That's What Friends Are For: How Years, Days, and Minutes of Social Engagement Relate to Cognition in Older and Younger Adulthood

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Abstract

Cognitive functioning plays a fundamental role in healthy ageing. Although slowing of cognition is a somewhat normal part of the aging process, neurodegenerative illnesses such as dementia are not typical and currently have no effective treatments. As cognitive decline is a risk factor of developing dementia, recent years have seen an increasing focus on identifying lifestyle factors that can slow cognitive decline across the lifespan. The purpose of this thesis was to consider associations of social resources with cognitive performance across different timescales analysed within a Bayesian statistical framework.

The first study used longitudinal data to examine whether social resources (social activity engagement and loneliness) play a compensatory role in buffering the effects of ageing on cognitive decline among those with limited opportunity to develop cognitive reserve (proxied by low educational attainment). A meaningful four-way interaction indicated the most vulnerable group of older adults (in terms of decline in processing speed over time) were those who had low education, were lonely, and had low levels of social activity participation. In contrast, there was a meaningfully slower rate of processing speed decline for those who had low education, were not lonely, and had high levels of social activity participation. However, the four-way interaction was no longer meaningful when participants who were classified as having dementia subsequent to baseline were excluded from the analysis. Finally, cross-sectional analyses demonstrated that meaningful activity in general (regardless of whether the activity was social in nature) was associated with better verbal fluency performance.

The second study used daily diary data to examine whether older adults' cognitive performance on a given day was related to the activities they engaged in, the degree of enjoyment they attributed to a positive social exchange, or the severity of a negative social exchange experienced on that day. No within-person associations of activity engagement or affective social exchanges and processing speed performance were found. Moreover, tests of between-person x within-person social exchange interactions did not reveal meaningful results, indicating that the novelty of the activity or affective social exchange did not impact the strength of the daily covariation.

The final study used an experimental design with young adults to investigate whether perspective-taking was a mechanism explaining acute boosts between social interaction and cognition that have been reported in previous research. Findings suggested perspective-taking benefiting processing speed above and beyond effects of practice. Specifically, perspective-taking conditions (social and alone) showed a larger increase in simple scores when compared to a passive control condition. There was no observable difference in improvement scores between the two perspective-taking conditions (social or alone).

Overall, the empirical findings did not provide strong evidence of social resources impacting cognition. Specifically: (a) where it appeared that social resources protected those with low educational attainment from the effects of cognitive decline, there was a high possibility of this effect reflecting reverse causality, (b) no reliable covariation between social activities or affective social exchanges and cognition were observed among older adults at the daily level, and (c) social interactions boosted processing speed in the short-term relative to a control group, however did not appear to be of additional benefit above and beyond the effects of perspective-taking. Finally, the few associations of social resources with cognitive performance that emerged tended not to generalise across multiple cognitive domains. In the final chapter, possible explanations for the discrepancies between the findings of this thesis and the broader literature are discussed.

Declaration

I certify that this thesis does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university; and to the best of my knowledge and belief, does not contain any material previously published or written by another person except where due reference is made in the text.

Signed: …………………………..

Daniele Despina Antoniou

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CHAPTER 1: Introduction

1.1. Overview

Cognitive functioning plays a fundamental role in healthy ageing. Older adults who are cognitively impaired are more likely to experience functional losses (Cigolle et al., 2007) decreased independence, and worse quality of life (Kelly et al., 2017). Although slowing of cognitive functioning is a somewhat normal part of the ageing process (Kuiper et al., 2016), more serious cognitive losses that disrupt everyday functioning including neurodegenerative illnesses such as dementia are not typical (Irwin et al., 2018). High economic and social burden are associated with later life cognitive decline and dementia (Prince et al., 2015). This is a major public health concern, given the rising ageing population and the likelihood that the prevalence of dementia will continue to increase with no current treatment. As it is recognised that people with cognitive impairment are at higher risk of developing dementia (Petersen et al., 2009), interventions aimed at slowing the process of cognitive decline have been prioritised in an effort to reduce the development of such neurodegenerative illnesses.

In keeping with this focus on prevention, scholars have prioritised the study of modifiable risk and protective factors, exploring lifestyle factors that may contribute to slowing cognitive decline and/or preventing dementia. Evidence has suggested a range of risk and protective factors that can affect cognitive functioning in older adulthood, including physical, cognitive, and social factors (Barber et al., 2012). This thesis primarily focuses on whether *social resources* can improve cognition in the short- and long-term. Establishing a better understanding of how social factors relate to cognition across the lifespan and the different possible mechanisms underlying such associations could ultimately inform population interventions designed to promote cognitive health.

The purpose of this thesis was to examine associations of social relationships with cognition across different methodological paradigms, and time scales. Although there is already evidence supporting a positive relationship between social resources and cognition in older adulthood (e.g., Desai et al., 2020; Evans et al., 2018; Kuiper et al., 2016; Lara, Martín-María, et al., 2019), this thesis intended to extend the existing literature in several ways. First, it is notable that only a limited number of studies have examined whether social resources can act as a compensatory factor for individuals who have not had the opportunity to develop cognitive reserve through other lifestyle pathways (e.g., Windsor et al., 2020). Therefore, the first aim of this thesis was to determine whether social resources can buffer the effects of cognitive decline amongst individuals with low levels of education (see Chapter 3). Furthermore, relatively few studies have focussed on the link between social activity engagement and cognition at the daily level (e.g., Bielak et al., 2019; Zhaoyang et al., 2021). Accordingly, the second aim of this thesis was to address whether cognitive performance on a given day was related to social activities engaged in that same day (see Chapter 4). Finally, where many mechanisms have been proposed in the literature to explain the social engagement-cognition relationship, not all mechanisms have been thoroughly investigated. Thus, a final contribution of this thesis was to determine whether perspective-taking was a possible short-term mechanism explaining an acute benefit of social interaction on cognition (see Chapter 5).

To preface the sections of this introduction to follow, this chapter includes: (1) a comprehensive review of the mechanisms and existing literature relating to long-term and short-term social engagement changes in cognition, (2) an overview of the different timescales and their relevance for the study of social networks and cognitive development, (3) a brief introduction to the Bayesian analytical approach used throughout this thesis (a more detailed summary of this statistical approach is provided in Chapter 2), and (4) a summary of the key research aims and hypotheses of each empirical study (Chapters 3 to 5).

1.2. Conceptualisation of social resources

One challenge when examining the possible protective effects of social engagement on cognition is the considerable variability in the way social resources have been conceptualised and measured throughout the literature. It has been suggested that social resources can be both objective and subjective in nature. Conceptualisation and operationalisation of different types of social resources have been characterised in terms of relatively more objective representations of social network structure (e.g., size, composition, contact frequency) and function (e.g., provision of aid, affirmation exchanges), and relatively more subjective representations of network quality (e.g., pleasant exchanges versus tensions; Fiori et al., 2007). Where social network size appears to be the most frequently used measure of social resources (Hughes et al., 2008), some studies have begun to demonstrate that network quality measures such as satisfaction with social relationships are stronger predictors of dementia risk than structural social resources (e.g., Amieva et al., 2010). Social resources are described in terms of their structure, function, and quality throughout this thesis. The distinction between different types of social resources is of interest given that objective and subjective social resources can affect cognitive health via different mechanisms. For example, having an objectively larger social network might facilitate greater opportunities for activity engagement which could positively affect cognition, consistent with the *Use It Or Lose It* perspective (Thoits, 2011). On the other hand, having a social network characterised by high quality, supportive relationships may help to protect from detrimental physiological effects of stress on cognition, consistent with the *Stress-Buffering hypothesis* (Cohen & Wills, 1985). Therefore, differing mechanisms depend on different social resource types (see Section 1.3.1 for an in-depth explanation of these long-term mechanisms).

1.3. Long-Term Methods and Mechanisms Linking Social Resources and Cognition

1.3.1. Long-Term Mechanisms Explaining a Social Engagement-Cognition Relationship

Researchers examining the relationship between engagement in social activities and improvements in cognitive abilities are increasingly interested in what mechanisms underlie this relationship. Findings from observational or longitudinal research are often explained by mechanisms that unfold over years or decades (e.g., Kuiper et al., 2016). Chapter 3 of this thesis uses longitudinal and cross-sectional data to examine aspects of these putatively long-term associations. This section aims to conceptually organise the long-term mechanisms suggested in the literature to date. Relevant mechanisms are classified within either a (1) stress-buffering or (2) mediation framework. Figure 1.1 provides an illustrative representation of the stress-buffering perspective (upper panel) and a summary of the different proposed mediation pathways that could account for the long-term social engagement-cognition relationship (lower panel).

Stress-Buffering Perspective

During recent years interest in the role of functional social relationships and their effect on cognition has increased. Numerous studies have indicated that people with social supports (e.g., spouses, family members, friends) who provide psychological and material resources are in better health than those with fewer supportive social contacts (e.g., see review by Kelly et al., 2017). The *stress buffering hypothesis* is a theory relating to *functional* social relationships used to describe how social ties can reduce the impact of major stressors that can negatively impact cognition. For example, chronic stress can result in excessive production of the hormone cortisol, where (although an important hormone for acute fight or flight responses) too much secretion over time can negatively affect the structure of brain regions important for memory (for example, atrophy of the hippocampus) (Fratiglioni et al., 2004; Wilson et al., 2003). These brain changes are known to presage cognitive decline and even pathological diseases such as Alzheimer's disease (Fratiglioni et al., 2004).

