indicated that the high ER group was significantly less likely to report a negative IAM as their most frequently recurring (residual = -3.62, familywise critical value = 2.32) compared to the low ER group. No other differences were significant (residuals < 2.25).

Figure 4

Distributions of Self-Reported Valence for Recurrent IAMs, Compared Between Younger Adults with Low Emotion Regulation and High Emotion Regulation (ns = 215)



Note. ER = emotion regulation.

Recurrent IAM Presence and Mental Health Across ER Groups

To assess whether presence of recurrent IAMs predicted mental health status, hierarchical multiple regression analyses were conducted using participants' responses on the item assessing occurrence of any recurrent IAMs. These analyses were very similar to those of Study 2a, except we assessed ER-related differences (rather than age-related differences) by adding interaction terms between recurrent IAM presence (present, absent) and ER group (low, high). VIFs were less than 3.31, indicating no issues related to multicollinearity.

Model 1 revealed that recurrent IAM presence was a significant positive predictor of symptoms of mental health issues across all measures (ps < .02). The addition of ER group and a presence × ER group interaction in Model 2 significantly improved all analyses (ΔR^2s > .32, ps < .001). ER group was a significant negative predictor of mental health issues, such that high ER predicted fewer symptoms of mental health issues across all measures (ps < .001). However, the interaction terms were all nonsignificant predictors (*p*s > .33), indicating that the significant relation between recurrent IAM presence and mental health status did not differ between ER groups (see Table 4).

Table 4

Hierarchical Multiple Regression Analyses with Recurrent IAM Presence, ER Group, and Their Interaction Predicting Mental Health Status (Symptoms of Depression, Stress, Posttraumatic Stress, General Anxiety, and Social Anxiety; ns = 422–429)

Variable	DASS-D			DASS-S			PCL-5			STICSA-T			SPIN		
	B	***SE* B**	**ß**	**B**	***SE* B**	**ß**	**B**	***SE* B**	**ß**	**B**	***SE* B**	**ß**	**B**	***SE* B**	**ß**
Model 1															
Recurrent IAM Presence[a]	1.26	0.54	0.11^{*}	1.72	0.49	0.17^{***}	8.54	1.84	0.22^{***}	5.23	1.28	0.19^{***}	3.49	1.54	0.11^{*}
Model 2															
Recurrent IAM Presence	-0.03	0.60	<0.01	0.58	0.52	0.05	4.92	1.85	0.09	1.85	1.29	0.07	-0.90	1.81	0.01
ER Group[b]	-7.13	0.59	-0.63^{***}	-6.65	0.51	-0.66^{***}	-25.76	1.80	-0.70^{***}	-18.91	1.26	-0.71^{***}	-19.56	1.76	-0.58^{***}
Recurrent IAM Presence × ER Group	0.12	0.86	0.01	-0.06	0.75	>-0.01	-2.54	2.65	-0.03	-0.03	1.84	>-0.01	2.28	2.57	0.04
Model 1 R^2		0.01^{*}			0.03^{***}			0.05^{***}			0.04^{***}			0.01^{*}	
Model 2 ΔR^2		0.39^{**}			0.42^{***}			0.48^{***}			0.48^{***}			0.33^{**}	

Note: [a] 0 = absent, 1 = present. [b] 0 = low, 1 = high. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Recurrent IAM Valence and Mental Health Across ER Groups

To assess whether valence of recurrent IAMs predicted mental health status, hierarchical multiple regression analyses were conducted using participants' self-ratings of valence for their most frequently recurring IAM. We assessed ER-related differences by adding interaction terms between valence and ER group (low, high). Valence ratings were mean centered to reduce VIFs and effects of multicollinearity (Iacobucci et al., 2016). After mean centering, VIFs were less than 2.45, indicating no issues related to multicollinearity.

Model 1 revealed that recurrent IAM valence was a significant negative predictor of symptoms of mental health issues across all measures (ps $< .01$), such that more positive valence predicted fewer symptoms. The addition of ER group and a valence × ER group interaction as predictors in Model 2 significantly improved all analyses (ΔR^2s $> .29$, ps $< .001$). ER group was a significant negative predictor of mental health issues, such that high ER predicted fewer symptoms of mental health issues (ps $< .001$). However, the interaction terms were all nonsignificant predictors (ps $> .19$), indicating that the significant relation between recurrent IAM valence and mental health status did not differ between ER groups (see Table 5).

Table 5

Hierarchical Multiple Regression Analyses with Recurrent IAM Valence, ER Group, and Their Interaction Predicting Mental Health Status (Symptoms of Depression, Stress, Posttraumatic Stress, General Anxiety, and Social Anxiety; ns = 193–198)

Variable	DASS-D			DASS-S			PCL-5			STICSA-T			SPIN		
	B	*SE* B	ß	B	*SE* B	ß	B	*SE* B	ß	B	*SE* B	ß	B	*SE* B	ß
Model 1															
Recurrent IAM Valence[a]	-1.18	0.30	-0.27***	-0.86	0.26	-0.23**	-3.92	1.06	-0.26***	-2.50	0.70	-0.25***	-2.23	0.80	-0.20**
Model 2															
Recurrent IAM Valence	-0.73	0.34	-0.14	-0.38	0.28	-0.08	-1.67	1.04	-0.10	-0.27	0.69	-0.08*	-0.44	0.91	-0.06
ER Group[b]	-6.65	0.70	-0.56***	-6.46	0.57	-0.64***	-27.34	2.14	-0.68***	-18.24	1.39	-0.68***	-16.85	1.83	-0.56***
Recurrent IAM Valence × ER Group	0.31	0.52	0.04	0.21	0.43	0.03	0.34	1.62	0.01	-1.35	1.05	-0.07	-0.70	1.38	-0.03
Model 1 R^2	0.07***			0.05**			0.07***			0.06***			0.04**		
Model 2 ΔR^2	0.37***			0.43***			0.50***			0.51***			0.34***		

Note: [a] Valence was mean centered. [b] 0 = low, 1 = high. ** $p < .01$, *** $p < .001$.

3.2.4 Discussion

In the current study, we examined the associations between ER and recurrent IAMs, disentangled from aging. To do so, we administered the same scales as in Study 2a to a new sample of younger adults, except with the addition of a measure of trait ER. By comparing those scoring in the lower and upper quartiles of self-reported trait ER, we examined whether aging-related modulations to recurrent IAMs could be replicated when considering differences in ER alone.

To begin, we found that the prevalence of recurrent IAMs was significantly different across low and high ER groups. Specifically, those with high ER were significantly less likely to have experienced a recurrent IAM in the past year, and significantly more likely to have never experienced a recurrent IAM relative to those low in ER. Given that recurrent IAM prevalence for the low ER group (56%) was similar to past studies (52–53%; Berntsen & Rubin, 2008; Yeung & Fernandes, 2020) as well as Study 2a (54–55%), this result could mean that younger adults with high ER are a population that is particularly unlikely to experience recurrent IAMs (38%). More work may be warranted to establish whether recurrent IAMs are as universal as previously believed. Researchers could consider whether individual differences beyond ER and aging (such as executive function or cognitive flexibility) can also influence the prevalence of IAMs.

In a similar vein, IAMs recurred significantly more frequently for participants with low compared to high ER. This is particularly interesting because younger and older adults did not show such a difference in frequency ratings in Study 2a. This suggests that individual differences in ER may indeed be related to recurrent IAM frequency, but that other age-related factors could have obscured this effect in Study 2a. Alternatively, our low and high ER groups could have varied on a key factor related to recurrent IAM frequency that we did not measure here.

We also largely replicated the differences in recurrent IAM valence seen in Study 2a. Those high in ER, much like the older adults in Study 2a, were significantly less likely to report a negative recurrent IAM compared to those low in ER. In contrast to Study 2a, we did not find as dramatic a reversal in distribution: high emotion regulators' recurrent IAMs were not disproportionately positive, as were older adults' recurrent IAMs. Thus, although ER can account for a significant decrease in negative recurrent IAMs, it does not seem fully responsible for the disproportionately high ratio of positive recurrent IAMs seen in Study 2a's older adults. As such, other aging-related changes may be necessary for recurrent IAMs to be mostly positive. Nevertheless, enhanced ER (while holding age group constant) was associated with fewer negative recurrent IAMs, supporting the hypothesis that one's capacity to regulate emotions can modulate the properties of recurrent IAMs.

Most notably, we replicated the finding that recurrent IAM presence and valence are significant predictors of mental health status. Experiencing at least one recurrent IAM within the past year predicted more symptoms of mental health issues (*p*s < .05; see Table 4). As well, of those who reported a recurrent IAM within the past year, more negative valence further predicted worse mental health (*p*s < .01; see Table 5). Critically, the invariance of these relationships across groups was also replicated: interactions between recurrent IAMs and ER group were nonsignificant, much like the interactions with age group in Study 2a. Our data thus indicate that the presence of a recurrent IAM, as well as its valence, predict symptoms of mental health issues (i.e., depression, stress, posttraumatic stress, general anxiety, and social anxiety) to a similar degree, regardless of one's trait level of ER.

Limitations

The use of the DERS-16 (Bjureberg et al., 2016) in the current study limits our ability to draw conclusions about ER in general and its relationship to recurrent IAMs. ER is a complex, multifaceted construct, including not just the difficulties one experiences when attempting to regulate one's emotions (Bjureberg et al., 2016), but also the types of strategies one typically uses, the frequency with which one uses them, and the flexibility with which one deploys appropriate strategies (Aldao et al., 2010; Cludius et al., 2020; Gross, 2013). Measuring additional components of ER could provide a more holistic and nuanced view of how ER might modulate recurrent IAMs and their relationships to mental health.

3.3 Chapter 3 General Discussion

Recurrent IAMs are commonly experienced among large samples of the general population (Berntsen & Rubin, 2008; Yeung & Fernandes, 2020). Importantly, some work has shown that properties of IAMs can change depending on individual differences (Berntsen & Rubin, 2008; Rubin & Berntsen, 2009). Of particular interest in Studies 2a and 2b were individual differences in age (Berntsen et al., 2017; Schlagman et al., 2009; Warden et al., 2019) and ER (del Palacio-Gonzalez et al., 2017; del Palacio-Gonzalez & Berntsen, 2020), which are theoretically related to the cognitive processes supporting recurrent IAMs. Furthermore, recent evidence showed that individual differences in mental health status were related to recurrent IAMs, even at the subclinical level (Yeung & Fernandes, 2020). Investigating whether these relationships between recurrent IAMs and mental health are consistent, regardless of one's age or level of ER, would speak to the generalizability and reliability of our claim that recurrent IAMs and their characteristics serve as a window into mental health status. In Studies 2a and 2b, we reasoned that the enhanced ER seen in older adults (Carstensen, 1995; Carstensen et al., 1999; Charles & Carstensen, 2010) could modulate how recurrent IAMs are experienced. In the same vein, individual differences in the extent to which younger adults can regulate their emotions (Gross & John, 2003) could also relate to recurrent IAMs and mental health. Across two studies, we compared the subjective characteristics of recurrent IAMs, as well as their ability to predict mental health status, between two groups: younger versus older adults in Study 2a, and younger adults with low versus high ER in Study 2b.

Critically, the current studies addressed the discrepancy in recurrent IAM valence seen across past studies. Although recurrent IAMs were found to be mostly positive in earlier research (Berntsen & Rubin, 2008), other work has reported the opposite pattern – recurrent IAMs have also been found to be mostly negative (Yeung & Fernandes, 2020). In comparing these studies, we identified participant age as a potentially important difference between samples. A large body of work supports that older adults, compared to younger adults, show greater preferences towards positive information (Carstensen et al., 1999; Mather & Carstensen, 2005; Reed & Carstensen, 2012) and enhanced ER (Giromini et al., 2017; Orgeta, 2009; Prakash et al., 2017). In line with these predictions, we found that age was indeed related to valence of recurrent IAMs: while younger adults' recurrent IAMs were disproportionately negative, older adults' recurrent IAMs were disproportionately positive in Study 2a.

We replicated and extended this pattern in Study 2b by contrasting recurrent IAM valence between low and high ER groups, within the same age group (younger adults). As predicted, younger adults high in ER were significantly less likely to report a negative recurrent IAM than those low in ER. Study 2b thus supported that enhanced ER is associated with fewer negative recurrent IAMs. However, an important caveat was that the valence distribution did not flip to the same magnitude as in Study 2a. In other words, although older adults' recurrent IAMs were disproportionately positive in Study 2a, the valence distribution was still disproportionately negative for younger adults with high ER in Study 2b. While ER accounted for a significant reduction in negative recurrent IAMs, it was not sufficient to fully explain the reversal in valence; other age-related effects could have contributed to this pattern. In sum, our data suggest that whether recurrent IAMs are generally positive or negative can depend heavily on the individual differences of the chosen sample.

Most importantly, the current studies build upon our understanding of the relationship between recurrent IAMs and mental health status. Because the characteristics of recurrent IAMs have been found to predict symptoms of mental health issues (Yeung & Fernandes, 2020), we wanted to replicate this effect as well as investigate whether individual differences in age or ER could alter the links between recurrent IAMs and mental health. Notably, older adults are typically better at dissipating negative affect than younger adults (Mather & Carstensen, 2005). This downregulation of negative emotion is an important facet of ER (Gross, 2013) which could buffer against the maladaptive consequences of negative recurrent IAMs (Samide & Ritchey, 2021). Specifically, differences in age or ER could alter whether recurrent IAMs reflect mental health status because these individual factors could dampen the distress evoked by negative recurrent IAMs (Berntsen & Hall, 2004; Brewin et al., 2010). However, we found that interactions between recurrent IAM characteristics and age (Study 2a) as well as ER (Study 2b) were nonsignificant predictors of symptoms of mental health issues. Instead, both recurrent IAM presence and valence were significant predictors of mental health when age and ER groups were *combined*. Because neither age nor ER significantly altered the link between recurrent IAMs and mental health status, our work suggests that despite better ability to dampen emotional reactions (and fewer negative recurrent IAMs overall), recurrent IAMs continued to reflect mental health status.

Our findings regarding prevalence largely replicated past work, lending additional support that recurrent IAMs are experienced by large proportions of the general population. We found that most of the younger adults in Study 2a (55%) as well as most of the younger adults with low ER in Study 2b (56%) had experienced a recurrent IAM within the past year. These data closely replicate prevalence estimates from past studies (52–53%; Berntsen & Rubin, 2008; Yeung & Fernandes, 2020). Interestingly, our older adult sample from Study 2a reported similarly high prevalence (54%) as these younger adult samples, suggesting that recurrent IAM prevalence may not decline with age. Failing to observe an age effect here replicates numerous studies on IAMs (Berntsen et al., 2017; Schlagman et al., 2009; Warden et al., 2019). On the other hand, this result is contrary to Berntsen & Rubin (2008), who found a slight, but significant, reduction in recurrent IAM prevalence with age. It remains possible that we may have failed to detect this same decrease due to differences in sample size (*n*s = 274–341 in Berntsen & Rubin, 2008; *n*s = 95 in Study 2a); further replication could assess the stability of this pattern.

Another interesting finding in our work was that younger adults with high ER were significantly less likely to have experienced a recurrent IAM within the past year (38%), and significantly more likely to have never experienced one (35%) compared younger adults with low ER. One potential interpretation of this result is that better ability to exert control over one's emotions could buffer individuals against developing recurrent IAMs. This concept aligns with the idea that preexisting traits, including tendency to use certain emotion-related thinking styles (e.g., suppression, rumination), can serve as protective or vulnerability factors in the development of intrusive memories (Marks et al., 2018).

In addition to prevalence, we also examined how differences in age or ER could relate to recurrent IAM frequency (i.e., how often they recur). Our comparisons of frequency between age and ER groups replicated those of prevalence: again, we found no significant difference in frequency between age groups (Study 2a), which is consistent with past work on IAMs (Berntsen et al., 2017) as well as recurrent IAMs (Berntsen & Rubin, 2008). In contrast, IAMs recurred less frequently for younger adults with high compared to low ER (Study 2b). Coupled with the patterns seen for prevalence, these results suggest that trait ER could play a predictive role in not just the development of recurrent IAMs (Marks et al., 2018), but also the long-term trajectory of these memories.

Chapter 4:
Computational Text Analysis of Recurrent IAMs

4.1 Study 3

4.1.1 Introduction

Autobiographical memory (AM), or memory for the personal past (Baddeley, 1992; Brewer, 1986), is considered fundamental to the study of human thought and behaviour (Berntsen & Rubin, 2012; Rubin, 1986; Sotgiu, 2021). These memories reflect not only our experiences (Conway & Pleydell-Pearce, 2000; Conway, 2005), but also our emotions (Holland & Kensinger, 2010), our social and cultural contexts (Fivush, 2011), and most recently, our mental health status (Barry et al., 2021; Yeung & Fernandes, 2020, 2021). Given this, the study of AM has appeared across multiple subareas of psychology, including cognitive (e.g., Conway, 2005), clinical (e.g., Berntsen & Rubin, 2007), developmental (e.g., Howe & Courage, 1997; McLean, 2005; Newcombe et al., 2007), social (e.g., Beaman et al., 2007; Pasupathi, 2001), and personality psychology (e.g., Kihlstrom, 1981). Research to date has especially highlighted AM as a memory system (Baddeley, 1992; Rubin, 2012), specifying its theoretical structure (Anderson & Conway, 1993; Conway & Rubin, 1993) and organisation (Barsalou, 1988; Conway & Bekerian, 1987; Mace et al., 2013), as well as the nature of its retrieval (Brewer, 1986).