The stress buffering hypothesis posits that subjective feelings of social support can buffer (i.e., protect from) such pathological effects of stress on the brain. It has been suggested that having support from social ties can help to alleviate psychological distress via two different points in the causal chain linking stress to cognitive decline (Cohen & Wills, 1985). First, social supports may intervene between the anticipation of a stressful event and a detrimental stress reaction by preventing a particular situation from being appraised as highly stressful. This can be achieved by supports reinforcing one's perceived ability to cope with certain situations or by reframing whether the situation is as harmful as initially thought to be. Second, social support might intervene between the experience of an event appraised as stressful and the onset of the pathological, physiological, or behavioural outcome. For example, social supports could help with providing solutions to problems, reducing the perceived importance of the problem, or reducing someone's reactivity to perceived stress.

Mediation Perspective

A distinct model considering the process through which social support has a beneficial effect on cognition is the *Main Effect hypothesis* (Cohen & Wills, 1985). This model proposes that social resources are beneficial to cognitive health independent of stress exposure or reactivity, promoting bio-psycho-social processes that in turn help to sustain cognitive functioning. Whereas the stress-buffering hypothesis relates primarily to social support as a network *function*, the main effect hypothesis relates more to *structural* aspects of social relationships, and in particular the extent to which social connections facilitate intellectual engagement (Kuiper et al., 2016).

There are several proposed avenues linking social connection to cognition via a mediation pathway. First, the main effect hypothesis proposes that having larger social networks increases the likelihood of having positive experiences with that network which can positively affect cognition (i.e., through broaden-and-build processes, see Fredrickson, 2004). Second, having larger social networks may yield multiple sources of information that can help people to make effective use of the available health messages and resources. For example, social network members may help to decrease detrimental behaviours known to negatively affect cognitive functioning (Anstey et al., 2007; Beydoun et al., 2014; Kim et al., 2012; Plassman et al., 2010). These ideas are consistent with Berkman et al.'s (2000) notion of *downstream factors* which recognises that social ties and social networks impact health behavioural pathways (e.g., smoking, alcohol consumption, diet, exercise, adherence to medical treatment, and help-seeking behaviour). For example, norms about health behaviours are often acquired through comparison of self to others. Further, *social control* refers to the active and direct roles of social ties in encouraging a person to adhere to positive health care behaviours (Thoits, 2011). These differing main effect pathways all demonstrate how having larger networks can help to maintain positive mental and physical wellbeing which ultimately positively affects cognition.

A further well-known cognitive ageing theory that fits the mediation perspective is the *Use It or Lose It hypothesis* (Hultsch et al., 1999). This model posits that the brain works similarly to a muscle. Just as stimulating body muscles through physical activity increases strength, this theory suggests that stimulating the brain with intellectual, physical, and social activities may contribute to cognitive stability in older age (Kuiper et al., 2016). A corollary to the Use It or Lose It perspective is the *Disuse hypothesis* (Thomas et al., 2010). It has been suggested that less engagement in stimulating activity (including social engagement) with ageing results in disuse of the brain, which in turn may explain why having poorer social relationships would relate to cognitive decline.

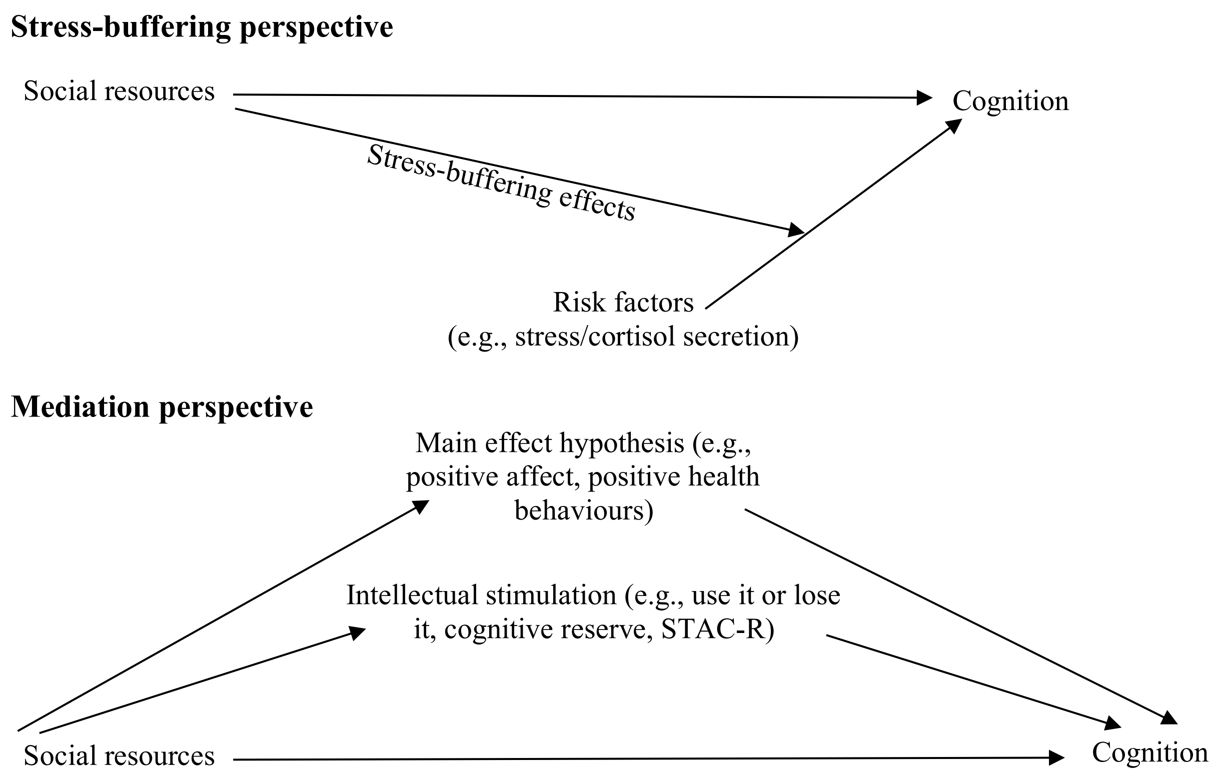
Another perspective on cognitive ageing aligning with a mediation model linking social networks with cognitive performance is *Cognitive Reserve theory* (Stern, 2002). Theories of cognitive reserve were developed to account for the phenomenon that brain pathology and clinical presentation of dementia are not always directly related. Passive models define cognitive reserve as the amount of brain damage that can be sustained before clinical presentation of dementia emerges, whereas active models hypothesise processes of compensation (i.e., recruitment of alternate neural networks) for cognitive difficulties arising from neuropathology by changing how the task is processed in the brain (Stern, 2002). It has been suggested that engaging in social activities (which are often cognitively effortful and require cognitive stimulation) can help to build cognitive reserve and therefore optimise cognitive performance (Ihle et al., 2019; Kelly et al., 2017). Specifically, in line with an active model, positive effects of activity engagement build up over time forming neural reserves, and/or plasticity of neural networks, that in turn protect against cognitive decline in older age (Scarmeas & Stern, 2003). The cognitive reserve hypothesis emphasises the cumulative effects of activity engagement, pointing to a long-term effect duration (Cullati et al., 2018). Historically, cognitive reserve has been measured by proxy variables such as education or occupational attainment.

An adjunct to the cognitive reserve theory is the *Scaffolding Theory of Ageing and Cognition – Revised (STAC-R) model* which was developed to better understand *how* compensatory neural processes explain varying levels of cognitive functioning. Empirical evidence from structural and functional neuroimaging studies have found that it is possible to enhance neural scaffolding activity (i.e., to create compensatory neural processes) by engaging in lifestyle activities, including exercise, intellectual activities, new learning, and formal cognitive training (Reuter-Lorenz & Park, 2014). Both cognitive reserve and STAC-R theory posit that engagement in lifestyle factors (including social factors) can enhance or deplete neural resources, influencing the development of brain structure and function (and therefore cognition) over time.

In sum, there are many long-term mechanisms that have been used to explain the relationship between social resources and cognition. These processes- although distinct- do not represent competing models. It is conceivable that such processes work in tandem to support cognition in older age. The fact that different mechanisms (e.g., stress-buffering versus mediation perspectives) invoke the importance of different types of social resources (e.g., function versus structure) also highlights the complexity of the social engagement-cognition relationship. Findings of key empirical studies that provide evidence relating to long-term links between social engagement and cognition are summarised in the section that follows.

Figure 1.1

An Illustration of Proposed Mechanisms Explaining a Social Engagement-Cognition Relationship



1.3.2. Empirical Evidence for a Long-Term Social Engagement-Cognition Relationship

Longitudinal research is central to the study of cognitive ageing, as it allows for the study of within-person changes over time and overcomes several of the problematic aspects of cross-sectional approaches such as the confounding of developmental and cohort differences (e.g., see Hofer & Piccinin, 2010; Sliwinski & Buschke, 1999). One key benefit of employing longitudinal designs is their ability to separate individual differences at the between-person level (i.e., at baseline) from within-person change over time. Long-term longitudinal designs also have the added benefit of measuring developmental phenomena of interest over long time periods, allowing investigation of effects of ageing (Hofer & Piccinin, 2010). In the sections to follow, I review the relevant literature on social resources and cognitive ageing arising from long-term longitudinal designs and cohort studies.