A relatively neglected area in AM research, however, is the analysis of content in AMs (i.e., what people report remembering). In this study (Yeung, Stastna, & Fernandes, 2022), we demonstrate the utility of computational text analysis methods, such as frequency analyses and topic modeling, in characterizing the content of recurrent IAMs. The common paradigm to study AM typically asks participants to recount their memories verbally (Kopelman et al., 1989; Levine et al., 2002; Piolino et al., 2009; Renoult et al., 2020; Williams & Broadbent, 1986). However, these descriptions are rarely analyzed directly; instead, current methods typically transform the original verbal data into abstract features. For instance, researchers might try to understand these memories by manually reading each description and judging the amount of episodic or semantic content contained within it (Kopelman et al., 1989; Levine et al., 2002; Renoult et al., 2020; Tulving, 1972). Although these methods can reliably detect properties of AMs (e.g., valence), the actual content of the memory is lost. As an illustrative example, one memory could involve receiving a bad grade, while another could involve the death of a loved one; if both are judged as being similarly unpleasant, current methods might fail to discern between these memories despite their meaningful differences. Indeed, influential theoretical models suggest that researchers ought to understand memory content, both because individual differences have direct influences on content (compared to indirect influences on the features derived from content; Conway, 2005) and because "there is no process-pure episodic or semantic memory content" (Rubin, 2012, p. 23). As such, our current understanding of autobiographical memory is incomplete without examining content (Barsalou, 1988).

Content Analyses of Autobiographical Memory

Accordingly, many past researchers have attempted to understand AM content using manual content analyses. For instance, some of these studies have involved researchers developing their own coding schemes a priori (e.g., sorting AMs into predefined categories). As an early example of this, Woike et al. (1999) trained research assistants to manually read each memory description and score them on the degree to which the memories expressed certain motives (e.g., agency, communion). Similar approaches have involved sorting AM texts into content categories based on psychosocial stages (e.g., AMs involving friends/peers reflecting "identity/identity confusion"; Conway & Holmes, 2004) or labelling AMs based on how they described certain relationships (e.g., conflict or closeness; McLean & Thorne, 2003). In comparison, other coding schemes have prioritized retaining information about the events that originally occurred. One such study coded AMs of social interactions in terms of individuals present, the participants' wishes in the situation (e.g., to be helped), and the outcome (Thorne, 1995). Though these coding strategies all capture content to some degree, they still limit the scope of analysis since they reduce content to a small set of dimensions that are defined by the experimenter ahead of time (e.g., whether the memory is related to a specific construct or not).

Other manual content analyses have categorised AMs according to post hoc codes (e.g., those developed during the process of reading participants' AM descriptions). In work by Robinson (1976), the author identified categories of experiences in participants' AMs, the three most common of which were accidents & injuries, romantic episodes, and first experiences. A drawback of this work, however, is that these categories only encompassed 27% of participants' memories; the categories for the remaining 73% were not reported. A similar approach was taken by Grysman (2015) when performing a content analysis on AMs of stressful events. Six mutually exclusive content categories were created by the author (e.g., performance, health, relationship), and 17% of the memories were classified as "other" and excluded from further analyses. Despite these methodological limitations, analyses of AM content have provided some insight into the fundamental nature of the AM system, such as the hierarchy of information contained in AMs (Barsalou, 1988; Hutchinson et al., 2020; Robinson, 1976).

Content Analyses of Involuntary Autobiographical Memory

Analogously to how content analysis has provided insights into the organisation and functions of AM, it also stands to answer important questions about the nature of involuntary autobiographical memories (IAMs). IAMs are memories of one's personal past that are retrieved unintentionally and effortlessly (Barzykowski & Staugaard, 2016; Berntsen, 1996; Ebbinghaus, 1885/2013). Past work has indicated that IAMs are experienced frequently among large and diverse samples (Ball & Little, 2006; Berntsen, 2010; Brewin, Christodoulides, & Hutchinson, 1996; Krans et al., 2015; Mace, 2004; Rasmussen & Berntsen, 2011; Rubin & Berntsen, 2009). Interestingly, IAMs are also often experienced recurrently, such that memories of the same episode repeat involuntarily (Berntsen & Rubin, 2008; Brewin, Christodoulides, & Hutchinson, 1996; Bywaters et al., 2004; Yeung & Fernandes, 2020, 2021). IAMs, recurrent or otherwise, appear to be an everyday phenomenon.

Despite being common, very little is known about what IAMs are about. In one study, Schlagman et al. (2006) examined the content of nonrecurrent IAMs reported by younger and older adults ($N = 21$). To do this, they conducted a manual thematic content analysis (Smith, 2000), in which two independent coders read each memory description and generated a list of content categories to represent major themes that could be discerned across the memories. The coders then assigned a single content category to each memory, and manually assigned valences to each content category (e.g., "Holidays" as positive vs. "Deaths/funerals" as negative). Using these methods, Schlagman et al. (2006) found that certain topics were more representative of younger compared to older adults (e.g., "Accidents/illness"), and that older adults reported fewer IAMs from the negative content categories. Further, memories about other people ("Person"; Schlagman et al., 2006) were highly prevalent across the sample, which is a finding that has since been replicated in another manual content analysis of involuntary cognitions (Krans et al., 2015).

In contrast to the topics found in previous studies of IAMs, content analyses of intrusive memories (Newby & Moulds, 2011; Williams & Moulds, 2007a) have identified five content categories: interpersonal event, death/illness involving other, personal assault/abuse, illness/injury involving self, and other. A cursory comparison of these findings might lead one to conclude that everyday IAMs and intrusive memories constitute qualitatively different forms of AM due to these different content categories. However, the manual development of content categories and lack of a common approach to content analysis hinders our ability to draw such a conclusion. In fact, even across studies of intrusive memories, authors have arrived at different post hoc codes. For instance, Brewin et al. (1996) developed four content categories (illness or death, relationship or family problems, abuse or assault, and work or financial problems) in contrast to the five found in more recent work (Newby & Moulds, 2011; Williams & Moulds, 2007a). As well, although these studies' definitions of intrusive memories were similar to IAMs (e.g., emphasizing unintentional remembering of events), they also defined these memories as exclusively *negative* (Newby & Moulds, 2011; Williams & Moulds, 2007a). Accordingly, participants were instructed to only describe the content of *negative* IAMs they had experienced in the past week. As such, it becomes difficult to discern whether there are true differences in AM content between IAMs of different valences (e.g., benign or pleasant IAMs vs. negative intrusive memories), or whether these studies arrived at different content categories due to their contrasting analysis methods, expectations, and working definitions.

Though past work clearly demonstrates that there is scholarly interest in IAM content (Barzykowski et al., 2021; Hellawell & Brewin, 2004), these studies also highlight the limitations of current manual methods. For example, a priori expectations can colour what researchers seek and find in content; the use of different coding schemes between different studies makes comparison across the literature difficult; manual content analyses are prohibitively time- and labour-intensive, even with relatively small sample sizes; and robustness and reproducibility are difficult to estimate with manual content analyses. To overcome these limitations, we suggest that computational methods can (1) discover patterns in content with few a priori assumptions, (2) allow researchers to use the same techniques across any number of studies, (3) enable the analysis of far larger sample sizes (e.g., longer texts and/or a greater number of texts), and (4) increase robustness and reproducibility in AM research.

Computational Text Analysis

Computational text analysis – also known as computer-assisted text analysis, computational linguistics, corpus linguistics, text mining, text analytics, or natural language processing (NLP) – refers to the use of computational methods to analyze and understand human language data (Chowdhury, 2005; Hirschberg & Manning, 2015). Such approaches include lexical-based techniques, which count instances of words or phrases (e.g., dictionary methods, frequency analysis; Nelson et al., 2020), and machine learning (ML) techniques, which can discover, quantify, and assess extracted features in text data (e.g., topic modeling; Grimmer et al., 2021). Many authors to date have recommended the use of computational text analysis in research areas reliant upon text as data, including education research (Fesler et al., 2019), organizational research (Kobayashi et al., 2018), communication research (Guo et al., 2016; Maier et al., 2018), political science (Grimmer & Stewart, 2013; Quinn et al., 2010; Wilkerson & Casas, 2017), clinical psychology (DeSouza et al., 2021; Ophir et al., 2021; Tanana et al., 2021), and the social sciences as a whole (Banks et al., 2018; Lindstedt. 2019; Nguyen et al., 2020; Wiedemann, 2013). We suggest extending this recommendation to memory research, since computational methods offer both practical and theoretical advantages compared to current manual methods of understanding AM content.

A clear practical benefit is that computational text analysis is much faster than current manual methods. Manual content analyses typically require that highly trained researchers spend copious and laborious hours reading each text and evaluating them on certain criteria (e.g., coding them into categories, scoring them on certain dimensions). In contrast, computational methods can be conducted in a small fraction of these hours (Chang et al., 2021; Guetterman et al., 2018), enabling the analysis of more numerous or more lengthy texts. Importantly, computational text analysis can also enhance manual qualitative analyses by providing quantitative benchmarks upon which content analyses can be evaluated (Chang et al., 2021; Evans, 2014; Grimmer et al., 2021; Guetterman et al., 2018; Wiedemann, 2013). Metrics such as a topic's semantic coherence can be estimated using computational methods (Mimno et al., 2011), which allows researchers to make more informed decisions when performing content analyses (e.g., what codes to develop, how many of them, how to assign codes to texts, etc.). Finally, a key advantage of computational approaches is that they can model AMs in more theoretically plausible ways compared to manual methods. For example, computational techniques such as latent Dirichlet allocation (LDA; Blei et al., 2003) or structural topic modeling (STM; Roberts et al., 2019) treat documents as *mixtures* of topics (i.e., mixed-membership models), whereas manual content analyses typically assign exactly one mutually exclusive topic to each AM (i.e., single-membership models; Grysman, 2015; Krans et al., 2015; Newby & Moulds, 2011; Newby & Moulds, 2012; Schlagman et al., 2006). This assumption that any given AM text contains only a single topic contradicts cognitive models of the AM system (Barsalou, 1988), and limits our ability to probe current theoretical frameworks. Thus, computational approaches can facilitate AM research by better characterizing content and refining our conceptualization of these memories.

Applications of Computational Text Analysis

Despite these many potential advantages over manual methods, computational text analysis is quite rare in AM research. To date, those who have used computational methods almost exclusively opt for dictionary methods (Guo et al., 2016), such as Linguistic Inquiry and Word Count (LIWC; Pennebaker et al., 2015; see also Grysman, 2015; Himmelstein et al., 2018; Schryer et al., 2012; Simpson & Sheldon, 2020; Zasiekina et al., 2019; Zator & Katz, 2017). Dictionary methods like LIWC are lexical-based (Nelson et al., 2020), in that they count the instances of words used in texts. Critically, they convert these word counts into scores on predefined dimensions. In the case of LIWC, these dimensions are hard-coded into the software. For example, documents that use words like "think" or "know" frequently would be given a high "insight" score according to LIWC (Pennebaker et al., 2015). Based on Weintraub's (1981, 1989) original idea that the words used in everyday speech reflect one's psychological state, scores on these dimensions are often used to infer writers' cognitive environments, including their attentional focus, emotionality, social relationships, thinking styles, and other individual differences (Tausczik & Pennebaker, 2010).

Though dictionary methods have proven valuable (Eichstaedt et al., 2021) and have a lower barrier to entry (since they often require little to no programming skills), there are also many limitations to using these relatively simple tools (Banks et al., 2018; Benoit, 2020; Guo et al., 2016; Liu & Zhang, 2012; Nelson et al., 2020; Resnik et al., 2013; Ziemer & Korkmaz, 2017). First, dictionary methods are only applicable in certain domains (Liu & Zhang, 2012; Nelson et al., 2020), since researchers cannot assume that words always carry the same meanings regardless of their context. A dictionary developed for analyzing a specific type of writing may work well in that domain, but may mischaracterize texts in other domains (Liu & Zhang, 2012; Nguyen et al., 2020). Further, dictionary methods are conceptually similar to a priori coding schemes (Conway & Holmes, 2004; McLean & Thorne, 2003; Woike et al., 1999), in that they use predefined sets of words, manually designed to capture target constructs (Crossley et al., 2017; Guo et al., 2016). As such, they can miss detecting novel and potentially important features of texts (Grimmer et al., 2021; Guo et al., 2016; Nelson, 2020). Finally, they also abstract texts into scores on certain dimensions (Pennebaker et al., 2015). Though tools like LIWC offer a great number of dimensions with which texts can be described, these features are ultimately a step removed from the actual content of the text itself. Indeed, even recent advances using more complex NLP methods have focused on extracting meaningful features of AM text data, such as the memory's narrative flow or amount of episodic versus semantic detail (Sap et al., 2020; Sap et al., 2022), rather than the content of the memory itself.

Instead, frequency analyses may serve to highlight content more directly. Rather than converting counts to scores on dimensions (e.g., "insight"), frequency analyses retain counts as the unit of analysis. These techniques have already been used to visualize the content of text data, largely in the form of word clouds (Benoit, 2020; Henderson & Segal, 2013), which represent frequencies through graphical means such as font size or colour. Word clouds have been hailed as a quick and simple means of conveying content, as well as interpreting texts (DePaolo & Wilkinson, 2014). Indeed, some memory researchers have used word clouds to visualize the content labels (e.g., places, activities, or people involved in the event) that participants had given to recent AMs (Sreekumar et al., 2018). While word clouds can indeed convey an intuitive sense of content, a common pitfall is that they have "some visual appeal but often no clear communication of any particular result" (Benoit, 2020, p. 490). Studies indicate that word clouds are often difficult and slow to comprehend, especially compared to simpler vertical/horizontal lists of words (Halvey & Keane, 2007; Rivadeneira et al., 2007). Word clouds also offer little more than visual inspection when attempting to compare content across different sets of texts – a task that is typically of interest to AM researchers (e.g., comparing content across memories of different valences). In our current work, we suggest that another lexical-based technique, keyness analysis, can supplement frequencies by identifying words that are significantly distinctive of certain sets of texts (Scott & Tribble, 2006; Stubbs, 2010).

Further, the ML-based techniques we use in the current study (e.g., topic modeling) stand to capture content beyond the level of single words or phrases. A drawback of lexical-based techniques, whether at the word- or phrase-level, is that they isolate terms from their contexts. Without the surrounding text for each term, interpretability can become an issue for frequency analyses (e.g., whether “kind” refers to the adjective, as *being kind*, or the noun, as *a kind of memory*; Benoit, 2020). As an alternative, topic modeling can be used to extract “topics”, or groups of words that can be interpreted as themes in the overall set of documents (Blei et al., 2003). Rather than inspecting single words or phrases, topics allow researchers to examine how themes appear across and within texts. For instance, instead of drawing conclusions based on the presence or absence of a single word (e.g., “bad”), researchers using topic modeling can test hypotheses based on themes (e.g., co-occurrences of words such as “sad”, “feel”, “guilt”, and “anxious”). Encouragingly, work has indeed shown that topic models can increase understanding of texts above and beyond dictionary methods by producing topics derived from one’s own data, rather than dimensions from a general dictionary (Resnik et al., 2013).

Here, we demonstrate the utility of computational text analysis methods such as frequency analyses and topic modeling in characterizing the content of recurrent IAMs. Though scholars debate as to what recurrent IAMs are typically about (e.g., benign vs. traumatic topics; Berntsen, 2010; Berntsen & Rubin, 2008; Brewin et al., 2010), this controversy has yet to be addressed using content analysis. If recurrent IAMs generally focus on emotionally positive (Berntsen & Rubin, 2008) or negative (Brewin, Christodoulides, & Hutchinson, 1996; Brewin et al., 2010; Bywaters et al., 2004) material in nonclinical samples, we ought to observe these patterns in text data from large samples of general populations. Our aim here was to verify and then expand upon the topics reported in past studies of IAMs, while also demonstrating more robust and reproducible methods of analyzing patterns in AM content. Most importantly, in the current study, we present scalable computational methods that can characterize content in thousands of participants’ recurrent IAMs.

4.1.2 Methods

Participants

Undergraduate students were recruited at the University of Waterloo, who participated in the current study in return for course credit. Data were collected in five waves between September 2018 and February 2020, with each wave occurring at the start of an academic term (i.e., Fall/September, Winter/January, Spring/May). In total, 6,187 unique individuals participated, and they produced 3,624 text responses. Of these participants, 71% were women, 28% were men, and 1% were nonbinary, genderqueer, or gender nonconforming. Mean age was 19.9 (*SD* = 3.3, range = 16–49).

Materials

Recurrent Memory Scale. The Recurrent Memory Scale (Yeung & Fernandes, 2020) assessed participants' recurrent IAMs. Participants indicated if they had experienced at least one recurrent IAM within the past year, not within the past year, or never (Berntsen & Rubin, 2008). If they had experienced at least one within the past year, they wrote a brief description[2] of their one most frequently recurring IAM and rated it on a series of 5-point Likert scales (e.g., frequency of recurring, valence). See Study 1 and Appendix A for details (Yeung & Fernandes, 2020).

Procedure

Undergraduate students enrolled in at least one psychology course at the University of Waterloo self-registered for the 60-minute online study. After providing informed consent, participants completed a battery of questionnaires in a randomized order, including the Recurrent Memory Scale. For the current study, we analyzed only the text responses from this scale; all other measures collected were unrelated to the current study. All procedures were approved by the University of Waterloo's Office of Research Ethics (Protocol #40049).

Data Preparation

Prior to analysis, we first used supervised ML to detect and remove invalid texts (e.g., texts with meaningless or irrelevant content, such as those describing dreams), which could introduce noise if retained (Banks et al., 2018; Maier et al., 2018). We trained models on a subset of recurrent IAMs that was previously hand-coded by two research assistants as either valid or invalid (n = 949; Yeung & Fernandes, 2022a). Trained models were then used to classify the unlabelled recurrent IAM texts (n = 2,675) as either valid or invalid. Using this approach, 4.9% of the unlabelled texts were classified as invalid by the ML model (cf. research assistants classified 7.5% of the labelled subset as invalid).

After removing these invalid texts, we then removed texts from duplicate participants. Since participants could participate in our study multiple times (i.e., across the multiple waves of data collection), we retained data from only the first session any individual completed. Texts were also removed listwise if the participant provided no response for at least one of the key variables (e.g., self-reported valence ratings).

[2] Instructions for writing the text response were as follows: "Please think about the most frequent recollection that has recurrently popped into your mind by itself within the most recent year. The following questions will ask you about that memory. Please briefly describe your memory of the event in 3-5 sentences, without any identifying information" (Yeung & Fernandes, 2020).

Finally, text data were preprocessed following current recommendations (Banks et al., 2018; Kobayashi et al., 2018; Maier et al., 2018), including tokenization, cleaning, stop word removal (Porter, 2001), frequency trimming, and lemmatization (Benoit & Matsuo, 2022). Texts were represented using a bag-of-words, unigram approach (Grimmer & Stewart, 2013), which decomposes texts into singular words without retaining information about word order.