Review of Systematic Reviews and Meta-Analyses

There have been several recent systematic reviews and meta-analyses synthesising evidence regarding the longitudinal relationships between different types of social resources and pathological as well as non-pathological cognitive decline. One early systematic review and meta-analysis identified 19 longitudinal cohort studies investigating whether poor social relationships are related to the development of dementia (Kuiper et al., 2015). Meta-analysis revealed that low social participation, less frequent social contact, and more loneliness were associated with incident dementia in the general population. Another systematic review differentiated studies investigating social relationships and cognitive decline according to measures of structural social relationships, functional social relationships, and a combination of both (Kuiper et al., 2016). The authors concluded that poor social relationships were associated with an increased risk of non-pathological cognitive decline irrespective of the type of social resources assessed. A further systematic review by Kelly et al. (2017) evaluated the association between different aspects of social resources with cognitive functioning in cognitively healthy older adults. This review evaluated 39 studies including updated observational literature as well as being the first systematic review in this area to include data from randomised controlled trials and twin studies. Evidence suggested a positive relationship existed between social resources and cognition; however, this relationship was not reliable across all types of social resources and cognitive abilities assessed. For example, social activity was related to global cognition, executive functioning, working memory, visuospatial abilities, and processing speed, but not episodic memory, verbal fluency, reasoning, or attention. Further, social network size was related to global cognition but not episodic memory, attention, or processing speed. Social support was related to global cognition and episodic memory but not attention or processing speed, and composite measures of social relationships were related to episodic memory and verbal fluency but not global cognition.

Evans et al.'s (2019) systematic review and meta-analysis examined whether social isolation in particular was associated with poor cognitive functioning in later life. Low levels of social isolation characterised by high levels of social activity engagement and large social networks were associated with better late-life cognition, including measures of global cognitive functioning, memory, and executive functioning. Lara et al. (2019) conducted a systematic review and meta-analysis of 10 longitudinal studies examining the association of loneliness and mild cognitive impairment and/or dementia. Loneliness was found to be positively associated with increased risk of dementia. Finally, Desai et al. (2020) systematically reviewed longitudinal studies investigating whether living alone was a risk factor for incident dementia. Twelve studies were identified as a part of the meta-analysis which found that living alone was a greater risk of dementia than other risk factors including physical inactivity, hypertension, diabetes, and obesity.

Taken together, the findings of recent comprehensive systematic reviews and meta-analyses offer a broad consensus toward a positive relationship between social resources and cognitive performance in older adulthood, with some exceptions (see Kelly et al., 2017). The next section provides a further updated perspective on the literature by reviewing recent empirical studies that focussed on a long-term social engagement-cognition relationship (i.e., utilising longitudinal or cross-sectional data) conducted since the reviews discussed above were published. Sub-sections are organised according to whether studies included measures of social network structure, function, or quality.

Review of Recent Cross-Sectional and Longitudinal Literature

Social Network Structure.

Most of the research published since the review papers described above have focussed on the relationship between structural social resources and cognitive functioning. A consistent finding in recent literature is that greater amounts of social activity participation is associated (both cross-sectionally and longitudinally) with better cognitive health (Bae et al., 2019; Paiva et al., 2021; Zhou et al., 2018; Zuelsdorff et al., 2019). Social network size- another marker of structural social resources- has also been associated with cognitive outcomes. For example, Casey et al. (2021) reported results of cross-lagged analyses that found a bi-directional relationship between social network size and cognition in older adults without dementia. Specifically, declines in social network size predicted subsequent declines in executive functioning scores, but at the same time declines in language scores predicted subsequent declines in social network size. Further, Elovaino et al. (2018) found that more frequent social contacts and being married were associated with lower probability of being on a low cognitive performance trajectory over a 21-year period.

Whereas the consensus has generally been that a positive relationship between social network size and cognition exists (Kuiper et al., 2016), some recent studies have found that the association only holds for women but not for men (Wu et al., 2020), that the association is evident at baseline but does not remain over time (Nie et al., 2021), or that no relationship is evident for certain populations – for example, clinically depressed older adults (Kuiper et al., 2020). One explanation for the lack of associations between social network size and cognition reported in some studies, is that the frequency of engagement with social networks may be a better predictor of cognitive functioning than network size itself (Kuiper et al., 2020). Another possible explanation was that Kuiper et al.'s (2020) measure of social network size did not specify the social network composition (e.g., friends versus family), and it has been shown that a relatively higher proportion of friends in one's network may be protective, whereas a relatively higher proportion of family may be associated with poorer cognitive performance (Aartsen et al., 2004). To explain the reason why network size and activity associations were stronger at baseline than over time, Nie et al. (2021) suggested the possible operation of reverse causality, as maintaining strong social networks requires some degree of cognitive capacity.

Social Network Function.

A small number of studies have investigated associations between social support and aspects of cognition in older adulthood. The majority of these studies found that social support was positively associated with different cognitive outcomes including speed, flexibility, and memory (Oremus et al., 2020; Paiva et al., 2021; Scholes & Liao, 2021; Xiao et al., 2021; Zuelsdorff et al., 2019). Oremus et al. (2020) used cross-sectional data to examine the association between social support availability and memory in persons aged 45 – 85 years. Higher levels of all social support availability measures (namely emotional/informational, tangible, positive, and affectionate) were positively associated with better performance on immediate and delayed recall. Of the four social support availability subscales assessed, the strongest associations were observed for overall social support availability scores and the emotional/informational subscale. An additional cross-sectional study by Paiva et al. (2021)

examined the independent contributions of social connectedness and social engagement in predicting cognition. Higher levels of social engagement and social connectedness were independently associated with higher levels of cognitive performance. An interaction also emerged showing that those who performed best reported both higher social connectedness and higher social engagement. Interestingly, when one of these aspects was lacking, the other played a role in protecting cognitive performance (i.e., for those with low levels of social engagement but high levels of social connectedness (and vice versa) the cognition score was relatively stable). A study by Zuelsdorff et al. (2019) also examined the associations of perceived support and verbal interactions with cognition using longitudinal data assessed at six waves over two-year intervals. Social support was positively associated with speed and flexibility, whereas verbal interactions were associated with verbal learning and memory. Thus, the authors concluded that where social support may be useful in buffering stress, verbal interactions may be a form of environmental enrichment that can help maintain cognition in older adults. The studies focusing on functional social network attributes reviewed here are reasonably consistent in suggesting that social support could play a role in supporting cognitive functioning, as well as indicating that social support and social activity engagement may contribute to different domains of cognitive performance, potentially complementing each other to support better cognitive outcomes more generally.

Social Network Quality.

Since publication of the systematic reviews discussed above that focussed on associations of social network quality (in terms of social isolation and loneliness) with cognitive outcomes (Evans et al., 2019; Lara, Martín-María, et al., 2019), several additional relevant studies have been published. Some have replicated the findings pointing to social isolation, loneliness, and negative social interactions having a negative impact on cognitive outcomes in older adults (Ishtiak-Ahmed et al., 2019; Joyce et al., 2021; Okamoto & Kobayashi, 2021; Read et al., 2020; Xiang et al., 2021). However, others have not found associations of social isolation or loneliness with cognition (e.g., Kuiper et al., 2020; Okely & Deary, 2019).

Further, recent studies considering both social isolation and loneliness together have consistently found that social isolation, but *not* loneliness, predicts cognitive functioning, cognitive decline, and dementia risk (e.g., Elovainio et al., 2018; Evans et al., 2018; Jang et al., 2021; Yu et al., 2021). For example, a cross-sectional study found that social isolation, but not loneliness, was significantly associated with objective cognitive impairment (Jang et al., 2021). Another cross-sectional study found that social isolation, but not loneliness, was associated with increased risk of dementia (Elovainio et al., 2020). Further, the authors found that of the participants with higher genetic risk of developing dementia, those who were socially isolated were at greater risk of developing dementia than those who were not socially isolated (i.e., genetic risk x social isolation interaction). Finally, a longitudinal study of Chinese older adults found that social isolation (measured at baseline) was associated with decreases in episodic memory and mental status at four-year follow-up even after controlling for loneliness, whereas loneliness (also measured at baseline) was not significantly correlated with cognition at follow-up once covariates were added to the model (Yu et al., 2021).

In terms of explanations of why social isolation but not loneliness may impact cognition when considered together, one study flagged that their loneliness measure was highly correlated with their depressive symptom measure which was a covariate in the model and thus may have explained why the size of the association decreased (Yu et al., 2021). Nonetheless, the consistent finding that social isolation and not loneliness predicted cognition shows that these distinct constructs may have differential cognitive health consequences and emphasises the need for nuanced assessments (Jang et al., 2021). Of course, it is important to also recognise that other recent work has found evidence for loneliness predicting negative cognitive outcomes over time (Kyröläinen & Kuperman, 2021; Lara, Caballero, et al., 2019). However, the findings from studies examining both social isolation and loneliness together have raised some questions as to the robustness of the associations of loneliness and cognition reported in the earlier systematic reviews/meta-analyses.

Cognitive reserve.

Researchers have conceptualised social integration as providing a possible pathway to developing cognitive reserve and have examined this by considering interactions of social resource variables with more established markers of reserve (i.e., education, occupational complexity). For example, Evans et al. (2018) found that social isolation (at baseline) was associated with cognitive functioning at baseline and two-year follow-up, and that cognitive reserve (proxied by education, occupational complexity, and cognitive activity) moderated the longitudinal relationship. Their findings suggested that maintaining a socially active lifestyle in later-life may enhance cognitive reserve and ultimately benefit cognitive functioning. Windsor et al. (2020) investigated whether social resources could act as a buffer for cognitive outcomes for those with low educational attainment. Where the authors reported a relationship between larger social network size and better performance on tests of perceptual speed and verbal fluency, there was no interaction of social network size with education. This meant that there was no evidence of social resources compensating for low cognition resulting from educational disadvantage. However, Murayama et al. (2019) also investigated whether social capital can act as a buffer for cognitive impairment in those with low educational attainment (suggesting limited opportunities for establishing cognitive reserve early in life) and found that social networks did buffer the low education-cognitive impairment relationship. In addition, Perry et al. (2021) found that a higher degree of social network size, lower density of social ties, and presence of weak social ties moderated the association between brain atrophy and cognitive functioning, while marriage/cohabitation moderated the association between perceived stress and cognition (i.e., all interactions supported a role for social ties sustaining cognitive reserve). Future research is necessary to determine whether social resources can act as a buffer for cognitive outcomes for those with limited educational opportunities (this research question is addressed in Chapter 3). Such findings would have important implications for interventions that might target social resources to improve cognitive outcomes in older age and possibly prevent cognitive decline and even dementia.

Although observational studies, and in particular longitudinal cohort studies provide a key lens through which to study the nature of changes in social relationships and cognition that occur in the second half of life, it is not appropriate to draw strong causal inferences based on the findings reviewed above. One reason for caution concerns the possible influence of extraneous variables (e.g., personality traits or cultural influences) that cannot be ruled out, even in well-controlled studies. Another issue concerns the potential for reverse causality. For example, findings from a longitudinal study might indicate that as a person becomes less socially active, their cognition also declines. One explanation may be that social resources help to maintain cognitive performance. However, an equally plausible explanation is that as a person's cognition declines, they tend to withdraw from social connections. Support for reverse causality is evident in a longitudinal study by Stoykova et al. (2011), who found that when bias of reverse causality was not controlled for (i.e., no exclusion of participants who developed dementia over the longitudinal study interval), there was a statistically significant association between social network and global cognitive decline measured by the Mini Mental State Exam. However, when participants who developed dementia were excluded, there was no significant association of social networks with cognitive decline. Given these limitations, it is important to also consider evidence from micro-longitudinal and experimental studies to obtain a more complete picture of the conditions under which associations of social resources with cognition are observed, as well as the possible mechanisms underlying such associations.

1.4. Overview of Different Timescales and their Relevance for the Study of Social Networks and Cognitive Development

Whereas research has traditionally focussed on implications of social engagement for long-term changes in cognition, recently studies have also begun to focus on acute changes and short-term variability in cognitive performance. Gerontological science and lifespan developmental psychology recognise the dynamic interplay of developmental processes across different timeframes and levels of analysis. Time frames may vary from as short as seconds or minutes to as long as years or decades (Cairns et al., 2001). In this section, I discuss the value in complementing findings from traditional methods, including laboratory and long-term longitudinal research designs, with *slice of life* methods (Smyth et al., 2017) including daily diaries, ecological momentary assessment, and experience sampling to achieve a more complete understanding of the role social relationships play in the attainment and maintenance of cognitive health across the lifespan.

1.4.1. Sources of Variability

There are two primary sources of variability that characterise social relationships: between- and within-person variability. *Between-person variability* refers to the notion of social relationships varying across individuals. For example, people differ in the nature of their relationships (e.g., those with generally higher versus lower social activity engagement). Observational and longitudinal approaches to research have often targeted this type of variability, with the goal of explaining whether between-person differences in social network attributes account for why some individuals have better or worse cognitive outcomes than others (e.g., see Kuiper et al., 2016). Chapter 3 (which used long-term longitudinal and cross-sectional design) and Chapter 5 (which used an experimental design) of this thesis captured this type of variability.

Within-person variability on the other hand refers to fluctuations in social relationship variables occurring within the individual across contexts (e.g., social relationships may offer different levels and types of support in home versus work contexts), time (e.g., social relationships may change over weeks, months, or years), and across relationships (e.g., a person may interact more or less with certain friends or family members). Although longitudinal methods can also target within-person variability to capture how social resources and cognition can change together across time, shorter-term types of variability are best captured in slice of life type methods that involve repeated measurements across shorter time intervals (e.g., repeated testing occasions from moment-to-moment or day-to-day). One example research question that requires within-person data is whether individuals who engage in more social activity than usual on a given day also perform better on tests of cognitive functioning relative to their mean, on that same day. Research that examines this type of variability has been sparse (see the micro-longitudinal literature review in Section 1.5.2), and more work in this area is needed to better understand short-term mechanisms that could underlie the longer-term links between social resources and cognition that are commonly observed in longitudinal studies (e.g., Kuiper et al., 2016). Chapter 4 of this thesis addresses this gap in the literature by targeting within-person variability using daily diary data to determine whether social activity and cognition covary from day-to-day.

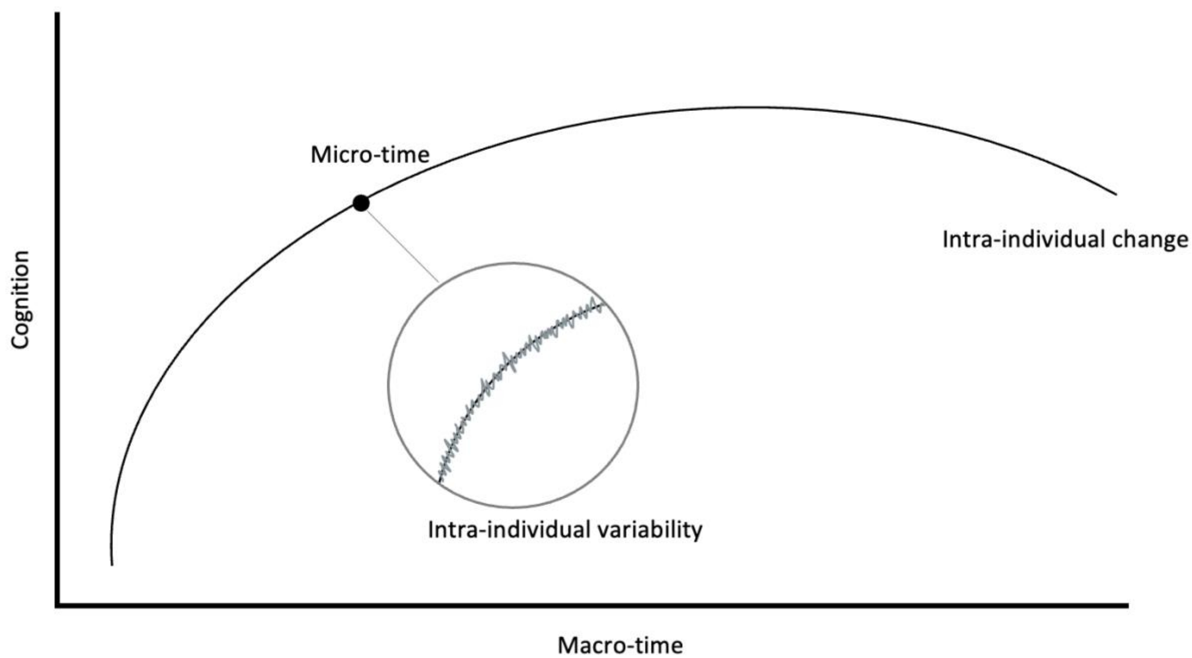
Social relationships are multifaceted and highly variable both between- and within-individuals as they unfold across time and contexts (Smyth et al., 2017). Consider how social relationships can be both stable and dynamic. That is, social relationships are characterised by both short-term variability (e.g., daily ups and downs) and longer-term variability (e.g., more long-lasting shifts that develop over years). Smyth et al. (2017) used an example of a husband and wife who argue one day about one person being late to an event, but the next day is forgiven (reflecting short-term variations in interactions with social relationships). In the longer term, normal life events (e.g., becoming grandparents or death of a loved one) may lead to more enduring shifts in closeness between spouses. Therefore, it is important to measure both short- and long-term changes in social relationships as each can reveal different information about processes of social development, and their correlates, including cognition.

An additional complexity is the notion of outcomes of within-person fluctuations depending on between-person trajectories (Smyth et al., 2017). For example, couples may respond differently to daily minor conflict if they are in a relationship that has long-term quality dynamics characterised by a more positively or negatively valanced affective climate. Thus, in examining how social relationships may influence cognitive health across the lifespan, it may be of benefit to capture the more enduring qualities of social relationships as well as day-to-day fluctuations that occur in response to changing contextual circumstances across shorter timescales. Chapter 4 of this thesis contributes to the field by not only considering how short-term (i.e., daily) fluctuations in social activities covary with fluctuations in older adults' cognition at the within-person level, but also whether this relationship changes based on an individual's average levels of social activity (between-person). By integrating information about short-term fluctuations and between-person variability likely to be more reflective of enduring (long-term) characteristics of social relationships and cognition, data from shorter-term methods allow us to consider the effects that social relationships have on cognitive health, as well as how the accumulation of these effects impact cognitive health over time in ways that conventional observational and experimental research designs do not (Smyth et al., 2017).

Finally, in reference to within-person fluctuations, the lifespan development framework highlights the distinction between intraindividual *change* and intraindividual *variability*. Phenomena of intraindividual *change* are the typical focus of more traditional longitudinal research conducted over *macro-time* scales (e.g., months or years). Much of the research evidence regarding social resources and cognition is derived from research of this type (see the review in Section 1.3.2). In contrast, intraindividual *variability* refers to fluctuations (otherwise known as oscillations, “noise”, instability, or inconsistencies) that occur over *micro-time* scales (e.g., minutes, hours, days, weeks) (Ram & Diehl, 2015). Specifically, intraindividual variability has been defined as short-term, reversible, within-individual change (Li et al., 2004). Figure 1.2 displays an illustration of how intraindividual change and variability processes fit together (adapted from Ram & Diehl, 2015). Specifically, intraindividual change is depicted as the smooth line that manifests over longer-timescales (macro-time). On the other hand, intraindividual variability is depicted by the shorter, jagged lines within the magnified circle (micro-time). These jagged lines reflect the fluctuations that occur over shorter timescales. Ultimately, the intraindividual change and variability terminology effectively distinguishes two timescales of within-person behavioural change that are driven by processes that evolve on macro- and micro-timescales respectively.