Frequency Analysis

To get a general overview of what recurrent IAMs were about (and how content might differ across valences), we used frequency analyses to identify common or distinctive words in sets of documents (Ball, 1994). Like dictionary methods, these relatively simple lexical-based techniques (Nelson et al., 2020) count the occurrences of tokens (e.g., words or phrases) – however, unlike dictionary methods, they do not transform the data by assigning these tokens to specific, manually defined categories (e.g., "insight"; Pennebaker et al., 2015). Instead, counts remain as the basic unit of analysis. These data were visualised as both word clouds and frequency plots. We further tested whether frequencies differed across certain sets of documents using keyness analyses, which statistically compare frequency counts between a target and reference corpus (Scott & Tribble, 2006; Stubbs, 2010).

Topic Modeling

We used structural topic modeling (STM; Roberts et al., 2019) to discover topics in participants' descriptions of their recurrent memories. STM is a method of unsupervised machine learning that estimates hidden topic structures that could have plausibly produced the observed set of documents (i.e., corpus). By using texts as the input, topic modeling can output topics, or groups of words, that can be interpreted as themes in the input texts (Blei et al., 2003; DiMaggio et al., 2013; Roberts et al., 2014).

Data and code supporting the findings of this study are openly available on the Open Science Framework (https://doi.org/10.17605/OSF.IO/3584C). This study was not preregistered.

4.1.3 Results

Frequency Analysis

Overall Frequencies. Frequencies were computed using the quanteda package in R (Benoit et al., 2018). Overall frequencies were calculated based on the entire corpus in terms of document frequency (percent of documents in which a given word appears)[3]. These frequencies were then visualized using

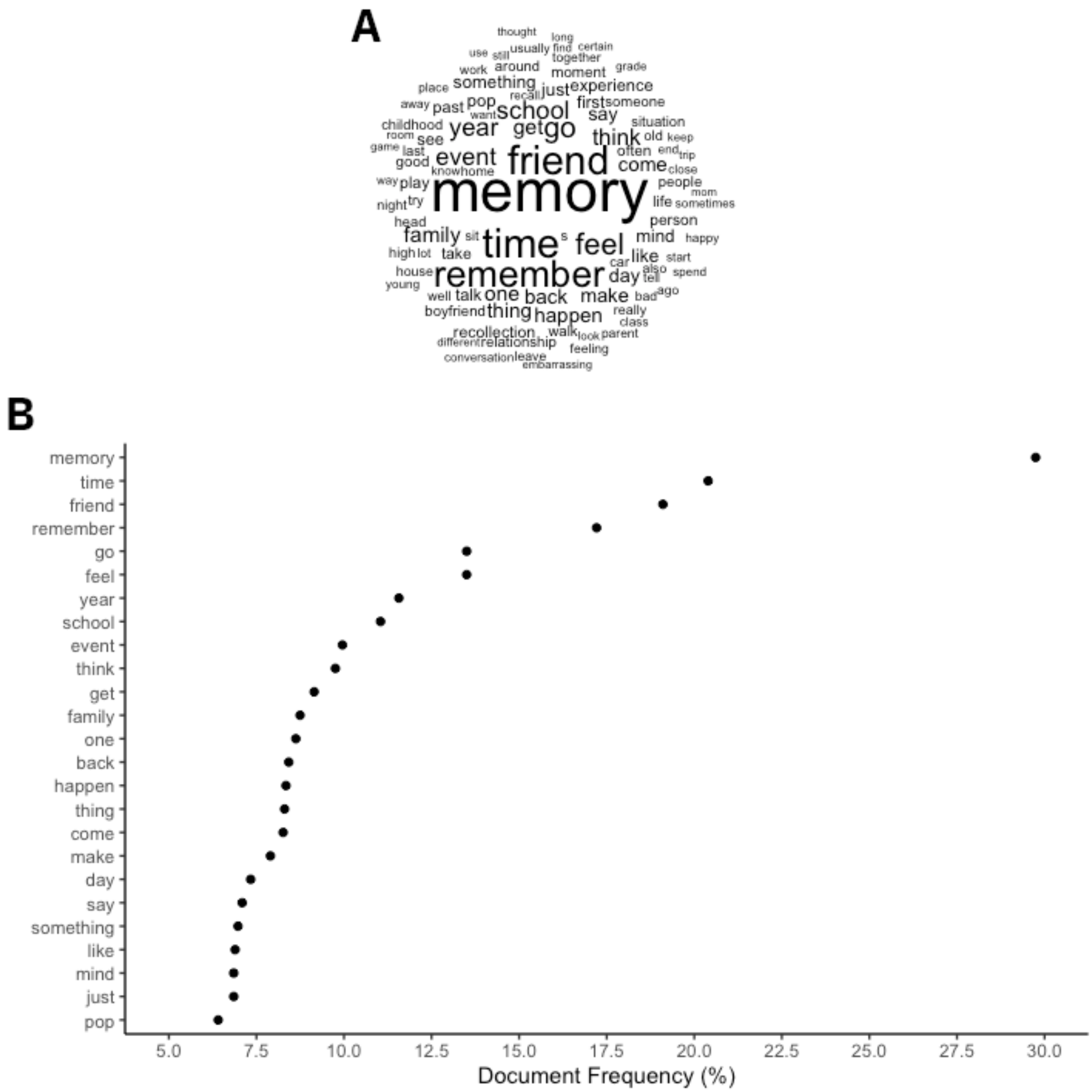
[3] We also calculated frequency in terms of token frequency (raw counts of each word across the entire corpus). Results were nearly identical between token frequency and document frequency (see supplemental materials at https://doi.org/10.17605/OSF.IO/3584C). Here, we present document frequencies since they are more readily interpretable.

both word clouds (Figure 5 Panel A) and frequency plots (Figure 5 Panel B). In the current word clouds, larger font size indicates higher frequency.

These basic frequency analyses illustrate that recurrent IAMs feature language that would be expected of AMs in general (Levine et al., 2002). For example, the most common words included language about the act of remembering (e.g., “memory”, “remember”, “think”), people present (e.g., “friend”, “family”), emotions felt (e.g., “feel”, “happy”, “bad”), and time (e.g., “time”, “year”, “day”). Comparing Panel A and B in Figure 5, we can see that a greater number of words can be displayed in word clouds versus frequency plots (e.g., 100 versus 25 most frequent words). However, it is more difficult to find any one word in a word cloud compared to a frequency plot. As well, the reliance on font size to convey frequency can both obscure and misrepresent patterns in the data. Longer words can be conflated with bigger font size, biasing some words to appear more frequent than they are (Viégas & Wattenberg, 2008). For example, “memory” is used in twice as many documents as “remember” according to Panel B, yet this difference is hard to perceive in Panel A.

Figure 5

Most Frequent Words in Recurrent IAMs



Note. Panel A: Word cloud of the 100 most frequent words in recurrent memories. Panel B: Frequency plot of the 25 most frequent words in recurrent memories.

Comparing Frequencies Across Valences. We further tabulated frequencies across valences to identify words that were similar and/or distinctive for each valence category (negative, neutral, and positive). For these frequencies, we used participants' self-reported valence ratings of their memories to categorize texts as either negative, neutral, or positive[4]. Document frequencies were then calculated as the number of documents in which a word appeared for each valence category, divided by the total number of documents in each valence category.

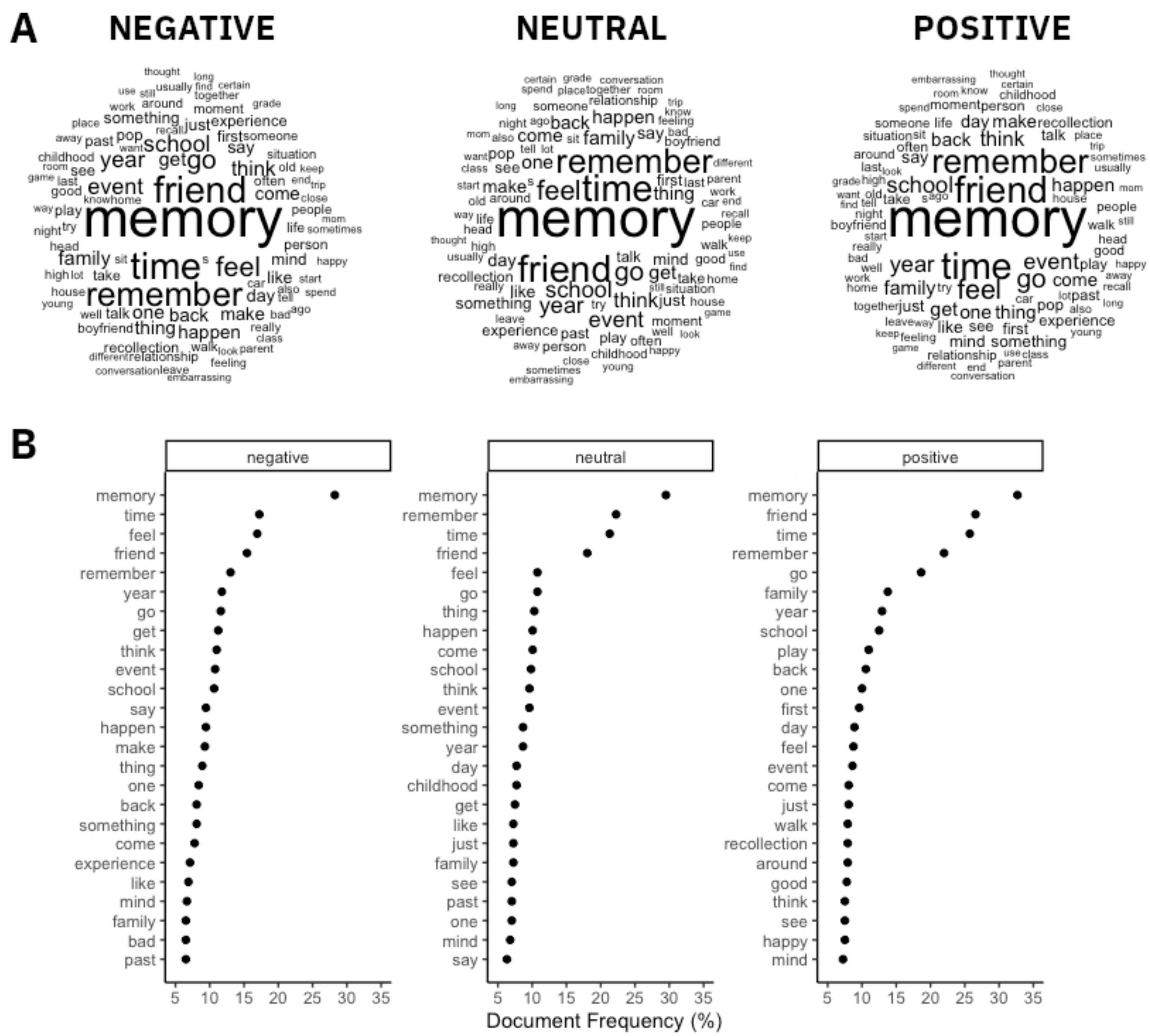
Highly frequent words were largely similar across all valences. For example, words related to the act of remembering (e.g., "memory", "remember") and the episodic nature of these memories (e.g., "time", "event", "happen", "feel") were used prominently in recurrent memories of all valences. As well, recurrent memories appeared to often involve friends ("friend") and school ("school") across all valences (Figure 6).

Panel A and B of Figure 6 once again illustrate noticeable differences between word clouds and frequency plots. Comparisons between valences are rather challenging using word clouds; discerning the presence or absence of any single word across the clouds is not an easy task. Further, when words are indeed present across different valences, it is quite difficult to contrast font sizes across clouds. For instance, the word "time" was used in 17% of negative documents, compared to 21% of neutral documents and 26% of positive documents. While these differences can be observed in a frequency plot, such a pattern is imperceptible when comparing word clouds.

[4] For this analysis, self-reported ratings of *negative* and *very negative* were collapsed into one category (negative). Likewise, self-reported ratings of *positive* and *very positive* were collapsed into one category (positive).

Figure 6

Most Frequent Words in Recurrent IAMs by Valence



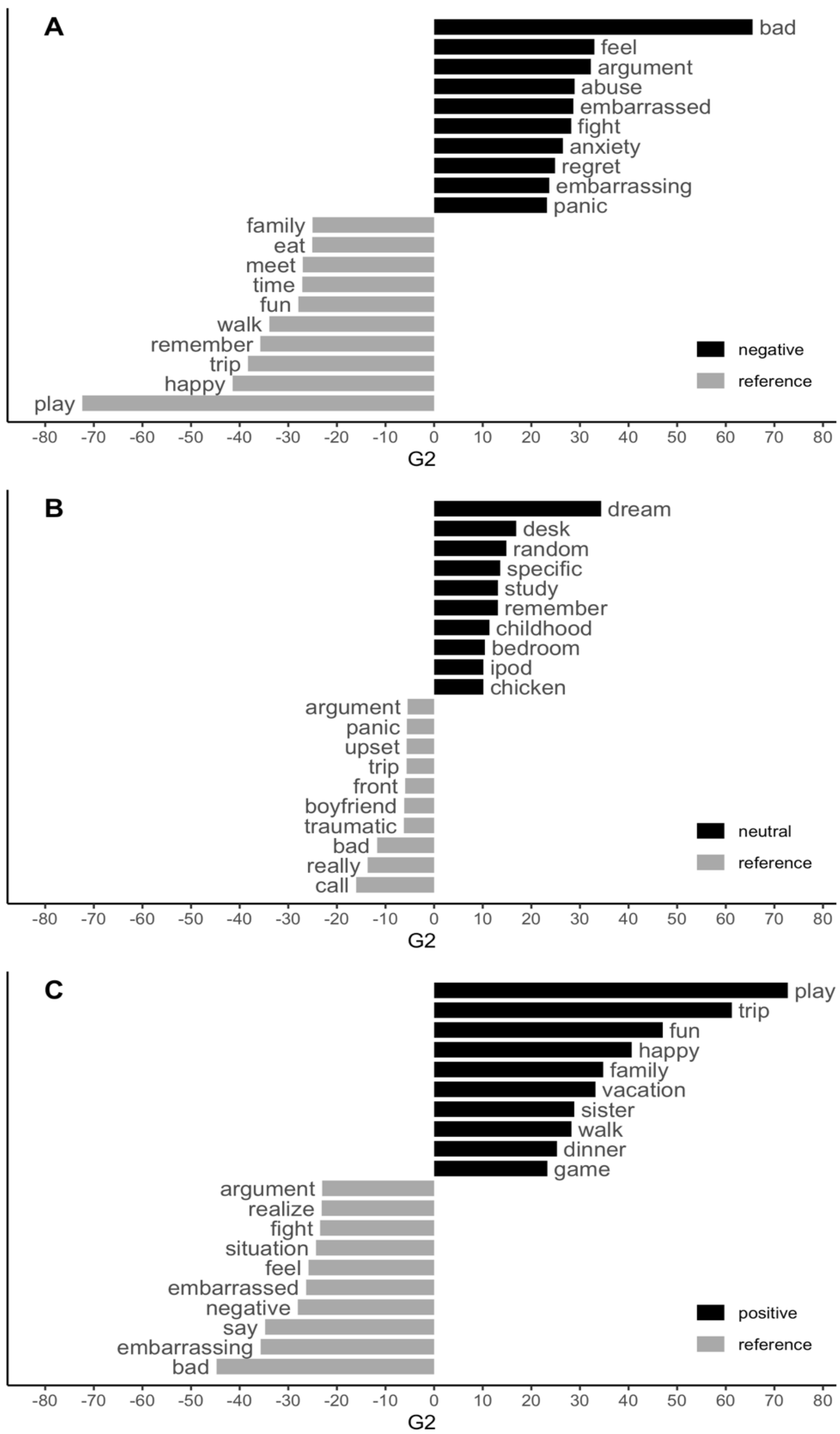
Note. Panel A: Word clouds of the 100 most frequent words in recurrent memories that were self-rated as negative, neutral, or positive. Panel B: Frequency plots of the 25 most frequent words in recurrent memories that were self-rated as negative, neutral, or positive. Document frequencies were calculated for each valence category independently. For example, the negative category was calculated by taking the number of negative documents a word appeared in, divided by the total number of negative documents.

Keyness Across Valences. Finally, keyness was calculated for words of each valence category, compared to all other valence categories combined (Benoit et al., 2018; see Figure 7). In other words, the target corpus contained all documents from one valence category, while the reference corpus contained the documents from all other valences. To calculate keyness, we used likelihood-ratio tests with Williams' corrections (Benoit et al., 2018; Pojanapunya & Todd, 2018; Scott & Tribble, 2006).

Based on these analyses, distinctive words for negative recurrent IAMs included words about negative emotions (e.g., "embarrassed", "anxiety", "regret") and adverse events (e.g., "argument", "abuse", "fight"). Positive recurrent IAMs followed a similar pattern in that distinctive words included those about positive emotions (e.g., "fun", "happy"), pleasant events (e.g., "trip", "vacation", "dinner"), and family (e.g., "family", "sister"). In contrast, neutral recurrent IAMs included distinctive words about metacognitive aspects of remembering (e.g., "random", "specific", "remember").

Figure 7

Keyness of the Most Distinctive Words in Recurrent IAMs by Valence



Note. Keyness statistics of the ten most distinctive words for each valence. Target corpora were text descriptions of recurrent IAMs that were self-rated as negative, neutral, or positive. Reference corpora were text descriptions of recurrent IAMs for all other valences combined (e.g., target = negative, reference = neutral & positive combined). Panel A: Negative recurrent IAMs as the target corpus. Panel B: Neutral recurrent IAMs as the target corpus. Panel C: Positive recurrent IAMs as the target corpus. Higher positive G2 values reflect words that are significantly distinctive of the target corpus; lower negative G2 values reflect words that are significantly distinctive of the reference corpus.

Topic Modeling

To examine content at the level of topics (rather than single words), we implemented structural topic modeling (STM) using the stm package in R (Roberts et al., 2019).