Figure 1.2

Graphical Representation Explaining the Difference Between Intraindividual Variability, Intraindividual Change, Micro-Time, and Macro-Time



Note. Figure adapted from Ram and Diehl (2015).

1.4.2. Overview of the Available Short-Term Methods for Assessing Intra-Individual Variability in Social Resources and Cognition

Assessing development over micro-time scales offers insights that are not easily obtained through experimental, cross-sectional, or longitudinal research methods conducted over macro-time scales. One of the designs pertinent to this thesis (see Chapter 4) that captures micro-changes is the *daily diary* method. Daily diary studies typically involve end of day assessments collected over a period of several days or weeks. This type of study design is useful for examining the relationship between daily experiences and fluctuations in bio-psychosocial outcomes including cognition (Sliwinski, 2008). One example of a daily diary study used in the social engagement-cognition research field was conducted by Bielak et al. (2019), who assessed covariation of engagement in different activity types with cognitive functioning on that same day by asking individuals to answer questions about activity engagement and complete cognitive tests every night for 7 days. On days when social-private activities (i.e., socialising with close others) were higher, participants performed better on tests of memory and processing speed. Further, on days that social-unfamiliar activities (i.e., meeting someone new) were higher, participants performed better on tests of word recognition. By obtaining information about individual's actual daily activities over short-term intervals, daily diary methods are believed to be more ecologically valid (i.e., representative of, and applicable to daily life) than lab-based designs. Further, daily diary approaches alleviate memory distortions as participants are not required to recall information from previous days, weeks, or months, but rather report what they have experienced that day. Finally, arguably the most valuable feature of daily diary designs is that they allow for assessment of within-person processes. This feature entails a shift from assessing mean levels of social activity engagement and cognition in a group of individuals to instead measuring the day-to-day fluctuations within an individual, as well as identifying predictors, covariation, and consequences of these oscillations (Almeida, 2005).

A more intensive short-term longitudinal approach is experience sampling which involves frequent assessments throughout the day allowing for more fine-grained analysis. For example, Allard et al. (2014) was the first study to our knowledge investigating the social engagement-cognition relationship using an ecological momentary assessment (EMA) approach. This study used mobile assessments that occurred five times per day over a one-week period. At each assessment, participants were presented with questions about daily life experiences including whether any social activities (telephone or in person) were performed since their last assessment. Brief tests of semantic memory were also randomly administered during two of the five daily assessments. However, no significant relationship between daily social activity and semantic memory performance were found. Further, Zhaoyang et al. (2021) used experience sampling methods to examine how daily social interactions related to older adult's cognitive functioning in daily life by asking participants to complete surveys about social interactions and mobile cognitive tests five times a day for 14 consecutive days. Greater frequency of daily social interaction positively covaried with cognitive functioning performance on the same day and over the next two days. The authors also found that positive interactions were a stronger predictor than total or negative interactions.

A benefit to using micro-time scales is the higher degree of real-world or "ecological" validity that they offer. Standard lab or single occasion testing environments are relatively more artificial in nature and may in part capture unmeasured sources of within-person variability. This can make it more difficult to generalise findings from such studies to real-world environments. Researchers have addressed such concerns using EMA methods. EMA approaches allow for ecological data collection as it occurs in real-world environments as participants go about their daily activities. Individuals are assessed in their current "momentary" state. Finally, EMA involves multiple assessments which can track changes over time and across different situations. Recent advances in mobile technology have allowed researchers to include objective assessments of cognitive functioning into studies that use EMA methods (Moore et al., 2017; Schweitzer et al., 2017; M. J. Sliwinski, 2008). Evidence of embedding cognitive tests into EMA methods have indicated great between-person reliability for average scores, and evidence of reliable within-person variability across measurement occasions when compared to assessments made in controlled laboratory environments (Sliwinski et al., 2018). Thus, these short-term longitudinal study designs have been used to answer questions about the social engagement-cognition relationship and to consider shorter term fluctuations that may explain longer term cognitive changes. Using daily diary or momentary sampling techniques represents a promising avenue for researchers studying associations of environmental, social, psychological, physiological, and behavioural factors with cognition in people's everyday environments.

Finally, *measurement-burst designs* (originally described by Nesselroade, 1991) offer the ability to measure both intraindividual change and variability. Measurement burst designs involve longitudinal, repeated measurements that are planned around closely spaced measurement rather than widely spaced or single occasion measurements (Sliwinski, 2008). For example, micro-time can be measured by obtaining data from individuals at closely spaced repeated measurement points (e.g., seconds, minutes, hours, days, weeks) to reflect a "burst" of measurement. Then, the same individuals are also assessed at multiple time points with wider intervals (e.g., months, years) to reflect macro-time changes. Thus, measurement-burst designs can combine both short-term and long-term longitudinal designs to better answer research questions pertinent to the timescale of interest.

1.5. Short-Term Methods and Mechanisms Linking Social Resources and Cognition

1.5.1. Short-Term Mechanisms Explaining a Social Engagement-Cognition Relationship

The small number of studies investigating acute links between social exchanges and cognition have suggested several possible mechanisms accounting for the relationship. These mechanisms differ from long-term mechanisms which predominantly invoke biological processes such as the role of social support in buffering negative effects of stress hormones on the brain, or the role of social engagement in supporting compensatory neural reserve. Instead, short-term mechanisms tend to focus on immediate changes in affect or motivation (e.g., Fredrickson, 2004), acute stress levels (e.g., Sapolsky, 2015), or resource priming (e.g., Ybarra et al., 2008). Each of these proposed mechanisms are discussed in turn.

Emerging research has begun to consider *affect* as a variable that could contribute to short-term links between social engagement and cognition. Frederickson's broaden and build theory suggests that positive emotions broaden an individual's scope for attention which in turn promotes improvement in cognition (Fredrickson, 1998, 2001, 2004). There have been numerous studies demonstrating that positive affect is related to better cognitive performance in the short-term (Bryan et al., 1996; Bryan & Bryan, 1991; Isen, 1987, 1999; Isen & Means, 1983; Masters et al., 1979). From an evolutionary perspective, one of the primary purposes of positive affect within cooperative groups is thought to be fostering group cohesiveness. This serves to create bonds between group members and positive feelings toward tasks that groups complete together which makes it more likely for the task to be completed optimally (Spoor & Kelly, 2004). Taken together, the evidence points to positive social interactions and positive affect reinforcing each other in a bi-directional way over short time scales, with positive affect also stimulating short-term improvements in cognition through broadening attentional focus.

Stress has also been well documented to affect cognitive performance. Researchers have determined that the relationship between stress response and its effects can be described by a U-shaped curve (McEwen, 2007; Sapolsky, 2015; Seery et al., 2010). Imagine the acute stressor of a university student taking an exam. If the student had too low or too high stress when completing their exam, we are likely to see lower performance. Alternatively, moderate stress levels are ideal for best performance. From a physiological standpoint, experiencing an acute stressor causes a release of catecholamines, glucocorticoids, and cortisol, which in turn increases heart rate and diverts blood from the internal organs to the skeletal muscles to facilitate a fight, flight or freeze type response (Sapolsky, 2015). Stress responses may be adaptive in the short-term where these physiological responses can ultimately improve executive function and working memory (McEwen, 2007; McEwen et al., 2016). However, such effects may also be determined by the level of stressor severity and associated physiological arousal. For example, it has been proposed that short-term negative social interactions involving an unfamiliar other or someone of higher status (as opposed to low arousal interactions with familiar others) may increase stress, and in turn negatively impact cognitive functioning (Kelly et al., 2017).

Resource priming theory was proposed by Ybarra et al. (2008) to explain short term gains in cognitive performance among people participating in a social interaction. The premise of resource priming is that engaging in social activity pre-activates general mental operations needed for cognitive tasks. It is most plausible that such a mechanism underlies near transfer benefits across tasks that engage the same general cognitive skills (Diamond & Ling, 2016). The extent of resource pre-use has also been suggested to contribute to the benefits on cognition. Specifically, it has been shown that optimal levels of social interactions can be cognitively energising, whereas more intense or demanding interactions can be draining. An analogy of this is athletes who warm up their muscles before a competition do so without over-doing it and tiring themselves out for optimal performance in the competition. On the other hand, if they were to engage in higher levels of warmup with no rest, they might be impaired in their later performance. Similarly, performance on cognitive tasks should benefit from earlier social interactions with low and moderate difficulty and self-timing that allows for rest. However, performance on cognitive tasks may be temporarily impaired by earlier social interactions with high levels of difficulty, in line with what is typically found in depletion experiments (e.g., Muraven & Baumeister, 2000). Finally, it has been argued that the process of successful resource priming, if practiced regularly, can lead to long-term gains in cognition (Ybarra et al., 2008).

The analogy of a leaking balloon can be used to illustrate how long- and short-term processes might fit together to better explain the complexities underlying the social engagement-cognition relationship across the lifespan. Consider a completely blown-up balloon that has a small hole where air slowly escapes. The balloon represents overall cognitive function, and the small hole allowing air to slowly escape over time represents normal ageing-related declines in cognition that occur over decades. If the balloon is left with no additional air being pumped into it over a long period of time it will continue to slowly deflate. Alternatively, if the balloon is consistently blown into on a shorter-term basis (e.g., day-to-day or week-to-week) the size of the balloon will not shrink so dramatically. In this analogy, blowing into the balloon refers to intellectual stimulation achieved through social connections, where it has been proposed that social exchanges can produce short term boosts to cognitive performance (e.g., Ybarra et al., 2008) that also serve to sustain longer term functioning, just as short bursts of air may keep the leaky balloon continually inflated. In this thesis, I draw on data from both short- and long-timescales (specifically; long-term longitudinal and cross-sectional (Chapter 3), micro-longitudinal (Chapter 4), and experimental (Chapter 5) study methodologies) as a means of addressing current gaps in knowledge related to social resources and cognitive functioning.