Model Selection. Researchers must select an a priori number of topics to be identified when using STM (Roberts et al., 2019). To choose an appropriate number of topics, we examined model performance when setting the number of topics at each integer k, where k = [5–25]. We set this range based on past manual content analyses of voluntary and involuntary AMs (Grysman, 2015; Krans et al., 2015; Schlagman et al., 2006), as well as recommendations for relatively small corpora (e.g., those containing hundreds to thousands of documents; Roberts et al., 2019). To construct the topic model, we included participants' self-reported valence ratings of their memories as a theoretically relevant covariate (Roberts et al., 2014; Roberts et al., 2019), allowing us to estimate relationships between topic prevalence and memory valence.

Model Validation. To estimate reliability of the model, we simulated and inspected models with the same parameters across a varying number of topics (Blei & Lafferty, 2009; Maier et al., 2018). We then selected an appropriate number of topics using a two-stage approach (Grimmer & Stewart, 2013; Quinn et al., 2010). First, internal validation (based on computed metrics derived from the data) guided the initial selection of candidate models. Second, external validation (based on human judgment and performance measures) guided the selection of the final model out of the candidate models.

Internal Validation. To choose candidate models out of all possible topic numbers, we examined data-driven measures of model fit. Researchers can derive internal metrics such as coherence, held-out likelihood, residuals, and lower bound (Blei et al., 2003; Maier et al., 2018; Mimno et al., 2011) for each model, which indexes model quality. Local maxima and minima for these internal metrics provided rationale to prefer certain topic numbers over others (e.g., high coherence, high held-out likelihood). Based on these scores, we selected three candidate models for further inspection (8, 16, and 24 topics; see supplemental materials at https://doi.org/10.17605/OSF.IO/3584C for details).

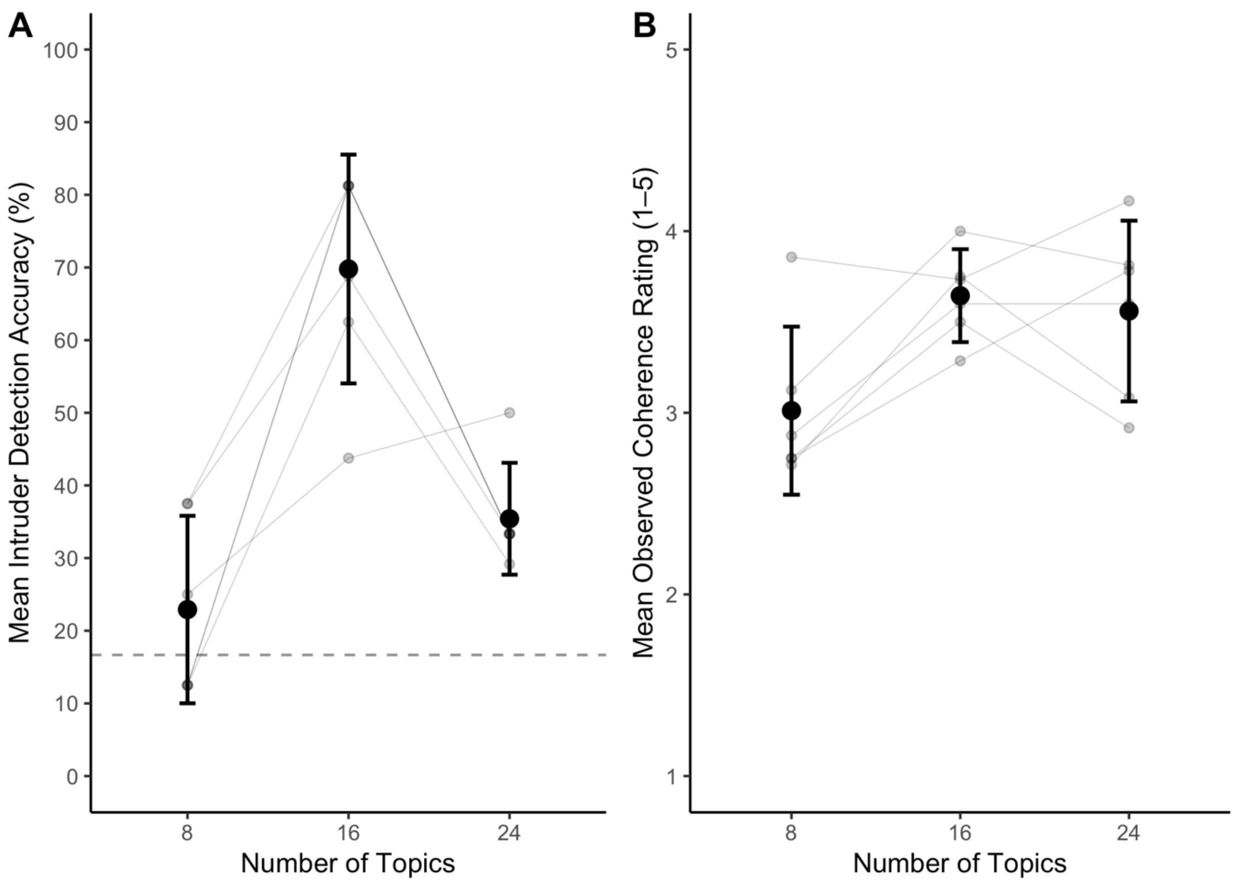
External Validation. To select a final model out of the three candidate models, we then conducted a word intrusion task (Chang et al., 2009). Participants were research assistants that were naïve to the study's goals and hypotheses ($N = 6$). On each trial, participants were shown six words and instructed to select the one word that did not belong with the others (i.e., the intruder). Unbeknownst to participants, each of these six-word sets represented a topic from one of the candidate models. For each six-word set, five were highly representative words for one topic in one of the candidate models, as determined by highest frequency-exclusivity (FREX; Bischof & Airoldi, 2012) scores. The remaining word was highly representative of a *different* topic from the same candidate model. Theoretically, participants should detect intruder words more accurately when topics have high semantic coherence (e.g., "apple" is easy to pick out as an intruder when the other words are "dog, cat, horse, pig, cow"). In contrast, intruder detection performance should drop when topics have low semantic coherence (e.g., "apple" is difficult to pick out as an intruder when the other words are "car, teacher, platypus, agile, blue"; Chang et al., 2009).

As an additional index of topic quality, we also measured observed coherence (Lau et al., 2014) during the word intrusion task. After participants submitted their answer on each trial, they were shown the five words that were highly representative of one topic (i.e., without the intruder) and were asked to rate the five words in terms of how coherent (e.g., meaningful, interpretable) they were (1 = *very incoherent*, 5 = *very coherent*).

We then compared accuracy and observed coherence across the candidate models using one-way analyses of variance (ANOVAs), with topic number as a within-subjects factor (8, 16, 24; see Figure 8). These ANOVAs were significant for both accuracy ($F(2, 10) = 20.9$, $p < .001$) and observed coherence ($F(2, 10) = 8.3$, $p = .007$). Post hoc Tukey tests indicated that accuracy was significantly higher with 16 topics ($M = 70\%$) compared to 8 topics ($M = 23\%$; $p = .005$) and 24 topics ($M = 35\%$; $p = .02$). For observed coherence, post hoc Tukey tests showed that ratings were significantly higher with 16 topics ($M = 3.64$; $p = .03$) and 24 topics ($M = 3.56$; $p = .02$) compared to 8 topics ($M = 3.01$). Based on participants' higher intruder detection accuracy (Chang et al., 2009) and observed coherence scores (Lau et al., 2014), we selected the 16-topic model for our final model, as opposed to the 8- and 24-topic models.

Figure 8

Accuracy and Observed Coherence in Word Intrusion Task by Topic Number



Note. Responses during the word intrusion task. Panel A: Intruder detection accuracy. Panel B: Observed coherence ratings. Error bars represent 95% confidence intervals. Dashed line in Panel A indicates chance performance. Grey points indicate individual participants' data, with grey lines between points indicating data points from the same participants.

Evaluation of Final Model

Intratopic Semantic Validity. To confirm that topics were meaningful, deliberation among researchers was conducted (as in Banks et al., 2018; Maier et al., 2018; Quinn et al., 2010). For each topic, all researchers were given the top ten most representative terms (using FREX scores), internal metrics (e.g., semantic coherence, exclusivity), and twenty representative documents (e.g., those predicted to contain high proportions of the topic). Each researcher then independently created a label for each topic, without input from any other researcher. Then, we "deliberately decided in a discussion (a) whether a topic was semantically coherent and, thus, a valid topic in theoretical terms and (b) what label should be given to the topic" (Maier et al., 2018, p. 108). Using this method, topics may be discarded if all researchers agree it should be removed and topics may be kept if at least one researcher indicates that it is meaningful/coherent (Maier et al., 2018). None of the researchers discarded any of the topics here, due to incoherence.

During deliberation, it was found that our independently developed labels were quite consistent across all topics; even prior to discussion, there was a majority agreement across all authors for the labels assigned to 15 of the 16 topics (no majority agreement for topic 14). Consensus for all labels was then reached for all sixteen topics via discussion. This process resulted in researcher-assigned labels (see Table 6) for each topic (Grimmer & Stewart, 2013), which we used as general descriptors of each topic.

Table 6

Topics in Recurrent IAMs

Topic Number	Researcher-Assigned Label	Top Ten FREX Score Words	Topic Prevalence (%)
1	Stressful events	sad, forget, hospital, feel, without, guilt, anxious, relive, try, strong	5.6
2	Negative past relationships	relationship, negative, situation, involve, traumatic, previous, past, experience, emotion, similar	10.1
3	Physical activities and performance	game, play, enjoy, song, dance, listen, performance, music, soccer, around	4.2

4	Embarrassing events	fear, elementary, moment, set, embarrassing, work, peer, embarrass, along, able	5.1
5	Close relationships	spend, together, boyfriend, first, breakup, break, interaction, girlfriend, rude, cheat	6.4
6	Illnesses, injuries, and deaths	ago, accident, away, member, year, pass, last, family, drive, car	5.7
7	Confrontations, fights, and arguments	attack, fight, lose, argue, argument, end, parent, realize, unable, leave	6.3
8	Abuse and trauma	assault, abuse, date, ex, sexually, dream, significant, trauma, fail, seem	4.7
9	Conversations	someone, conversation, say, person, something, else, appear, fact, message, tell	6.3
10	Environments and locations	street, trip, walk, house, light, outside, hit, cat, travel, dad	5.8
11	Interactions with friends	friend, group, another, mine, talk, good, take, boy, highschool, chat	7.4
12	Communication and miscommunication	question, ask, teacher, class, guy, high, answer, send, interview, put	5.9
13	Subjective experiences of retrieval	frequent, childhood, mind, recollection, pop, recurrently, random, recent, sometimes, come	8.7
14	Subjective descriptions of detailed and/or time-specific recollections	specific, can, part, child, detail, stuff, nothing, remember, study, suddenly	5.3
15	Experiences with family members	watch, mom, sister, grandma, vacation, movie, eat, cousin, park, home	8.5
16	Reflections on decisions	get, like, just, every, back, etc, life, happy, thing, regret	3.9

Note. FREX = frequency-exclusivity (Bischof & Airoldi, 2012).

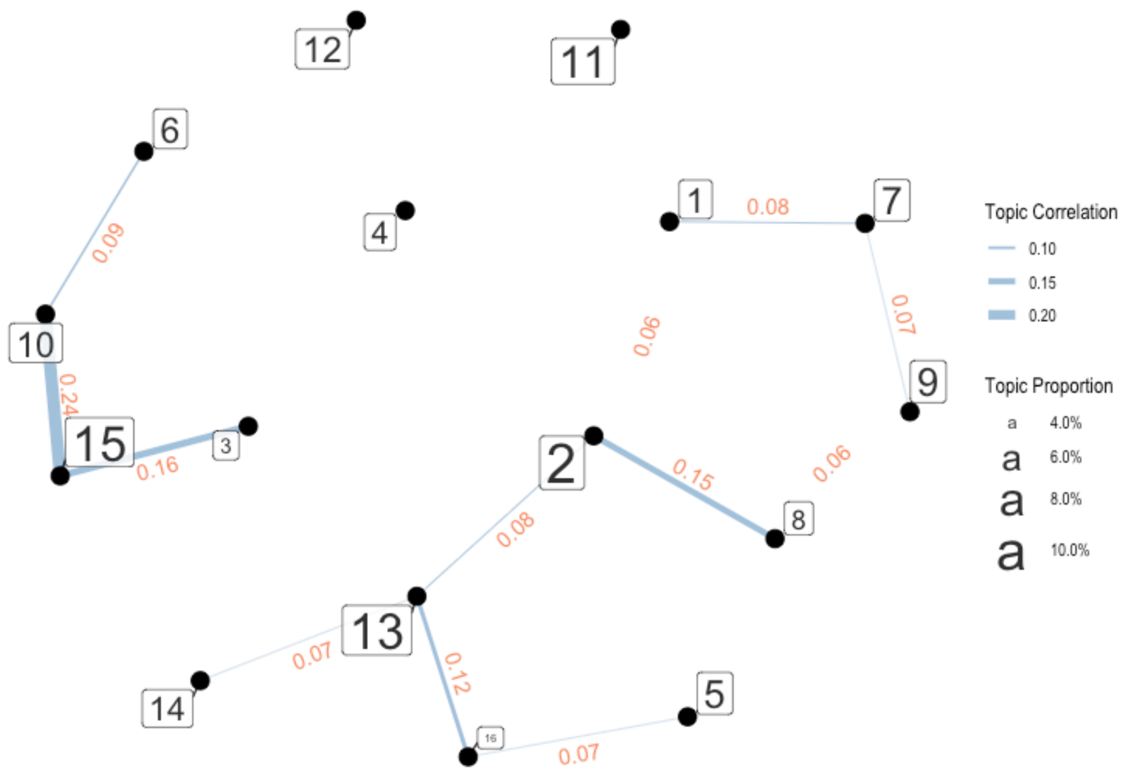
Intertopic Semantic Validity. To assess the overall quality of the topic structure, we inspected relationships between topics (Banks et al., 2018; Maier et al., 2018; Quinn et al., 2010) by calculating correlations between topics[5] (Roberts et al., 2019; Schwemmer, 2021). Positive correlations between topics reflect a tendency for both topics to be used in the same documents.

Many of these correlations supported the semantic validity of the topic structure (see Figure 9). For instance, we observed a significant positive correlation between topic 3 (“game”, “play”, “enjoy”, “song”) and 15 (“watch”, “mom”, “sister”, “grandma”), suggesting that recurrent IAMs about physical activities and performance tended to also describe experiences with family members. Similarly, topics 2 (“relationship”, “negative”, “situation”, “involve”) and 8 (“assault”, “abuse”, “date”, “ex”) were significantly and positively correlated, indicating that memory content about negative past relationships tended to co-occur with memory content about abuse and trauma. These patterns provide evidence of validity for the current topic structure, suggesting that the topics that were discovered are interpretable and co-occur in sensible ways.

[5] Topic correlations were also clustered hierarchically (Coppola et al., 2016; Roberts et al., 2019), illustrating which topics were most similar to each other, and which would be merged first given a desire for a smaller number of topics (Kobayashi et al., 2018; Maier et al., 2018; Quinn et al., 2010). Conclusions were very similar to the correlation analyses (e.g., topics 10 and 15 clustering together, topics 2 and 8 clustering together; see supplemental materials at https://osf.io/3584c/?view_only=53bc2dbb2fa8447ba307757aa9bc0529).

Figure 9

Correlations Between Topics in Recurrent IAMs



Note: Points represent each topic, with lines between topics indicating significant positive correlations between topics. Thicker lines between topics represent stronger positive correlations. Sizes of topic labels represent larger prevalence of the topic in the overall corpus.

Predicting Topic Prevalence by Valence

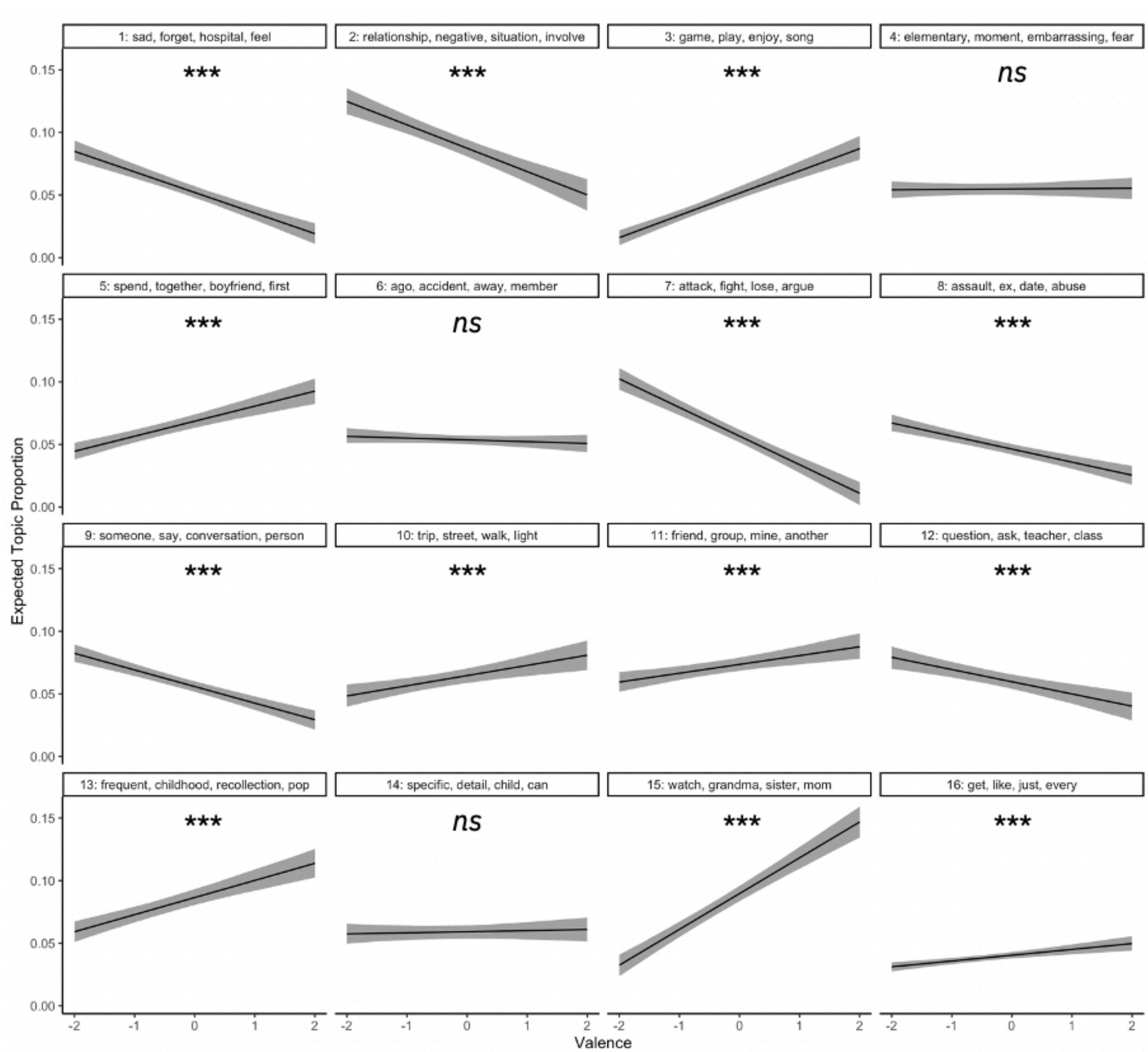
As a final step, we examined the predictive validity (Grimmer & Stewart, 2013; Quinn et al., 2010) of the topic model by predicting topic prevalence using participants' self-reported valence ratings of their memories[6] (see Figure 10). Most topics (13/16) were significantly predicted by participants' valence ratings, speaking to the highly emotional nature of IAMs (Berntsen, 2010; Berntsen & Rubin,

[6] Self-reported valence ratings were recoded from 1 to 5 (1 = *very negative,* 3 = *neutral,* 5 = *very positive*) to -2 to 2 (-2 = *very negative*, 0 = *neutral*, 2 = *very positive*).