1.5.2. Empirical Evidence for a Short-Term Social Engagement-Cognition Relationship

RCTs Focussed on Promoting Cognitive Health in Older Adults

In recent years, a small number of randomised controlled trials (RCTs) have examined whether boosts in cognition result from participants engaging in social interactions. A comprehensive systematic review by Kelly et al. (2017) identified three studies investigating the impact of social activities on cognitive functioning in healthy older adults over the age of 50. One study considered whether a social intervention could improve cognition among lonely older adults compared to a control group (Pitkala et al., 2011). The social intervention consisted of meeting once a week for 6 hours over a 3-month period. Participants engaged in one of three streams of activities depending on their interests (art and inspiring activity, group exercise, or therapeutic writing). Participants were randomly allocated to the social intervention condition (engaging in activity in groups and involved discussion) or an active control condition for each activity. It was found that participants in the social interaction interventions improved in cognitive performance (measured by the ADAS-Cog, a global composite measure of cognitive ability) more than participants in the active control group. Thus, the authors concluded that social intervention improved lonely older adults' cognition. The second RCT was conducted by Mortimer et al. (2012) who developed a forty-week intervention where participants were allocated to either Tai Chi, walking, social interaction, or no intervention groups, and undertook

MRI scans and neuropsychological tests pre- and post-intervention. The authors found significant increases in brain volume in the social activity compared to no intervention groups. Social interaction also led to improvement on verbal fluency (and trended in the same direction for time to complete Trails A and recall of Auditory Verbal Learning test), but no improvements were shown for a range of other tests (measuring memory, attention, speed, and executive functioning). Finally, Park et al. (2014) examined whether sustained engagement in learning new skills activated cognitive functioning, and used a social interaction condition as their active control group. No cognitive benefits resulting from social engagement (on measures of processing speed, mental control, episodic memory, or visuospatial processing) were observed. However, the authors acknowledged that more work was needed in this area to draw definitive conclusions, especially as only five participants were allocated to the social control condition.

Aside from these studies mentioned in the Kelly et al. (2017) review, a small number of additional experimental interventions have been conducted with older adults to further investigate whether social activity results in improvements in cognitive functioning. Dodge et al. (2015) examined whether online (computers, webcams, and interactive internet interface) conversation-based cognitive stimulation positively impacted cognition in healthy older adults. Specifically, participants randomly allocated to an intervention condition communicated daily for 30-minutes over 6-weeks, whereas participants randomly allocated to the control condition completed one weekly telephone interview. Results indicated that among participants who had normal cognition (as indicated by a clinical dementia rating of 0 in a screening test), the social interaction group improved more than the control group on tests of semantic fluency and phonemic fluency, but did not show improvement in immediate memory, delayed memory, psychomotor speed, executive function, selective attention/inhibition, or premorbid and general intelligence. For participants who had mild cognitive impairment, a non-significant trend for improvements in speed was observed among those in the social group, but not those in the control group. The authors concluded that increasing daily social contacts using technology could offer a cost-effective home-based cognitive intervention.

Another study by Bae et al. (2019) examined the effects of a multi-component intervention involving physical, cognitive, and social activities on cognitive performance in older adults with mild cognitive impairment. The 24-week program was effective in improving spatial working memory from baseline to post-intervention, but not other cognitive outcomes (e.g., MMSE score, memory, trail-making performance, or symbol-digit substitution scores). The change in spatial working memory was attributed to physical activity changes and not social activity. Otake-Matsuura et al. (2021) examined whether a group conversation intervention program (photo-integrated conversation moderated by a robot – PICMOR) improved cognitive functioning in older adults. Participants in the intervention condition prepared a photo for discussion around a certain topic and took turns discussing the photos within a group setting (participants received weekly 30-min intervention sessions followed by 30-min explanation about the intervention, once a week for 12 weeks). Participants in the active control condition took part in 30-minutes of unstructured group conversation and 30-min of health education about successful ageing, once a week for 12 weeks. Where both conditions included a social component, the researchers aimed to address whether the amount of speech or the number of words in each conversation intervention (i.e., conversation intensity) was a fundamental variable contributing to cognitive performance. The PICMOR protocol was designed to guarantee intensity of conversation in the intervention condition. Results of the trial indicated that participants in the intervention condition improved in verbal fluency from pre- to post-test, and the amount of speech and richness of words was greater for the intervention group. The authors concluded that the manner of participation in conversations (e.g., the amount of speech) may be key to gaining cognitive benefits. Finally, Galinha et al. (2021) found that a 34-week group singing intervention had positive effects on cognition (specifically, verbal memory performance) when compared with a wait-list control group. Further analyses revealed that social wellbeing scores reduced from baseline to post-test in the waitlist control group, however, did not differ in the group singing intervention. The authors suggested that these findings indicated the potential protective effect of the group singing intervention on social wellbeing. Thus, the authors concluded that socialisation was a critical aspect in maximising older adult's cognition resulting from group singing.

In sum, the findings of RCTs raise the possibility that social activity interventions could improve global cognition and increase brain volume among older adults. However, the benefits may not transfer across multiple cognitive domains including memory, attention, fluency, processing speed or executive functioning (Kelly et al., 2017). The dosage of social interaction may also be an important contributing factor (Otake-Matsuura et al., 2021). Of note, a recent systematic review (Sprague et al., 2019) examined 11 types of behavioural interventions targeting cognitive functioning in healthy older adults. These interventions were designed with a different focus (e.g., physical exercise), however many included a social component. Therefore, the role of social activity cannot be ruled out. For this reason, the authors separated studies that had an active + social control group to control for social engagement in the intervention condition. The results found that participants in the social control groups often improved on cognitive outcomes to a similar degree to those in intervention conditions that involved a social component. Thus, this research also provides indirect evidence supporting possible benefits of social engagement for cognition in older adults.

Experimental Studies Examining Acute Changes in Cognitive Performance Following Social Interaction

A series of studies using younger university student samples have examined whether a single episode of social interaction results in short-term boosts in cognitive performance. Ybarra et al.'s (2008) experimental study of university students randomly allocated participants into one of three groups: (1) social interaction condition where participants discussed a topic with an assigned partner for 6 minutes after having 4 minutes to prepare their position (allocated to them randomly by a flip of a coin), (2) intellectual activity condition where participants completed a reading comprehension task, a crossword puzzle, and a mental rotation task alone for 10 minutes, or (3) a control condition where participants watched television alone for 10 minutes. The authors found better post-intervention reading span (d = 0.75) and processing speed (d = 0.67) performance for participants who engaged in a social interaction compared to those in a control condition who watched television alone. The authors also found that engaging socially was equally as effective in 'boosting' cognition immediately following the experimental manipulation as undergoing intellectual activities, as there was no statistical difference between the two post-intervention findings (d = 0.01) (Ybarra et al., 2008).

Ybarra et al. (2011) conducted an additional series of experiments which showed that participants who engaged in cooperative social interaction had better post-intervention executive functioning performance than both those in a control condition (d = 0.73) and those engaging in a competitive social interaction (d = 0.91). However, no group differences in post-intervention speed performance were found. A second experiment in this series found that when competitive social interactions were structured to allow for perspective-taking processes, the competitive social interaction group outperformed the control group (d = .91) and a brain games (intellectual activities) group (d = 0.60) on a post-intervention reading span task. Again, no significant differences were found between any condition for processing speed performance.

The final study in this series (Ybarra et al., 2011) investigated perspective-taking as a mechanism that could account for the acute link between social exchanges and executive functioning performance demonstrated in the previous studies. Results showed that participants in a perspective-taking condition where participants were required to try their best to understand their opponent in a game, outperformed those in a perspective-taking prevention condition where participants were required to try their best to not let their opponent understand them or take their perspective in a game, on a post-intervention executive functioning task. No differences between conditions were found for processing speed. These findings contribute to the evidence that perspective-taking processes may be the aspect of social exchanges that is central to stimulating better short-term executive functioning. It is important to note that as there were no pre-intervention measures of cognition taken in the Ybarra (2008, 2011) studies, it is unclear whether the superior performance among those engaged in a social task reflected an improvement in performance, and therefore these findings are interpreted with caution (see *Chapter 5* for a description of my replication and extension of Ybarra et al.'s work). Finally, although these studies did not use an older adult population, their findings lay the groundwork for assuming short-term improvements in performance in at least some cognitive abilities arising directly from social interactions.

In sum, most of the existing experimental studies and RCTs point to some benefits for cognition arising from social interactions, whether those interactions take place over the course of a multi-week intervention (e.g., Dodge et al., 2015; Galinha et al., 2021; Otake-Matsuura et al., 2021) or a single test experiment (Ybarra et al., 2011). While there are many benefits of randomised controlled trials and laboratory experiments, such as the ability to draw causal inferences with greater confidence and greater internal validity, these designs are limited in their ability to examine relationships of social resources and cognitive outcomes across multiple time scales in ecologically valid settings (Smyth et al., 2017). As discussed above in Section 1.4.2, acquiring ecologically sensitive data represents a promising means of complementing experimental and long-term longitudinal approaches in the study of possible factors contributing to preservation or decline in the cognitive system.