2008) as well as AM in general (Holland & Kensinger, 2010). These patterns also support the predictive validity of the topic model: intuitively positive topics (topic 3: “Physical activities and performance”) were significantly more prevalent in memories that were self-rated as positive. In contrast, intuitively negative topics (topic 7: “Confrontations, fights, and arguments”) were significantly more prevalent in memories that were self-rated as negative.

Figure 10

Predicted Topic Prevalence Using Self-Reported Valence Ratings



Note. Valence refers to participants' self-reported ratings of their recurrent memories (-2 = *very negative*, 0 = *neutral*, 2 = *very positive*). *** = $p < .001$, *ns* = nonsignificant. For further details, see supplemental materials (https://doi.org/10.17605/OSF.IO/3584C).

4.1.4 Discussion

Though the field of AM relies heavily on text data, researchers to date have few tools at their disposal when analyzing these data. We applied computational methods to enable principled and practical ways of analyzing thousands of AM texts. Our current findings show that this approach can produce – and augment – the results of a manual content analysis. For example, we have demonstrated that these techniques can mimic or enhance the granularity of topics present in AMs. Further, these techniques give researchers new avenues for testing hypotheses about the nature of AMs, allowing one to directly examine how person- or memory-level variables (e.g., self-reported valence ratings) predict content. With these computational tools, we suggest a means to enable future research on autobiographical memory content at an unprecedented scale.

Frequency Analyses

Our frequency analyses suggested that recurrent IAMs often contain language characteristic of episodic memory (e.g., memory content that is located in a specific time and place, with an awareness of oneself having experienced the event; Tulving, 1972). For instance, highly frequent words like "time", "year", and "day" indicated a tendency for recurrent IAMs to involve events that occurred at specific times. Many highly frequent words were also characteristic of semantic memory (e.g., knowledge of facts or information about the self; Conway, 2005; Tulving, 1972). These included terms like "remember", "mind", and "pop", which seem to express the metacognitive experience of involuntary remembering (Barzykowski & Staugaard, 2016; Levine et al., 2002). This mixture of episodic- and semantic-like content is consistent with past findings that recurrent IAMs typically contain both episodic and semantic details (Yeung & Fernandes, 2020). Overall, these findings lend some support to the idea that recurrent IAMs can be understood using existing frameworks of AM in general (Berntsen, 2010), rather than conceptualizing them as operating through special mechanisms (Brewin et al., 2010).

Comparing highly frequent words across memories of different valences (negative, neutral, or positive), we also find that many of the most frequent words are identical (e.g., "memory", "time", "remember", "friend"). Looking at the frequency analyses, only a few of the highly frequent words distinguished the valence categories from each other (e.g., "bad" in negative vs. "good" in positive). Based on this pattern, one might conclude that content is largely comparable across valence categories, even though past work suggests that negative valence constitutes a qualitatively different type of recurrent memory (i.e., intrusive memories; Brewin et al., 2010). Inspection of the keyness analyses, however, suggests some support for the hypothesis that content differs across valences. According to the highly distinctive words for each valence, certain events appeared significantly more often in negative recurrent IAMs (e.g., "argument", "abuse", "fight") compared to other valence categories. Similarly, some events were significantly distinctive of positive recurrent IAMs (e.g., "trip", "vacation", "dinner").

Topic Modeling

Our results from topic modeling also support that recurrent IAMs fit well within extant frameworks of AM in general (Berntsen, 2010). Topics spanned a variety of concepts, from the mundane to the extreme. For example, topics such as "Experiences with family members" (topic 15) and "Physical activities and performance" (topic 3) indicate that many participants experience recurrent memories of commonplace, everyday events. More extreme events such as "Abuse and trauma" (topic 8) were also experienced as recurrent memories, but this topic accounted for a relatively small proportion (4.7%) of content across our sample of recurrent IAMs.

Importantly, the topics we identified using computational text analysis were also largely consistent with previous manual content analyses, replicating major content categories as expected. In line with existing AM literature, content related to relationships, accidents, and people emerged as the most prevalent topics. For example, where Schlagman et al. (2006) identified a "Conversations" content category in a sample of nonrecurrent IAMs, we identified a topic consisting of representative words such as "someone", "conversation", "say", and "person" (topic 9: "Conversations"). Interestingly, our prevalence estimate for this topic was also comparable to past work (8% in Schlagman et al., 2006 vs. 6.3% in the present study). Likewise, the previously identified content category of "Romantic involvement (e.g., being intimate, romantic dinners, receiving gifts for valentine day)" (Schlagman et al., 2006) also seems to map onto our topic with representative words such as "spend", "together", "boyfriend", and "first" (topic 5: "Close relationships"). Another topic consistent with past work was topic 10 ("Environments and locations"), which was similar to the past content category of "Objects/places" (Schlagman et al., 2006). That we replicated a topic focusing on environmental contexts is of relevance for current models of episodic memory. These models suggest the key role of the hippocampus is in establishing/recreating the location or environment where an event originally occurred via place cell activity in the hippocampus (Eichenbaum et al., 1999; Lavenex & Lavenex, 2013). Content related to environments and locations in IAMs may be associated with the degree to which those memories rely upon such hippocampal mechanisms.

Critically, we also found greater granularity of topics compared to past work. Instead of a single content category of “Person (i.e., primarily about other people)” (Schlagman et al., 2006) or “Relationships” (Krans et al., 2015), we identified distinct topics related to interactions with friends (topic 11, e.g., “friend”, “group”, “another”, “talk”), close relationships (topic 5, e.g., “spend”, “together”, “boyfriend”, “first”), and experiences with family members (topic 15, e.g., “mom”, “sister”, “grandma”, “cousin”). Further, we identified novel topics related to metacognitive or semantic aspects of recurrent IAMs, including subjective experiences of retrieval (e.g., “recurrently”, “random”, “sometimes”, “recent”) and subjective descriptions of detailed and/or time-specific recollections (e.g., “specific”, “detail”, “remember”, “part”). These findings support that topic modeling can find meaningful themes in text despite making fewer a priori assumptions compared to typical manual content analyses (Quinn et al., 2010). In other words, topic modeling was able to discover topics that would be expected based on the literature (e.g., phenomenology of involuntary retrieval), even though these topics were not specifically sought after or even defined to the model.

Another important contribution from topic modeling was its ability to predict topic prevalence based on participants’ self-reported valence ratings of their memories. Previous studies have manually assigned valences to content categories based on intuition (Schlagman et al., 2006), in order to examine how emotional content in IAMs might differ across populations. Here, we found that participants’ own valence ratings of their memories could be used to assign valences to topics. For example, seemingly positive content such as topic 3 (“Physical activities and performance”, e.g., “game”, “play”, “enjoy”, “song”) was significantly more prevalent in memories with more positive valence. Seemingly negative content such as topic 7 (“Confrontations, fights, and arguments”, e.g., “attack”, “fight”, “lose”, “argue”) was significantly more prevalent in memories with more negative valence. Given these results, the present study supports that recurrent IAMs of different valence tend to contain different contents. Computational methods were able to delineate the specific topics that diverged based on valence.

Interestingly, our work also adds nuance to understanding content compared to past studies, since relationships between topics and valence were assessed rather than assumed. While only seven out of 17 content categories could be manually assigned as positive (4/17) or negative (3/17) in previous work (Schlagman et al., 2006), many more of the topics in our study were found to be predicted by participants’ valence ratings (13/16). For example, certain topics (e.g., topic 9: “Conversations”) were found to be predicted by negative valence in the current study, whereas prior studies did not label this content category (“Conversations”) as positive or negative (Schlagman et al., 2006). This ability to make predictions about content based on person- or memory-level factors represents a novel and valuable avenue of hypothesis testing (Grimmer et al., 2021) that would benefit the study of AM.

Advantages of Computational Text Analysis vs. Manual Analyses

We reasoned that computational methods could be valuable in AM research because computational text analysis is effective at discovering patterns in large textual datasets under unfamiliar conditions (Puschmann & Scheffler, 2016). In particular, it excels at finding patterns that are novel and unconstrained by researchers' a priori expectations (Blei & Lafferty, 2009; Grimmer et al., 2021; Nelson, 2020). In our preceding comparisons between the current results and previous findings, we have discussed many pieces of evidence supporting the validity of computational text analysis. But even beyond the fact that it produces valid results, how might computational methods affect the landscape of AM research?

For one, computational methods enable the analysis of far more text data (e.g., more numerous and/or more lengthy) than previously possible, and in a way that is both practical and effective. While traditional manual analyses have produced many important results for AM research, this method is not scalable. Limited sample sizes raise questions about statistical power as well as generalizability, to which manual content analyses offer few answers. Here, we analysed more than 4–40 times as many texts compared to recent manual analyses of AM content (Grysman et al., 2015; Krans et al., 2015; Schlagman et al., 2006).

Further, computational text analyses are fully reproducible, whereas manual analyses are nigh impossible to confirm. Topic models can be run and rerun a trivial number of times by any given researcher. In contrast, researchers cannot easily verify the manual assignment of content categories to individual texts (Nelson, 2020). In a related vein, it is difficult to determine the robustness or reliability of a manual content analysis (e.g., what if twelve content categories were created instead of six?). On the other hand, computational methods offer many ways of capturing robustness and reliability. For instance, researchers can simulate multiple models with different topic numbers, allowing the comparison of different solutions against each other.

Quantitative internal metrics can also help inform researchers' analysis decisions. Current manual methods rely on expertise and researcher judgment is often based on deep reading alone. Researchers must make decisions throughout the data analysis process (whether manual or computational), yet it is often unclear how or why researchers categorize texts the way that they do during manual content analyses (Nelson, 2020). To reinforce decision-making processes, computationally derived quantitative metrics (e.g., semantic coherence, exclusivity) can be used as an additional layer of evidence on top of the text alone.

Here, we have demonstrated many computational techniques that AM researchers could apply to their own work. Though the exact choice of which analyses to perform are context-dependent, validation steps are not optional (Benoit, 2020; Grimmer et al., 2021). For further guidelines on conducting computational text analysis, other authors have provided detailed reviews (Banks et al., 2018; Fesler et al., 2019; Kobayashi et al., 2018; Welbers et al., 2017). Our goal here was to apply these methods to expand the study of AM to much larger samples, and with greater granularity and reproducibility.

Limitations and Future Directions

Our current work focused on content analysis, but it is important to acknowledge that there is a place for transforming content into other component variables. Many research questions in the field of AM surround theoretical features of text that are derived from content, but not content itself. For example, our understanding of AM function has been shaped by assessing the episodic and semantic components of these memories (Kopelman et al., 1989; Levine et al., 2002; Renoult et al., 2020; Tulving, 1972). Although episodic/semantic features could be inferred from the current analyses (e.g., by qualitatively judging whether a word or topic is characteristic of episodic versus semantic details), the present study does not attempt to directly measure these variables. However, it should be noted that in exciting new developments, computational methods are being adapted to address these questions (Sap et al., 2020; Sap et al., 2022; van Genugten & Schacter, 2022). Furthermore, an important assumption is that episodic and semantic memory processes can be derived from content. Whether a detail is considered episodic or semantic is fundamentally based on the text description (Levine et al., 2002). As such, an outstanding question is whether episodic and semantic distinctions emerge from analyses of content, even if these are not explicitly extracted from the data.

4.1.5 Conclusions

Our study is the first to provide a comprehensive description of what recurrent IAMs are about, in a large sample of undergraduates, and directly examine how content in these memories is related to valence. By using computational text analysis techniques in a novel application (i.e., autobiographical memory), we present a series of robust and reproducible methods that expand upon prior content analyses of autobiographical memory. Our approach replicated and expanded upon previous content analyses of autobiographical memories, and highlighted how computational methods can quantitatively assess relationships between content and theoretically relevant variables (e.g., valence). We suggest the use of computational tools, such as topic modelling, as a means for future researchers to examine, understand, and test theories of autobiographical memory content at an unprecedented scope and scale.

Chapter 5:
Linking Recurrent IAM Content to Mental Health

5.1 Study 4

5.1.1 Introduction

Memories of events and experiences from one's personal past that are retrieved unintentionally and effortlessly are termed involuntary autobiographical memories (IAMs; Berntsen, 1996). Recent evidence suggests that IAMs are often experienced *recurrently* – that is, episodes of the same event can repeat involuntarily (Berntsen & Rubin, 2008). In particular, evidence has shown that recurrent IAMs are commonly experienced in everyday life: large proportions (52–55%) of general populations (e.g., undergraduates, nationally representative samples, community-dwelling older adults) have endorsed experiencing at least one recurrent IAM within the past year (Berntsen & Rubin, 2008; Yeung & Fernandes, 2020, 2021). However, recurrent IAMs have also been characterized as a primarily clinical phenomenon despite their prevalence among the public (Brewin et al., 1996; Bywaters et al., 2004). For instance, these memories have been described as a transdiagnostic component of many clinical disorders (e.g., depression, anxiety, posttraumatic stress disorder), acting as a mechanism by which psychopathology emerges or is maintained (Brewin et al., 2010). As such, recurrent IAMs have been simultaneously characterized as maladaptive or clinically relevant on one hand (Brewin et al., 2010), and benign or pleasant on the other (Berntsen & Rubin, 2008).

This discrepancy has been acknowledged by some researchers, who have suggested that while many people experience recurrent IAMs, it may be the case that only some subset of IAMs are dysfunctional or related to poor mental health (Berntsen, 2010; Clark & Rhyno, 2005; Iyadurai et al., 2019). Indeed, our recent work has supported these hypotheses, finding that recurrent IAMs with self-reported negative valence were related to elevated symptoms of depression, posttraumatic stress, social anxiety, and general anxiety (Yeung & Fernandes, 2020, 2021). However, solely relying on self-reported ratings of memories' autobiographical properties (e.g., valence) is a major limitation of this field to date. For one, valence ratings are confounded with content, since certain events are likely to be more negative or positive than others. Most prior attempts to characterize recurrent IAMs have been done without knowing what these memories are actually about, prompting us to ask if memory content could help explain differences between maladaptive and benign recurrent memories. Indeed, some suggest that content might provide insights into differences in recurrent IAMs across different disorders (Brewin et al., 2010; Bryant et al., 2011; Gehrt et al., 2022; Reynolds & Brewin, 1999). Some past content analyses of autobiographical memories have been fruitful at describing typical content categories, revealing common topics such as accidents, holidays, and interpersonal relationships (Schlagman et al., 2006; Grysman, 2015). Nevertheless, none of these studies specifically analysed recurrent IAMs, nor symptoms of mental health disorders, and they were limited to relatively small sample sizes due to the use of traditional, manual content analyses. Is there disorder-specific content in recurrent IAMs experienced by large samples of general populations?

5.1.2 Methods

In Study 3, we conducted the first large-scale content analysis of recurrent IAMs using computational techniques (e.g., machine learning, natural language processing; Yeung, Stastna, & Fernandes, 2022). Here in Study 4, we used the dataset from Study 3 to assess how symptoms of mental health disorders (i.e., depression, posttraumatic stress, social anxiety, general anxiety) might uniquely predict different content categories (i.e., topics) within recurrent IAMs (Yeung & Fernandes, in prep.). By using computational methods, we were able analyze data from a much larger sample size (N = 6,187) than in previously published literature, all while asking more nuanced questions about the use of topics as continuous variables in recurrent IAMs (rather than categorizing memories as containing single topics).

Data Preparation

Prior to analysis, we first used supervised ML to detect and remove invalid texts (see Yeung & Fernandes, 2022a). This included texts with meaningless or irrelevant content, such as those describing dreams, which could introduce noise if retained (Banks et al., 2018; Maier et al., 2018). Valid texts were then preprocessed following current recommendations (Banks et al., 2018; Kobayashi et al., 2018; Maier et al., 2018), including tokenization, cleaning, stop word removal (Porter, 2001), frequency trimming, and lemmatization (Benoit & Matsuo, 2022). Texts were represented using a bag-of-words, unigram approach (Grimmer & Stewart, 2013), which decomposes texts into singular words without retaining information about word order.