1.6. Bayesian Analytic Approach

Apart from addressing specific questions related to mechanisms linking social resources with cognition across different methodological contexts and longitudinal time scales, a final contribution of the current thesis was employing a Bayesian analytic approach as an alternative to conventional null-hypothesis statistical testing. Here, Bayesian parameters are used in place of *p*-values to make decisions about whether the data supports the alternative or the null hypothesis. This is contrary to frequentist approaches that can only provide evidence to reject or fail to reject the null hypothesis. To date, Bayesian methods have seldom been used in gerontological research. However, there is growing momentum around the application of such methods in the study of developmental phenomena. For example, a Bayesian reanalysis of several gerontological studies that originally reported nonsignificant results based on frequentist estimates revealed that only a small percentage of the findings showed strong evidence in favour of the null hypothesis (Brydges & Bielak, 2020) suggesting evidence for a lack of certainty in the data rather than evidence for the absence of effects or associations. The different parameters used in a Bayesian approach (e.g., highest density intervals, region of practical equivalence) and how to interpret these parameters to make meaningful conclusions about the data are discussed in Chapter 2.

1.7. Research Aims and Hypotheses

As there is now a substantial body of research evidence broadly supporting links between social resources and cognitive functioning in younger (e.g., Ybarra et al., 2008) and older (e.g., Kuiper et al., 2016) samples, the overarching aim of this thesis was to address several targeted research questions that have not yet been comprehensively examined in the existing literature. Considered together, these questions (detailed below) stand to contribute to a more nuanced understanding of how social resources might promote cognitive health within the context of additional biological, psychological, and contextual influences. To this end, the empirical studies reported here assess aspects of social network structure, function, and quality, and include data capturing cross-sectional relationships, and longitudinal relationships of social resources with cognition assessed over macro- (Chapter 3) and micro- (Chapter 4) time scales. Results of experimental work used to examine processes underlying short-term effects of social exchanges on cognitive performance are also reported (Chapter 5). The specific aims and hypotheses of the three studies included in the thesis are described below.

1.7.1. Study 1

The primary aim of the first study was to examine whether different types of social resources (social activity engagement and loneliness) moderated the adverse effects of social disadvantage on cognitive functioning in older adulthood. The key question concerned whether social resources play a compensatory role in cognitive reserve, evidenced by ameliorating cognitive decline among those with limited opportunity to develop cognitive reserve (proxied by low education). It was predicted that an interaction of social activity engagement and education would emerge in the prediction of levels and rates of change in cognitive test performance. Further, as a lack of social support may reduce resources that can be deployed in coping with stress (Kuiper et al., 2016), it was also expected that an interaction of loneliness (an indicator of socio-emotional stress) and education would emerge in predicting cognitive performance. Finally, interactions of social activity engagement, loneliness, and education (predicting the intercept and rates of change over time) were examined to determine whether people who might be best positioned to develop cognitive reserve are those who are both engaged in social activity and report lower levels of loneliness. To answer these research questions, data from the Australian Longitudinal Study of Ageing (ALSA; Luszcz et al., 2016) were used. Participants completed measures capturing individual differences in social activity engagement, loneliness, and cognitive data (assessing fluency and processing speed performance) at five time points over a 13-year period.

A second aim of the study was to assess the replicability of education x social resource interactions cross-sectionally utilising data from the Engagement, Lifestyle, and Meaning Study (ELMS). Interactions between different social resources (structure, function, and quality) and education were examined as predictors of fluency performance. A final aim was to examine whether social resources were associated with verbal fluency performance independently of broader engagement with life. Such a finding would suggest there may be something more unique to social interactions as a protective factor to cognitive functioning beyond a general sense of being engaged in purposeful activities. Previous research argues that having a larger network likely allows for more opportunity for engagement with that network (Kuiper et al., 2016). Therefore, it was expected that a meaningful relationship between network structure and fluency performance would no longer be evident after statistically controlling for engagement with life, given the likelihood that use it or lose it processes underlie both structural social resource and general engagement benefits for cognition. Alternatively, functional and quality aspects of relationships have been described to benefit cognition due to being protective of deleterious effects of stress on the brain. Given this mechanism is more conceptually distinct from 'Use it or Lose it' processes used to explain general activity benefits on cognition, it was suspected that function and quality social resources would remain positively associated with category fluency once engagement with life was included as a covariate in the model (see Chapter 3).

1.7.2. Study 2

The primary aim of the second study was to determine whether older adults' cognitive performance on a given day was related to the specific activities engaged in on that day, including social activities. To answer this research question, daily diary data from the Transitions in Later Life Study (TRAILLS) were used. Whether participation in a variety of activity domains (social-private, social-unfamiliar, information, cognitive, physical, games, and television; based on the factors described by Bielak, 2017) covaried with better daily cognitive outcomes measured by correct response time on a symbol search task was examined. An initial aim was to examine possible differences in associations of activity engagement with processing speed according to activity domain at the between-person level. Of additional key interest was whether engaging in different types of daily activities covaried with daily speed performance at the within-person level.

An additional aim of the study was to examine whether the affective valence of a social exchange on a given day (i.e., enjoyment levels of a positive social exchange and severity levels of a negative social exchange) were associated with day-to-day cognitive performance. Associations of this type would implicate affect as a factor involved in short-term mechanisms linking social engagement with cognition (Fredrickson, 2001, 2004).

The final aim of the study was to consider cross-level interactions (i.e., WP X BP) to examine whether average levels of enjoyment of positive/severity of negative social exchanges moderated the relationship between daily enjoyment/severity scores and cognition (i.e., whether the *novelty* of the positive/negative social exchange impacted the strength of the association). Specifically, it was expected that a weaker relationship between daily enjoyment of positive exchanges and better cognitive performance would exist for those who generally experienced more positive social exchanges than for those who typically experienced fewer positive social exchanges (as characterised by between-person positive exchanges). Similarly, it was expected that a weaker relationship between daily severity of negative exchanges and worse cognitive performance would be evident for those who reported experiencing more frequent negative social exchanges compared with those reporting less frequent negative exchanges (see Chapter 4).

1.7.3. Study 3

The primary aim of the third (and final) study was to further examine the role of perspective-taking as a short-term mechanism potentially underlying acute boosts in cognitive performance resulting from social interaction (Ybarra et al., 2008). The first aim (Experiment 1) was to determine whether cognitive benefits of perspective-taking were still observed when perspective-taking was performed alone as opposed to within a social interaction. In this study, comparisons of executive functioning performance of young adult participant pairs before and after (a) engaging in perspective-taking within a social interaction, (b) engaging in perspective-taking alone, and (c) not engaging in perspective-taking or a social interaction (control condition) were made.

Finally, to ensure that an intellectually stimulating control condition in Experiment 1 (which could also inadvertently benefit cognition) did not unintentionally confound the results, performance of participants assigned to an active control condition (equivalent to the control condition described above) was compared with performance of participants assigned to a passive control condition in Experiment 2 (see Chapter 5).

CHAPTER 2: Statistical Analyses

2.1. Overview

The statistical analyses undertaken in this thesis were performed using a Bayesian parameter estimation approach. Bayesian analyses were employed as they offer several advantages over traditional null-hypothesis significance tests (NHST), often applied in what have been referred to as frequentist or classical approaches. This chapter discusses aspects of the Bayesian approach specific to this thesis. I first focus on *prior and posterior distributions* and how they apply to the data presented in this series of studies. Next, I explain how applying a Bayesian analytical approach is more informative than a frequentist approach by describing how Bayesian estimates better answer data-based questions. I then describe two main features of Bayesian inference, the *highest density interval* (HDI) and the *region of practical equivalence* (ROPE) and explain how these can be used to identify null and meaningful effects. Finally, I discuss the specific application of Bayesian analyses in the studies reported hereafter, providing a guide for interpretation.

2.2. Prior and Posterior Parameters

A defining characteristic of the Bayesian analytic approach is that distributions, both *prior* and *posterior,* play a key role in the analytic process (Kruschke, 2015). Specifically in Bayesian inference, the probability for a given hypothesis is updated as additional information becomes available (*prior distribution*), whilst combining this with the knowledge derived from the new observed data to give the result; that is, the *posterior distribution*. The nature of prior distributions obtained from previous research can be specified to range from narrow values reflecting a well-understood phenomenon (precise parameter estimates derived from extensive previous data) to complete naivety (entailing no information beyond the practical limits of values when appropriate data to inform priors is not available). Although the studies in this thesis are not all necessarily novel, there is no previous work to my knowledge that used the same methodology. Therefore, for the models presented, non-committal weakly informative priors were used. This allowed the analyses to reflect the data without the influence of pre-existing knowledge. Thus, the approach used in specific relation to prior distributions was analogous to what could be expected of a frequentist approach where parameter estimates are informed solely by the available data.

2.3. Bayesian Versus Frequentist Inference

There are several advantages of Bayesian inference in comparison to frequentist approaches. First, NHST involves making decisions about the relationships in data based on *p*-values to either a) reject the null hypothesis, or b) fail to reject the null hypothesis. Importantly, a non-significant *p*-value cannot support *acceptance* of the null hypothesis. Rather, it indicates only that there is not strong support for the alternative hypothesis. The acceptance of the null or alternative hypothesis, however, are frequently of central interest to researchers. Bayesian inference allows conclusions to be drawn about the null and alternative hypotheses, while additionally providing estimates of how likely the conclusions are to be true given the data (Wagenmakers et al., 2018). Put another way, Bayesian analyses answer the critical question: Given the data, what are the most credible statistical parameters and how confident can we be in these values?

Second, the movement towards *New Statistics* (Cumming, 2013) advocates for emphasis on reporting effect sizes as a more informative way to describe relationships among variables, paired with appropriate indices of uncertainty. Given the limitations specified with *p*-values (e.g., *p*-values are highly dependent on sample size), there has been a push for frequentist researchers to move towards using point-estimates of effect sizes with confidence intervals (CIs) around these point estimates to replace significance testing (Cumming, 2013). This approach coincides with Bayesian ideals of focussing on the uncertainty of estimation as opposed to relying on binary yes/no decisions about whether an effect is deemed significant, as is the case with NHST (Kruschke, 2015). Utilising effect sizes and CIs also shifts the focus from reporting a single-point estimate (e.g., mean, standard deviation, and effect size) to instead reporting a range of plausible values.