Topic Modeling

We discovered topics in participants' descriptions of their recurrent memories using structural topic modeling (STM; Roberts et al., 2019). STM is a method of unsupervised machine learning that estimates hidden topic structures that could have plausibly produced the observed set of documents (i.e., corpus). By using texts as the input, topic modeling can output topics, or groups of words that can be interpreted as themes in the input texts (Blei et al., 2003; DiMaggio et al., 2013; Roberts et al., 2014). See Yeung, Stastna, & Fernandes (2022) for details about preprocessing, model selection, and validation. In prior work, we constructed topic models based on this dataset using only one covariate: participants' self-reported ratings of the memory's valence (Yeung, Stastna, & Fernandes, 2022). Here, we analysed this dataset in conjunction with mental health-related covariates: participants' current symptoms of depression (DASS-D), posttraumatic stress (PCL-5), social anxiety (SPIN), and general anxiety (STICSA-T). Data and code supporting the findings of this study are openly available on the Open Science Framework (https://osf.io/gur5v/?view_only=b6d48de3c1f145cc99062a357c25253c).

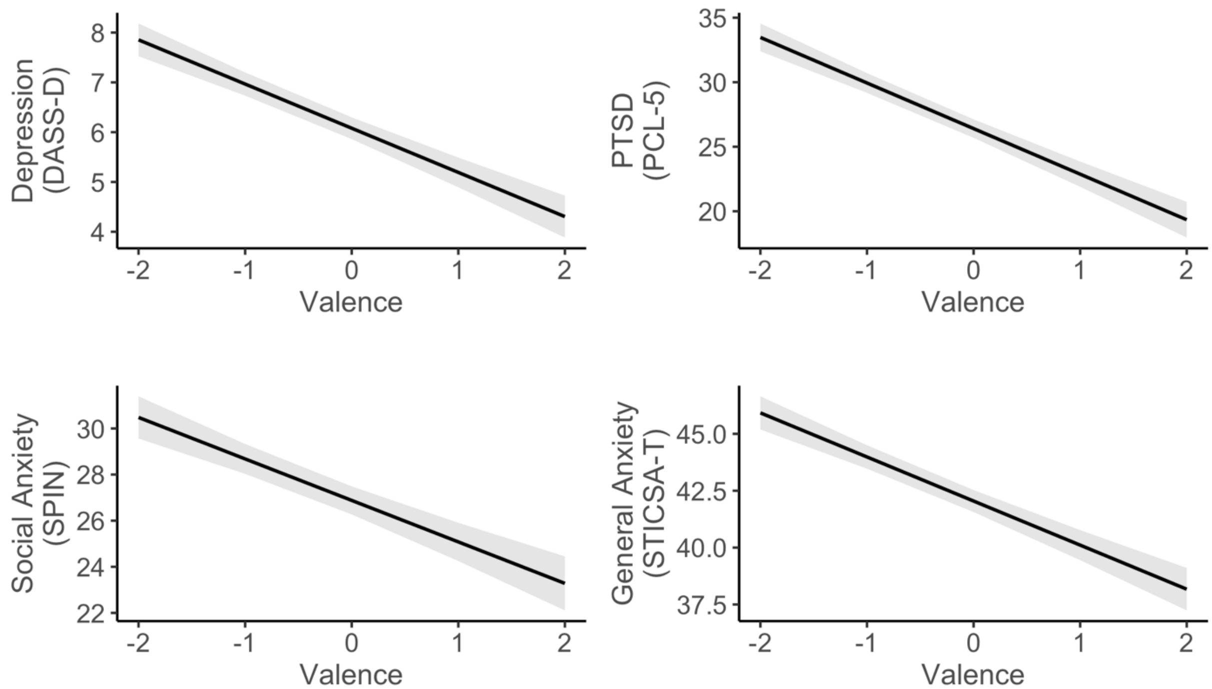
5.1.3 Results

Recurrent IAM Valence Predicts Symptoms of Mental Health Disorders

We replicated previous findings that negative valence in recurrent memories was significantly related to greater symptoms of depression, posttraumatic stress, social anxiety, and general anxiety (Yeung & Fernandes, 2020, 2021; see Figure 11). Linear regressions predicting symptoms of mental health disorders were all significant (ps < .001, βs = -0.89 – -3.53, adjusted R^2s = .026–.07).

Figure 11

Self-Reported Valence Ratings of Recurrent IAMs and Symptoms of Mental Health Disorders



Note. DASS-D = Depression, Anxiety, Stress Scales – Depression Subscale. PTSD = posttraumatic stress disorder, PCL-5 = PTSD Checklist for DSM-5, SPIN = Social Phobia Inventory, STICSA-T = State-Trait Inventory of Cognitive and Somatic Anxiety – Trait Subscale. Valence refers to participants' self-reported ratings of their recurrent memories (-2 = *very negative*, 0 = *neutral*, 2 = *very positive*). Shaded ribbons represent 95% confidence intervals.

Topic Structure and Modelling

To examine content at the level of topics (rather than single words), we implemented structural topic modeling (STM) using the stm package in R (Roberts et al., 2019). Model selection and validation are reported in Study 3 (as in Yeung, Stastna, & Fernandes, 2022). In brief, researchers must select an a priori number of topics to be identified when using STM (Roberts et al., 2019). To estimate reliability of the model, we simulated and inspected models with the same parameters across a varying number of topics (Blei & Lafferty, 2009; Maier et al., 2018). We then selected an appropriate number of topics using a two-stage approach (Grimmer & Stewart, 2013; Quinn et al., 2010). First, internal validation (based on computed metrics derived from the data) guided the initial selection of candidate models. Second, external validation (based on human judgment and performance measures) guided the selection of the final model out of the candidate models. The final topic structure[7] obtained is shown in Table 6 (in Study 3).

Predicting Topic Prevalence Using Symptoms of Mental Health Disorders

Symptoms of mental health disorders significantly accounted for unique variance in topic prevalence, even when controlling for valence ratings (see supplemental materials at https://osf.io/gur5v/?view_only=b6d48de3c1f145cc99062a357c25253c for details). We found unique relationships between specific topics and specific symptoms of disorders, above and beyond how positive or negative a memory was rated (see Table 7). The overall model can be seen in Table 7, after which we describe each mental health index, in turn.

Table 7

Significant Predictors of Topic Prevalence in Recurrent IAMs

Topic #	Predictor	B	*SE* B	*p*
1	Valence	-0.015	0.0016	< .001
2	Valence	-0.019	0.0024	< .001
2	PCL-5	0.00069	0.00025	0.006
2	SPIN	-0.00082	0.00026	0.002
3	Valence	0.019	0.0017	< .001
4	PCL-5	-0.00044	0.00018	0.02

[7] Inclusion of the additional mental health-related covariates (participants' scores on the DASS-D, PCL-5, STICSA-T, and SPIN) did not alter the topic structure obtained during the original study (Study 3, Yeung, Stastna, & Fernandes, 2022), which only included valence as a covariate.

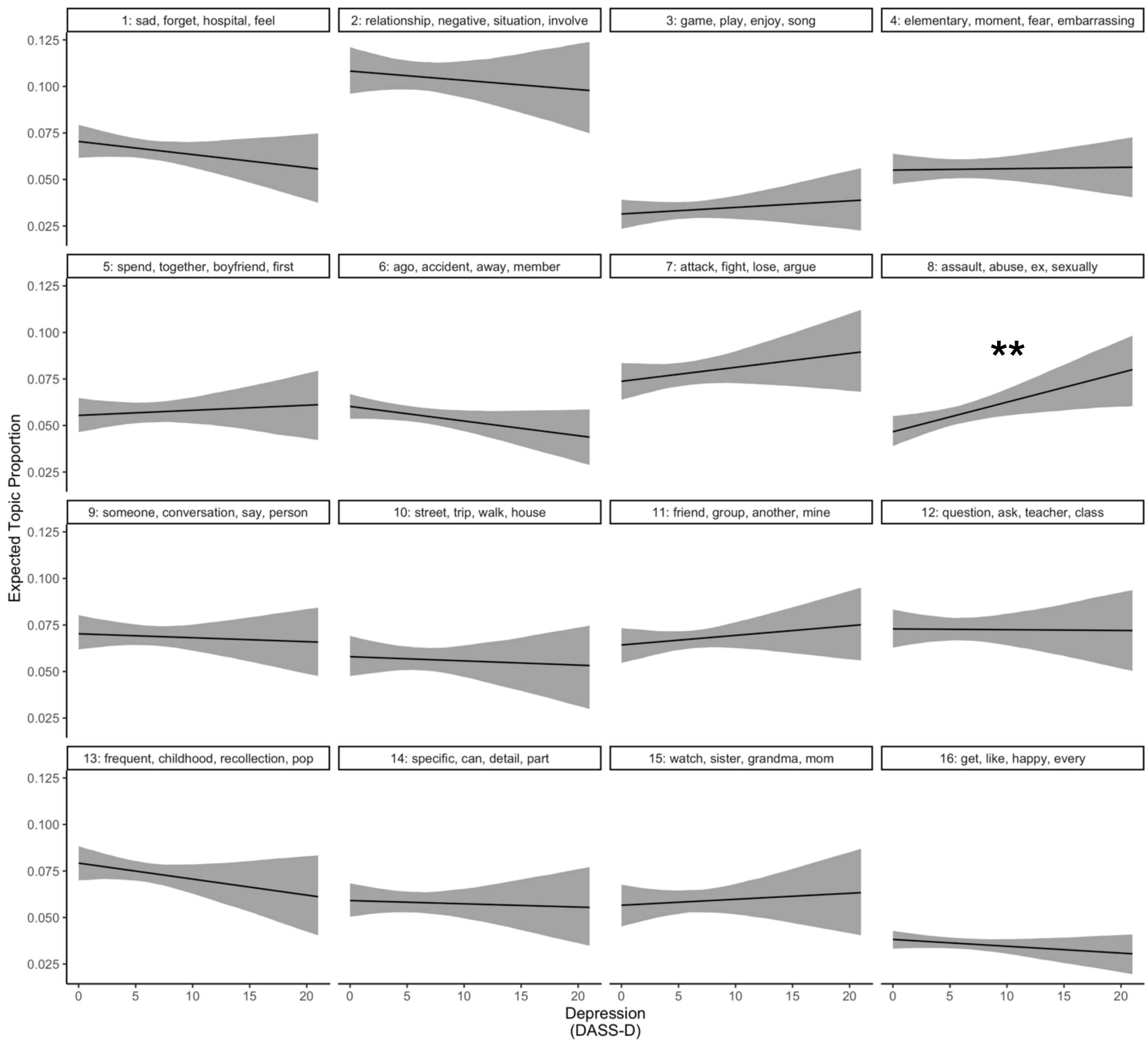
Topic #	Predictor	B	*SE* B	*p*
5	Valence	0.012	0.0020	< .001
7	Valence	-0.022	0.0020	< .001
8	Valence	-0.010	0.0017	< .001
8	DASS-D	0.0016	0.00060	0.009
8	SPIN	-0.00039	0.00017	0.03
9	Valence	-0.014	0.0016	< .001
9	PCL-5	-0.00042	0.00017	0.01
9	STICSA-T	0.00074	0.00030	0.01
10	Valence	0.0086	0.0023	0.0002
11	Valence	0.0061	0.0018	0.0006
11	PCL-5	-0.00037	0.00019	0.049
12	Valence	-0.011	0.0021	< .001
12	SPIN	0.00054	0.00026	0.04
13	Valence	0.012	0.0020	< .001
15	Valence	0.031	0.0024	< .001
16	Valence	0.0052	0.0010	< .001
16	SPIN	0.00027	0.00011	0.02

Note. DASS-D = Depression, Anxiety, Stress Scales – Depression Subscale, PTSD = posttraumatic stress disorder, PCL-5 = PTSD Checklist for DSM-5, SPIN = Social Phobia Inventory, STICSA-T = State-Trait Inventory of Cognitive and Somatic Anxiety – Trait Subscale. Valence refers to participants' self-reported ratings of their recurrent memories (-2 = *very negative*, 0 = *neutral*, 2 = *very positive*). Only significant predictors are presented here; if a predictor is absent for a topic, it was nonsignificant (see supplemental materials at https://osf.io/gur5v/?view_only=b6d48de3c1f145cc99062a357c25253c for additional details).

Depression. Depression symptoms were significantly and uniquely predictive of greater use of topic 8 ("Abuse and trauma"; see Figure 12).

Figure 12

Predicted Topic Prevalence Using Depression Symptoms

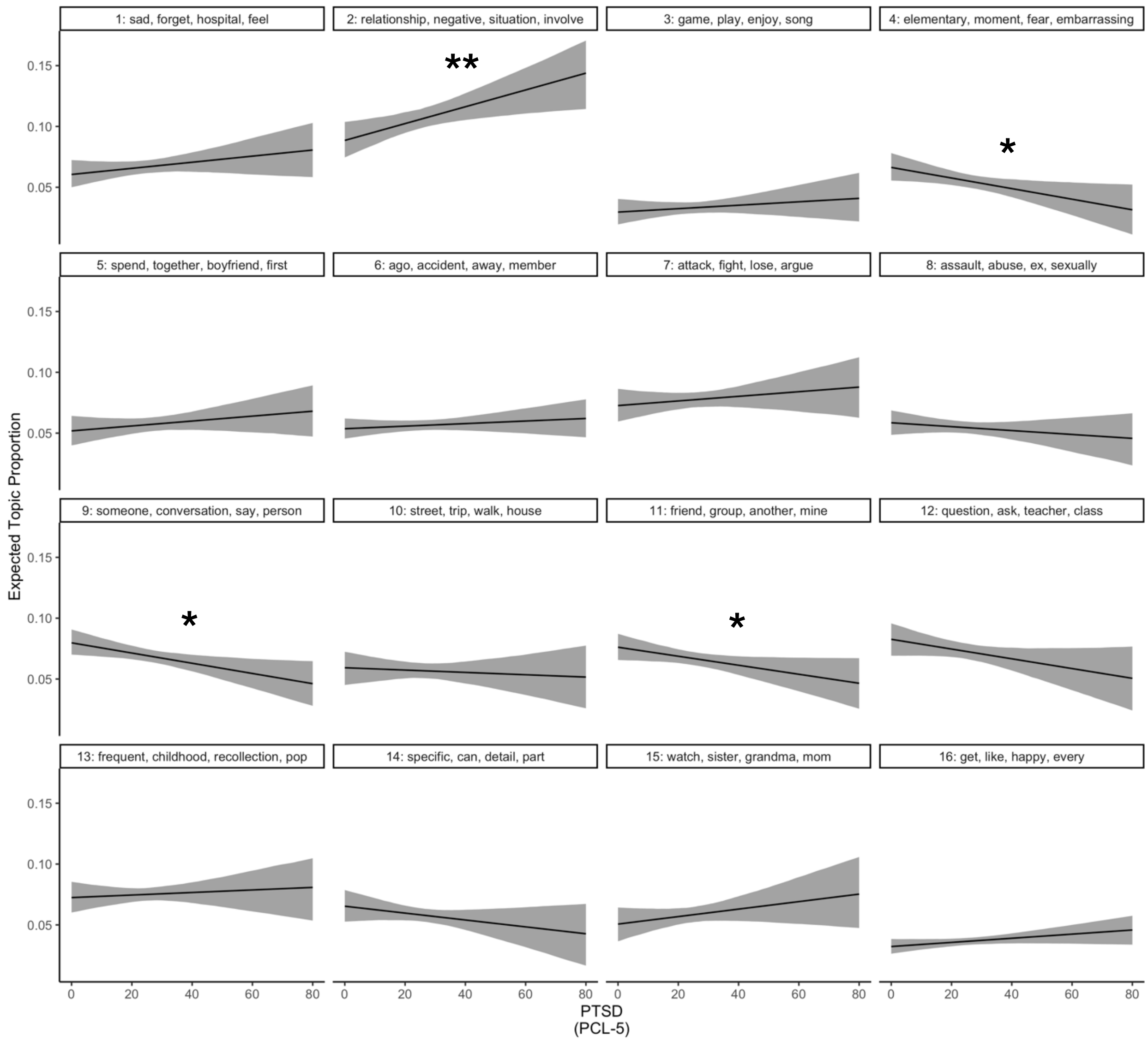


Note. DASS-D = Depression, Anxiety, Stress Scales – Depression Subscale. Different panels represent different topics, denoted by topic numbers and most representative words at the top of each panel. ** $p < .01$.

Posttraumatic Stress. Posttraumatic stress symptoms were significantly and uniquely predictive of greater use of topic 2 ("Negative past relationships"). Further, posttraumatic stress symptoms were significantly and uniquely predictive of less use of topic 4 ("Embarrassing events"), topic 9 ("Conversations"), topic 11 ("Interactions with friends"; see Figure 13).

Figure 13

Predicted Topic Prevalence Using Posttraumatic Stress Symptoms

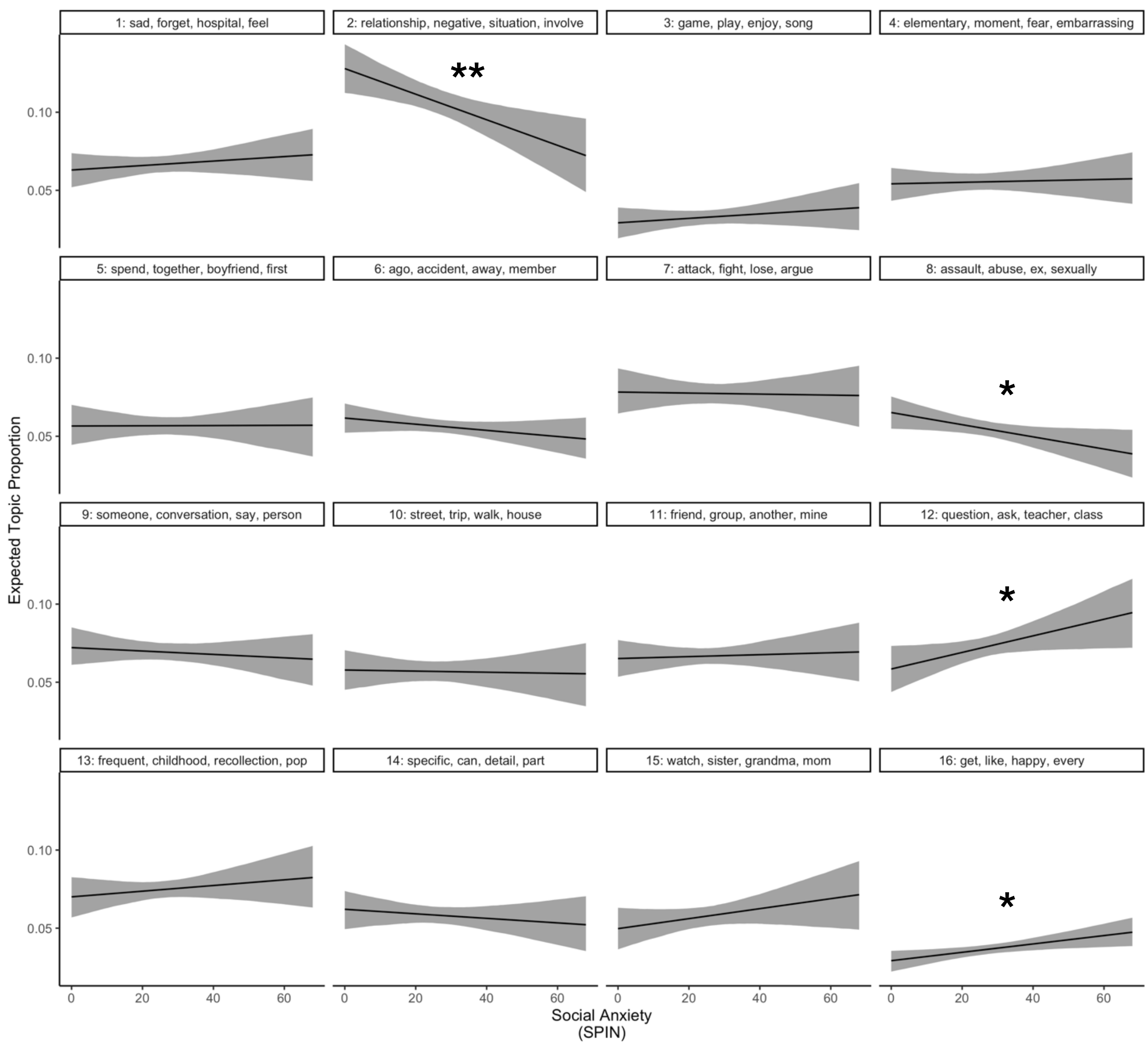


Note. PTSD = posttraumatic stress disorder, PCL-5 = PTSD Checklist for DSM-5. Different panels represent different topics, denoted by topic numbers and most representative words at the top of each panel. ** $p < .01$, * $p < .05$.

Social Anxiety. Social anxiety symptoms were significantly and uniquely predictive of greater use of topic 12 ("Communication and miscommunication") and topic 16 ("Reflections on decisions"). Further, social anxiety symptoms were significantly and uniquely predictive of less use of topic 2 ("Negative past relationships"), topic 8 ("Abuse and trauma"); see Figure 14).

Figure 14

Predicted Topic Prevalence Using Social Anxiety Symptoms

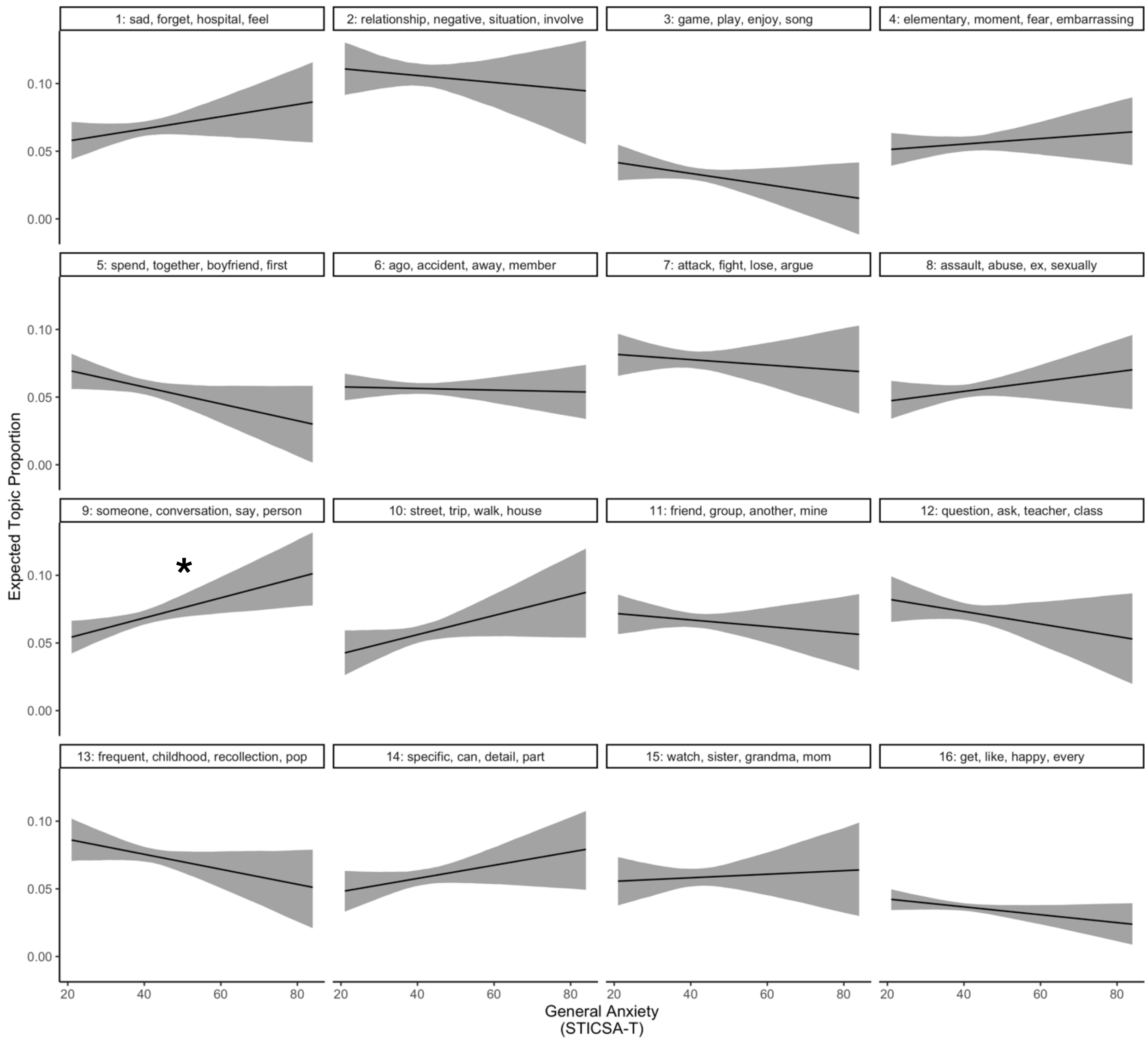


Note. SPIN = Social Phobia Inventory. Different panels represent different topics, denoted by topic numbers and most representative words at the top of each panel. ** $p < .01$, * $p < .05$.

General Anxiety. General anxiety symptoms were significantly and uniquely predictive of greater use of topic 9 (“Conversations”; see Figure 15).

Figure 15

Predicted Topic Prevalence Using General Anxiety Symptoms



Note. STICSA-T = State-Trait Inventory of Cognitive and Somatic Anxiety – Trait Subscale. Different panels represent different topics, denoted by topic numbers and most representative words at the top of each panel. * $p < .05$.

5.1.4 Discussion

Controversy surrounds the basic nature of recurrent IAMs. What are they typically about? Which of them – if any – are dysfunctional (i.e., related to worse mental health)? Some authors have speculated that only some subset of recurrent IAMs is maladaptive (Berntsen, 2010; Clark & Rhyno, 2005). Until now, it remained unknown whether and how the content of IAMs could distinguish a maladaptive recurrent IAM from a benign one. What we have shown here is that some topics were not significantly related to any mental health index, such as topic 3 (e.g., "game, play, song, dance") and topic 10 (e.g., "street, outside, walk, house").

This topic model then allowed us to test hypotheses about whether mental health variables could explain differences in recurrent memory contents (Berntsen & Rubin, 2008; Brewin et al., 2010; Yeung & Fernandes, 2020). Specifically, we used participants' symptoms of mental health disorders (i.e., depression, posttraumatic stress, social anxiety, general anxiety) to predict the prevalence of different topics within recurrent IAMs.

Mental Health Indices Predict Topic Prevalence

We found that each mental health index uniquely predicted the prevalence of distinct topics. For example, while posttraumatic stress symptoms were significant positive predictors of the "Negative past relationships" topic (e.g., "relationship, negative, situation, traumatic"), depressive symptoms were significant positive predictors of the "Assaults and abuse" topic (e.g., "assault, abuse, trauma, fail"). Furthermore, social anxiety symptoms were significant positive predictors of the "Communication and miscommunication" topic (e.g., "question, ask, teacher, class"), and general anxiety symptoms were significant positive predictors of the "Conversations" topic (e.g., "someone, conversation, say, person").

For each symptom type (e.g., depression, PTSD), elevated symptoms were uniquely related to having recurrent IAMs about specific topics. These findings support that there is indeed disorder-specific content in recurrent IAMs (Bryant et al., 2011; Gehrt et al., 2022), and that recurrent IAMs containing certain types of content are more likely to reflect psychopathology than other types of content (Brewin, Hunter, et al., 1996; Brewin et al., 2010). In fact, we replicated a relationship between the "Assaults and abuse" topic and symptoms of depression, but with a much larger sample size and in a nonclinical sample (Brewin, Hunter, et al., 1996; Kuyken & Brewin, 1994).

Overall, our results suggest that it is imprecise to say that negative recurrent IAMs are related to increased symptoms – the current work clarifies that specific types of content in recurrent IAMs are related to increased symptoms. Moreover, many negative topics were not significantly and uniquely related to symptoms of any disorder (e.g., “Stressful events”, “Confrontations, fights, and arguments”).

Our study is the first to provide a comprehensive description of what recurrent IAMs are about in a large sample of undergraduates. By using machine learning techniques in a novel application (i.e., autobiographical memory), we present a robust and reproducible topic model that both (a) expands upon prior content analyses of other types of autobiographical memory, and (b) reveals unique relationships between specific topics and mental health indices. Our work indicates that some, but not all, topics in recurrent IAMs are related to mental health. We show that these topics – and their links to mental health – are identifiable, distinguishable, and quantifiable.

Chapter 6:
General Discussion

> He never spoke to her of this misadventure, and ceased even to think of it himself. But now and then his thoughts in their wandering course would come upon this memory where it lay unobserved, would startle it into life, thrust it forward into his consciousness, and leave him aching with a sharp, deep-rooted pain. As though it were a bodily pain, Swann's mind was powerless to alleviate it; but at least, in the case of bodily pain, since it is independent of the mind, the mind can dwell upon it, can note that it has diminished, that it has momentarily ceased. But in this case the mind, merely by recalling the pain, created it afresh. To determine not to think of it was to think of it still, to suffer from it still. And when, in conversation with his friends, he forgot about it, suddenly a word casually uttered would make him change countenance like a wounded man when a clumsy hand has touched his aching limb.
>
> —Marcel Proust, *In Search of Lost Time*

Though involuntary remembering is thought to be a fundamental process carried out by the AM system (Berntsen, 2010; Ebbinghaus, 1885/2013), empirical research into this phenomenon has only just begun. Even more scarce – and controversial – is literature on *recurrent* IAMs. While some see these memories as largely pleasant and functional (Berntsen, 2010, 2021; Berntsen & Rubin, 2008), others frame them as unwanted and dysfunctional (Brewin et al., 2010; Cheung et al., 2015; Ehlers et al., 2004; Mihailova & Jobson, 2020; Newby & Moulds, 2011; Sündermann et al., 2013; Williams & Moulds, 2010). Even within the same texts by the same authors, differing opinions exist: are recurrent IAMs "exquisite pleasure[s]" (Proust, 1913–1927/1992, p. 60), or are they "sharp, deep-rooted pain[s]" (Proust, 1913–1927/1992, p. 381)?

In this dissertation, we bridged these opposing perspectives by providing a comprehensive characterization of recurrent IAMs in large samples. In doing so, we showed that recurrent IAMs are surprisingly common and frequent amongst general populations. Even within our nonclinical participants, however, recurrent IAMs self-rated as negative in valence were linked to greater symptoms of mental health disorders (e.g., depression, PTSD, social anxiety, general anxiety). We replicated this relationship between negative valence and worse mental health in a sample of older adults, as well as younger adults with high trait emotion regulation. Finally, we provided a novel perspective on the nature of recurrent

IAMs through the first large-scale content analysis of these memories using computational methods. Computational text analyses indicated that symptoms of mental health disorders predicted the use of specific topics in recurrent IAMs, unique from self-reported valence ratings, other topics, and symptoms of other disorders. In sum, this dissertation proposes that recurrent IAMs are general cognitive phenomena with specific and identifiable links to mental health.

In Chapter 2, we assessed the prevalence and properties of recurrent IAMs in a large-scale survey of undergraduates ($N = 2{,}184$). Results indicated that a large percentage of participants had experienced recurrent IAMs either within the past year (52%) or earlier (26%). Though this high prevalence of experiencing recurrent IAMs closely replicates past work, our distribution of valence ratings did not (Berntsen & Rubin, 2008). Specifically, our sample reported mostly negative recurrent IAMs (52%), whereas previous studies found a majority of positive recurrent IAMs (58%). Further, the self-reported valence of these recurrent IAMs was associated with symptoms of mental health disorders: those reporting negative recurrent IAMs had significantly more symptoms of depression, PTSD, social anxiety, and general anxiety relative to those with positive, neutral, or no recurrent IAMs. Altogether, Study 1 suggests that recurrent IAMs are surprisingly common, even in nonclinical samples. This finding speaks to the general nature of recurrent IAMs – if involuntary remembering is universal (Berntsen, 2010), our work goes further to suggest that *recurrent* involuntary remembering is the norm, as opposed to the exception. In addition, our work showed support for the idea that there is a dysfunctional subclass of recurrent IAMs (Berntsen, 2010, 2021). As predicted, valence may delineate the functional from the dysfunctional, given that negative valence was linked to significantly worse mental health status.

In Chapter 3, we extended this work by asking how individual differences might modulate the properties of recurrent IAMs, as well as their links to mental health. Knowing that older adults typically exhibit greater ability and/or motivation to regulate their emotions relative to younger adults (Carstensen, 1995; Carstensen et al., 1999; Charles & Luong, 2013), we reasoned that older age might be associated with more positive recurrent IAMs. This was exactly the pattern that we found in Study 2a: while younger adults' recurrent IAMs were again mostly negative (74%), replicating Study 1, older adults' recurrent IAMs were mostly positive (60%). To further probe the account that emotion regulation may be driving this age-related difference in valence, we ran a follow-up study investigating trait emotion regulation, isolated from the factor of age. By comparing a sample of younger adults who were either low or high in self-reported trait emotion regulation in Study 2b, we found that emotion regulation accounted for some, but not all, of the valence difference. Specifically, high emotion regulators did indeed report significantly fewer negative recurrent IAMs (45%) compared to low emotion regulators (71%). However, the distribution did not *reverse* as it did in Study 2a (i.e., the difference was of lower magnitude). Hence, Studies 2a and 2b suggest that while trait emotion regulation significantly modulated the valence of recurrent IAMs, it could not account for the entire difference observed between younger and older adults – other aging-related changes must also be modulating recurrent IAMs. Speculatively, changes in neural function or structure, such as reduced amygdala function in older age (Cacioppo et al., 2011), could support the valence reversal since they could contribute towards slower forgetting of positive material (Kalenzaga et al., 2016; Reed & Carstensen, 2012). A final contribution from Studies 2a and 2b was the finding that for all groups, negative valence predicted significantly more symptoms of mental health disorders – neither age nor emotion regulation significantly interacted with this relationship. As such, our work suggests that one's typical emotion regulation processes (e.g., dampening feelings of distress) may not be enough to interfere with the intense emotions evoked by negative recurrent IAMs (Berntsen, 2001; Berntsen & Hall, 2004). Alternatively, individuals may not have opportunities to effectively engage these regulatory processes (Berntsen, 2010; Rubin et al., 2008) due to the rememberer being unable to prepare for an involuntary retrieval. In sum, though recurrent IAMs are modulated by emotion-related individual differences, the link between valence and mental health appears relatively stable across samples.

In Chapter 4, we expanded upon our knowledge of recurrent IAMs by examining content in addition to self-reported valence ratings. While phenomenological reports of AMs' qualities remain as important sources of information in AM research, they provide a limited perspective on the nature of a memory. For one, valence ratings are entangled with content: any two memories might be given equal ratings of emotional valence (e.g., very negative), yet contain content that is dramatically different (e.g., receiving a bad grade vs. the death of a loved one). Further, an understanding of content is needed to provide a complete description of recurrent IAMs in general populations – without knowing what these memories are actually about, scholars can only speculate as to whether recurrent IAMs tend to involve certain types of events over others. To analyze content of recurrent IAMs in Study 3, we used computational text analysis methods (e.g., frequency analyses, topic modeling) to overcome barriers associated with manual content analyses. Results indicated that computational methods were able to mimic the quality of manual content analyses, plus many added benefits. First, we identified coherent topics that replicated content categories found in previous studies that had used manual methods. For example, consistent with past literature (Grysman, 2015; Schlagman et al., 2006), we found that many participants had recurrent IAMs related to topics such as other people, conversations, and deaths &

illnesses. These replications speak to the validity of using computational methods to analyze content. Importantly, we achieved greater granularity in terms of some topics: instead of one topic about "People" (Schlagman et al., 2006), we found evidence for distinct topics about family members, friends, and close and/or romantic relationships. Computational techniques also allowed us to directly test for statistical relationships between content and participants' phenomenological ratings of their recurrent IAMs. Here, we showed that valence ratings significantly predicted the use of most topics, and in expected directions, again supporting the validity of our analyses. This technique also provided insight into how topics should be interpreted. For instance, greater use of the "Conversations" topic was predicted by negative valence, suggesting that this content category was predominantly unpleasant (e.g., having said something that one now regrets). Study 3 builds a more complete picture of the diverse events that people have recurrent IAMs about, and puts forth a more rigorous and reproducible method of understanding AM content.

In Chapter 5, we used the computational framework from Study 3 to further probe current models of recurrent IAMs. Specifically, there exists some agreement that only a subclass of recurrent IAMs is dysfunctional or maladaptive (Berntsen, 2010, 2021; Marks et al., 2018). What remains unknown are the features of a recurrent IAM that contribute towards whether it becomes functional or dysfunctional. In Study 4, we asked whether content of recurrent IAMs could help distinguish this dysfunctional subclass, above and beyond the predictive power of valence ratings (observed in Studies 1 & 2). To do so, we reanalyzed the topic model from Study 3 by adding in symptoms of mental health disorders as predictors of topic use in recurrent IAMs. Results showed that each mental health index was significantly predictive of at least one topic, unique from participants' valence ratings as well as their symptoms of all other disorders. This provides empirical evidence for the presence of disorder-specific content in recurrent IAMs (Bryant et al., 2011; Gehrt et al., 2022), in that the language used and events described in these memories could be distinguished across different mental health indices. While negative valence was once again sufficient to predict elevated symptoms of mental health disorders, the finding that content still accounts for unique variance suggests that valence ratings are not a complete picture. It appears acceptable, but imprecise, to say that negative valence makes a recurrent IAM maladaptive. Rather, the use of specific topics in recurrent IAMs was significantly related to mental health status, even when holding valence constant. Though emotions evoked by recurrent IAMs remain as an important component in the relationship between these memories and mental health, this study suggests that content (e.g., types of events described, how the individual reconstructs them) is also vital to understanding recurrent IAMs. Our work here shows that phenomenology and content can be analyzed in tandem – and at much larger scale than previously thought possible – in order to answer critical questions about the fundamental nature of recurrent IAMs.

6.1 Limitations and Future Directions

This dissertation relied upon many past hypotheses focused on the negative, unwanted, or distressing quality of dysfunctional recurrent IAMs (Brewin et al., 2010; Cheung et al., 2015; Ehlers et al., 2004; Mihailova & Jobson, 2020; Newby & Moulds, 2011; Sündermann et al., 2013; Williams & Moulds, 2010). Though these hypotheses originate from other authors, it still raises the question of whether negative valence is *specific* to recurrent IAMs or *general* to cognition as a whole. To put it in other words, the present studies can only comment on the negative valence that was ascribed to the recurrent IAMs that we measured. However, it remains possible that those who ascribe negative valence to recurrent IAMs are also more prone to ascribing negative valence to experiences and thoughts of all kinds. Negative affectivity has been well-noted to have significant associations with symptoms of many forms of psychopathology, including depression and anxiety (Watson & Clark, 1984). As such, an important next step would be to distinguish individuals' tendencies to experience and dwell upon negative material (negative affectivity) from the subjective properties of their recurrent IAMs. We are currently in the process of addressing this concern by using voluntary AMs as a comparison against recurrent IAMs: if negative affectivity is driving the observed relationships between recurrent IAMs and mental health, we should find that voluntary AMs are equally predictive of mental health, since negative affectivity should impact both types of AMs to the same degree. Preliminary results suggest this is not the case: hierarchical multiple regression analyses indicate that recurrent IAMs are significantly better predictors of mental health disorders than voluntary AMs (Yeung & Fernandes, 2022b, in prep.).

A further limitation related to valence concerns its measurement in the current studies. Here, we opted for an item that asked participants to rate the memory as anywhere from very positive to very negative (see Appendix A). This choice was motivated by the fact that this item had already been used in previous work assessing recurrent IAMs in large, general populations (Berntsen & Rubin, 2008). Nevertheless, it is worth acknowledging that valence can be captured in a variety of other, meaningful ways. For one, researchers can distinguish between the valence of the event itself versus the valence evoked by remembering it (Nielsen & Berntsen, 2022). Consider the case of an individual remembering a positive event (e.g., a family vacation), but feeling negative emotions as they remember it (e.g., feeling homesick, or missing one's family members) – separate items could help distinguish these components of emotionality involved with the recurrent IAM. For example, while one item could ask about emotionality at the time of the event, another could ask about current impact on mood. All of these facets related to emotionality could extend our current findings by adding nuance to our conclusions about valence in recurrent IAMs. An alternative to administering different items that we are currently exploring (Yeung & Fernandes, in prep.) is sentiment analysis (Liu & Zhang, 2012; van Atteveldt et al., 2021), a computational technique of estimating expressed emotionality from unstructured text data. Extracting emotional tone from written descriptions of AMs would also offer a new perspective on emotionality, beyond the self-reported valence ratings obtained in the current work.

Further distinctions could also be drawn by examining participants' appraisals of their recurrent IAMs (e.g., how experiencing this memory impacts their self-perception; Cheung & Bryant, 2017; Mihailova & Jobson, 2018, 2020; Moscovitch et al., 2018; Williams & Moulds, 2010), or what meaning the participant ascribed to the event then versus what meaning they ascribe to it now (Çili et al., 2017; Wild et al., 2007). Cognitive models of intrusive memories highlight that the memories themselves may not be maladaptive in and of themselves – instead, downstream cognitive processes related to the memories in question may be responsible for maladaptive outcomes (e.g., elevated symptoms of mental health disorders). In particular, individuals' interpretations of their memories are thought to contribute towards the persistence and phenomenology of intrusive memories (Ehlers & Steil, 1995; Starr & Moulds, 2006). For instance, an individual might interpret or appraise one's intrusive memories as meaning that they have lost control over their mind (Steil & Ehlers, 2000) or that they have a mental health disorder (Cheung & Bryant, 2017). In the current studies, these interpretations were only partially indexed using participants' text descriptions of their recurrent IAMs. These text descriptions may have incidentally included appraisals, since participants were unconstrained in how they chose to describe their memories (and any thoughts or feelings they had surrounding those memories). As such, the content analyses conducted in Studies 3 and 4 may have captured some amount of participants' interpretations of their recurrent IAMs. Nonetheless, future research should more directly consider how interpretations or appraisals of recurrent IAMs might add predictive value when examining phenomenology or associations to symptoms of mental health disorders.

Limitations due to the current work's self-report response format were also mitigated by our movement towards content: quantifying and analyzing content added an important layer of information about individuals' memories, beyond responses on a Likert-type scale. However, other limitations exist when considering content, as well. Specifically, content is potentially entangled with lived experience –

one must have experienced certain types of events to have a recurrent IAM about it. This concern may apply to some of the more extreme topics (e.g., topic 8: "Assaults and abuse"), since it is likely that many participants did not use these topics simply because they had never experienced anything in that vein. Nonetheless, these content categories with (hypothetically) low base rates in general populations made up the vast minority of content in recurrent IAMs (e.g., 4.7% for topic 8). Most topics involved events so commonplace that it would be difficult to argue that participants had not experienced that type of event in their lifetime (e.g., "Interactions with friends", "Confrontations, fights, and arguments"). It also remains worth noting that recent estimates suggest that the majority of undergraduates (69–90%) have experienced at least one potentially traumatic event (Boals et al., 2020); base rates for even the more extreme events might be higher than expected. As such, for most topics, it would appear that content is more likely to be related to whether someone experiences recurrent IAMs about a type of event, rather than whether someone has lived through that type of event.

Another limitation of our present studies is their correlational and cross-sectional designs. Given these designs, our data are not able to make strong claims about directionality when considering the relationship between recurrent IAMs and mental health. In other words, we cannot yet conclude as to whether negative valence in recurrent IAMs leads to worse mental health, since it remains possible that worse mental health leads to more negative recurrent IAMs – while these relationships were statistically significant, they were neither causal nor directional. Instead, this dissertation laid down the groundwork of establishing that relationships between recurrent IAMs and mental health exist (even at the subclinical level) and can be observed consistently. Future work could address the additional research question of directionality using cross-lagged panel analyses (Kenny, 1975; Schuurman et al., 2016), which require multiple measurements over time, but can ascertain the directions of effects in a dynamic set of interrelated variables.

Another interesting avenue for future research is experimentally manipulating recurrent IAMs. Rather than attempting to estimate causal influences statistically, researchers could consider randomly assigning participants to conditions that may or may not influence the phenomenology (e.g., emotionality) of their recurrent IAMs. For example, one could track recurrent IAMs and their links to mental health over the course of imagery rescripting (Brewin et al., 2009; Holmes et al., 2007; Wild et al., 2007), which involves the deliberate reconstruction of memories (or images) in more positive terms. Other manipulations could also involve interference during retrieval of the recurrent IAM (e.g., performing irrelevant, secondary tasks with visuospatial or verbal demands; Hagenaars et al., 2017; Holmes et al., 2004; Iyadurai et al., 2018; James et al., 2015), which has previously been shown to impact the frequency of recurrent IAMs.

A final limitation concerns our use of retrospective measures to measure recurrent IAMs in these studies. It is important to note that during our online surveys, participants were asked to voluntarily retrieve information about their one most frequently recurring IAM (if they experienced any), which seems noticeably different from the subjective experience normally paired with involuntary retrieval. In the moment, recurrent IAMs are likely to feel unexpected, which can magnify the emotional experience associated with them. For instance, recurrent IAMs in everyday life might lead to feelings of loss of control or disrupt one's current activity. In contrast, our study gave participants time, space, and reasons to retrieve the memory, making the task less likely to evoke such feelings. Given these methodological choices, our data may be a conservative estimate with regard to emotional properties. To tap into recurrent IAMs as they occur in daily life, future research could adopt ambulatory assessment methods (Trull & Ebner-Priemer, 2013), such as ecological momentary assessment (EMA; Shiffman et al., 2008) or experience sampling methods (ESM; Larson & Csikszentmihalyi, 2014), instead of retrospective reports.

6.2 Current Extensions

To extend the program of research outlined in this dissertation, many additional projects are currently underway. As briefly mentioned earlier, one important next step in the study of recurrent IAMs is to compare them to voluntary AMs. Almost all of our conclusions to date about the human AM system have been informed by research on voluntary AMs – how might recurrent IAMs fit into or extend these frameworks? What similarities and differences exist between recurrent IAMs and voluntary IAMs, besides the critical distinction of voluntary/involuntary retrieval? For over a year, we have been administering online surveys probing for voluntary AMs in a format that closely matches our methods of assessing recurrent IAMs (Yeung & Fernandes, 2020, 2021). Preliminary analyses indicate that while many facets of phenomenology differentiate recurrent IAMs from voluntary AMs (e.g., vividness, emotionality, centrality), there remains substantial overlap between these types of memories (Yeung & Fernandes, 2022b, in prep.). Further explorations of these data will allow us to directly compare recurrent IAMs and voluntary AMs in terms of phenomenology, links to mental health, and content.

Another ongoing research stream continues to examine the individual differences that modulate or predict recurrent IAMs. By investigating the relationships between recurrent IAMs and other person-level variables, we can better understand how recurrent IAMs develop, and why. One research question here concerns potential links between trait measures of mind wandering and recurrent IAMs. Specifically, if our participants' recurrent IAMs are indeed involuntary, we should observe associations between the presence of recurrent IAMs and *spontaneous* mind wandering, but not *deliberate* mind wandering. Preliminary analyses support our hypothesis, adding further evidence of the validity of retrospective reports in measuring recurrent IAMs (Yeung & Fernandes, in prep.). Another research question includes investigating how trait visual imagery might influence the development of recurrent IAMs, since different styles of processing information (e.g., more visually vs. more verbally) are hypothesized to predispose individuals to experiencing intrusive memories (Marks et al., 2018).

In a related vein, the methods adopted in the current dissertation also allow us to disentangle individual differences from each other, since constructs might be differentiated based on their unique associations with recurrent IAMs. As an example, trait boredom and depression symptoms are often positively correlated, yet statistically (and conceptually) independent. Importantly, however, both are characterized by involuntary cognitions, such as recurrent IAMs. Knowing this, a current project (Yeung, van Tilburg, et al., 2022, in prep.) aims to identify how trait boredom and depression symptoms might be disentangled based on how recurrent IAMs manifest for different individuals along the spectra of boredom and depression. In this work, we have identified that specific topics in recurrent IAMs are uniquely predicted by trait boredom and not depression (e.g., topic 7: "Confrontations, fights, and arguments"), and vice versa (e.g., topic 2: "Negative past relationships"; Yeung, Stastna, & Fernandes, 2022, in prep.). Another stream of work has been focused on comparing recurrent IAMs between individuals with diagnosed mental health disorders (e.g., major depressive disorder) and matched controls from nonclinical samples. To this end, we have been collecting data from patients seeking treatment at Ontario Shores Centre for Mental Health Sciences, with the aim of discerning how recurrent IAMs differ between those with and without clinical diagnoses. These projects speak to the insights gained by modeling recurrent IAMs as general cognitive phenomena with transdiagnostic relationships to mental health, as well as the utility of understanding content using computational text analysis.

We are also pursuing multiple lines of work investigating how computational methods can enhance research in the field of AM. As previously mentioned, we have a current interest in sentiment analysis and its potential ability to approximate participants' ratings of their own memories' emotionality. Using our datasets of both recurrent IAMs and voluntary AMs, we can establish whether computational text analysis techniques (e.g., dictionary or lexical-based methods, natural language processing) can adequately mimic the ratings that participants gave to their own memories. Methodologically, establishing the validity of such tools in predicting emotionality – without using any participant ratings – would open many doors for retroactively answering questions about emotionality in AM data, even if those ratings were never directly collected. Further, we have developed computational methods of identifying invalid or noncompliant text responses in AM datasets (e.g., texts describing dreams or written refusals to respond). In this project, we used supervised machine learning to efficiently detect invalid responses with significantly better accuracy than other established methods (e.g., response time or character count; Yeung & Fernandes, 2022a). This use of machine learning to detect differences in text data offers a novel perspective into the ways that AMs can be shaped by their mode of retrieval (i.e., voluntary vs. involuntary), phenomenology, and the individual differences of those remembering them.

6.3 General Conclusions

Over the course of this dissertation, we have provided a comprehensive, large-scale characterization of recurrent IAMs, their phenomenology, and their links to mental health. Importantly, we also presented the first content analysis of recurrent IAMs using computational methods (e.g., machine learning, natural language processing). Our work demonstrates the general nature of recurrent IAMs – experiencing recurrent IAMs appears to be the norm, rather than the exception. Content analyses also confirmed that participants had recurrent IAMs about a wide variety of events, including the more mundane as well as more extreme. Despite how common recurrent IAMs were, we also found that they consistently predicted mental health, even at the subclinical level. Both valence and content had significant and unique relationships with symptoms of mental health disorders. This dissertation provides insight into the fundamental nature of recurrent IAMs and establishes novel computational methods of answering long-standing questions about the AM system.

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Appendix:

Recurrent Memory Scale

Table A1

Items in the Recurrent Memory Scale as Administered in Yeung & Fernandes (2020)

Item #	**Item**	**Response Option Labels**					**Notes**
1	Sometimes, people experience that memories from their personal past may come to mind by themselves. That is, the memory seems to spontaneously pop into mind, effortlessly and without having tried to remember it. Do you experience that the same recollections recurrently pop into your mind by themselves—so that memories for the same event repeat themselves in consciousness? We are not asking about dreams, but about recollections that you experience when you are awake. (***Presence***)	I have never had such recurrent recollections	I have had such recurrent recollections earlier in my life, but not within the most recent year	I have had such recurrent recollections within the most recent year	–	–	All items following Item 1 were only presented if the participant responded that they have had such recurrent recollections within the most recent year.
2	Within the most recent year, how many different recurrent recollections have returned to your	Open text (whole number	–	–	–	–	

	thoughts by themselves? We are not asking how often a single event might return to you, but how many separate events you have experienced recurrent memories for. (***Quantity***)	greater than zero only)					
3	Please think about the most frequent recollection that has recurrently popped into your mind by itself within the most recent year. The following questions will ask you about that memory. Please briefly describe your memory of the event in 3–5 sentences, without any identifying information. (***Text Description***)	Open text	–	–	–	–	
4	How often within the most recent year have you experienced that same recollection returning to your thoughts by itself? (***Frequency***)	Several times a day	Several times a week	Several times a month	Several times a year	Only once	Reverse coded so higher values are more frequent.
5	How long ago was the event that this recollection is about? (***Age of Memory***)	Years ago (open text, whole number only)	Months ago (open text, whole number only)	Days ago (open text, whole number only)	–	–	Units converted (e.g., 1 day ago = 1/365 years ago) and summed into a

							single value (e.g., years ago).
6	How complete and detailed is your memory for the event? (***Completeness/Detail***)	Not complete or detailed	A little complete and detailed	Somewhat complete and detailed	Rather complete and detailed	Very complete and detailed	
7	If you experience visual images of the event when remembering it, how vivid are these images? (***Clarity of Visual Imagery***)	Cloudy or no image at all	A little vivid	Somewhat vivid	Rather vivid	As vivid as normal vision	
8	When you remember the event, how much do you experience the event again? For instance, how much do you feel the same emotions again, or feel as if you are travelling back in time? (***Reliving***)	No reliving	Relived a little bit	Relived somewhat	Relived quite a bit	As if it were happening now	
9	When you remember the event, do you see this experience through your point of view, or how other people would view it? (***Vantage Perspective***)	Very much my own point of view	Somewhat my own point of view	Both my own and others' point of view	Somewhat others' point of view	Very much others' point of view	
10	Is the recollection emotionally very positive, positive, neutral, negative, or very negative? (***Valence***)	Very positive	Positive	Neutral	Negative	Very negative	Reverse coded so higher values

							are more positive.
11	Is the recollection emotionally not at all intense, a little intense, somewhat intense, intense, or very intense? (***Emotional Intensity***)	Not at all intense	A little intense	Somewhat intense	Intense	Very intense	
12	Do you feel that the event in your memory is a central part of your life story? For instance, do you feel that the event has coloured the way you think and feel about others' experiences, or feel that this event has become part of your identity? (***Centrality***)	Not at all	A little bit	Somewhat	Quite a bit	Very much	
13	During the event, were you afraid of being evaluated by others in the situation? (***Social Evaluation***)	Not at all	A little bit	Somewhat	Quite a bit	Very much	
14	Do you experience a sense of shame or criticize yourself while remembering your behaviour during the event? (***Shame***)	Not at all	A little bit	Somewhat	Quite a bit	Very much	

Note. Participants were able to skip any given item without providing a response.