While approaches to analysis that focus on effect size and indices of uncertainty may represent an improvement to NHST (Cumming, 2013), they are not without shortcomings. A common misconception of CIs is that the values within the interval represent more credible values than the values beyond the interval limits. However, CIs do not allow for such conclusions. Instead, CIs share some of the same limitations that apply to *p*-values (McShane et al., 2019). Specifically, given the primary goal of NHST is to determine whether a particular null value of a parameter can be rejected, CIs merely indicate the range of parameter values that can or cannot be rejected. However, they do not allow for the acceptance of the null or the alternate hypothesis (Kruschke, 2010; Wagenmakers et al., 2018). Bayesian inference on the other hand relies on credibility intervals; a special case of these referred to as *highest density intervals* (HDI) are used throughout this thesis. HDIs provide a guide for which values are plausible. They allow us to draw probabilistic conclusions about how likely it is that the true parameter falls within the credibility interval. For example, where appropriate instead of reporting single-estimates, I report distributions that describe the most plausible values for a given parameter and the relative credibility of each of these (see Chapters 3 to 5).

2.4. Parameters of Bayesian Inference

2.4.1. Highest Density Intervals (HDI)

Throughout the thesis, I used Bayesian *95%* HDIs ($HDI_{95\%}$) to represent the range of values that are most credible and cover 95% of the distribution of possible parameters (represented by the *width* of the interval*)*. This means that we can exclude any value that does not fall within the HDI as a credible value with 95% certainty. For example, when comparing two groups, if the value 0 does not fall within the $HDI_{95\%}$ for the distribution of difference scores, then we can be 95% certain that a true difference between groups exists. Therefore, we can describe values inside the $HDI_{95\%}$ interval as being "the 95% most credible values of the parameter" (Kruschke & Liddell, 2018, p. 271).

2.4.2. Region of Practical Equivalence (ROPE)

An important feature of Bayesian inference that differs to frequentist methods is the use of the region of practical equivalence (ROPE) as the criterion for determining whether evidence favours the null or alternate hypothesis (Kruschke, 2018). Specifically, the ROPE is a specified range of values that are regarded as practically equivalent to the null hypothesis (e.g., a difference of zero in the case of a two-group comparison). Thus, all values within the ROPE's defined interval are regarded as negligibly different from the null and are considered not to be meaningful.

The use of a ROPE is imperative for decision making as it is not useful to compare to exactly zero as the criterion for determining that there is no true effect. This is because as sample size increases and therefore as certainty in estimation precision increases, it becomes easier to confirm a theory (conclude the effect is meaningful) than to disconfirm the theory; unless the estimate is *exactly* zero (which rarely occurs). This is problematic given that when there is no true effect, increasing certainty in estimates by gathering more precise data should make us more confident in *accepting* the null hypothesis, not more certain in a decision to reject the null hypothesis. This phenomenon has been termed Meehl's Paradox (Meehl, 1967, 1997).

This issue can be overcome by complimenting the HDI with the ROPE to make decisions. Specifically, as the HDI becomes narrower with greater certainty in the estimates, when there is no true effect, the interval will eventually fall entirely inside the ROPE. This would indicate a difference on the dependent variable that is sufficiently small that we would consider groups to be practically equivalent on the outcome variable of interest (even when that estimate is not exactly zero). On the other hand, if the HDI does not overlap with the ROPE interval and the values are in the predicted direction, this would provide direct evidence in support of the alternate hypothesis (Kruschke, 2018). Thus, as we gather more data and the estimates become more precise, the answer converges on the correct one, highlighting the importance of using the ROPE in the decision-making process.

2.5. Using Bayesian Parameters to Define Null and Meaningful Effects

The interpretation and reporting of results included in this thesis are most easily described according to two levels. Visual representations of the key decision rules are illustrated in Figure 2.1. At the first level, there are three possible explanations that can be drawn from the relationship between the $HDI_{95\%}$ interval (i.e., the distribution of credible values around a parameter estimate) and the ROPE (i.e., the region within which parameter values are not considered meaningfully different from the null):

1. If the $HDI_{95\%}$ interval lies completely outside of the ROPE, then we can conclude, with 95% certainty, that there is a meaningful effect (i.e., reject the null hypothesis and, in contrast with NHST, accept the alternative hypothesis if consistent with the direction of

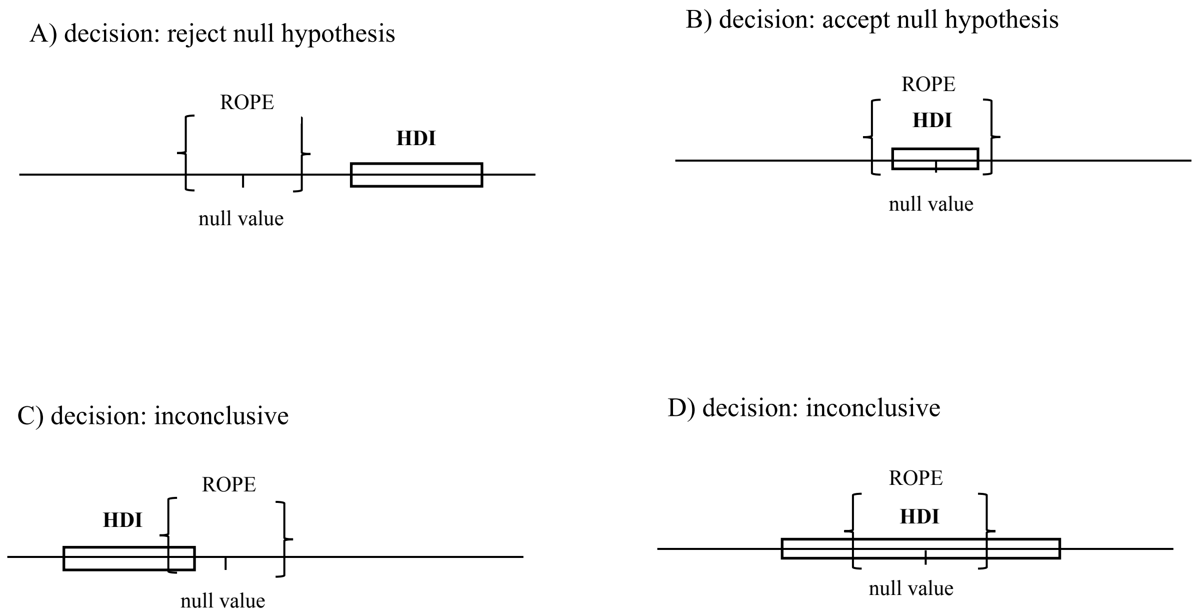
the hypothesis). Whether the values of the $HDI_{95\%}$ are above or below the ROPE interval indicates whether the effect is in the positive or negative direction respectively (see Figure 2.1, Pane A for a graphical representation of a meaningful, positive effect).

2. If the $HDI_{95\%}$ interval completely lies within the ROPE (as illustrated in Figure 2.1, Pane B), then we can conclude, with 95% confidence, that there is no meaningful difference (i.e., accept the null hypothesis).
3. If the $HDI_{95\%}$ interval falls partly outside the ROPE (Figure 2.1, Pane C), or if the ROPE completely lies within the $HDI_{95\%}$ interval (Figure 2.1, Pane D), then we have inconclusive evidence to accept or reject the null hypothesis with 95% certainty. If a finding was inconclusive, we used the second level of interpretation.

At the second level of interpretation, we determine the proportion of the HDI interval that lies below, within, and above the ROPE to aid interpretation for any inconclusive results. This value reflects the probability of a meaningful/null effect; thus, the first step is to interpret the relevant estimates quantitatively as a probability. To further aid interpretation of these estimates we adopted a rule of thumb to distinguish results that provide weak evidence supporting a conclusion from those that are inconclusive. Specifically, if at least 80% of the $HDI_{95\%}$ interval lies outside (below or above) the ROPE (denoted throughout the thesis as $P_{(meaningful)}$), we consider this weak evidence of a meaningful effect (e.g., Figure 2.1, Pane C reflects a weak, meaningful effect in the negative direction). Similarly, if 80% or more of the $HDI_{95\%}$ interval lies within the ROPE (denoted throughout the thesis as $P_{(within\ ROPE)}$), we consider this weak evidence to accept the null. If the evidence was too disbursed (e.g., Figure 2.1, Pane D), we would not be able to make meaningful conclusions, and this suggests more evidence (or more precise measurement) is needed to determine whether a true effect exists.

Figure 2.1

Example Plots of Decision Rules Based on ROPE and HDI Combinations



2.6. Application of Bayesian Inference in the Thesis

Throughout the thesis, results are based on Bayesian methods of analysis and interpretation. Specifically, I reported probability distributions as well as the point estimates and intervals used to summarise the distributions. In Chapters 3 and 4, I used standardised data (*z*-scores) for all predictor and outcome variables (save for binary variables which were coded as -1, 1). Therefore, for these chapters I refer to *B* as the single estimate value and report its associated $HDI_{95\%}$ interval (i.e., the distribution of the most credible values around a parameter estimate). I also used the suggested ROPE of ±0.05 to represent a range of values 0.05 standard deviations either side of zero that would be considered negligible (or equivalent to zero) in line with recommendations of setting ROPEs for correlational analyses with standardized data (Kruschke, 2018; Makowski et al., 2019). In Chapter 5, I compared differences between means of groups, where I relied on the Cohen's *d* estimate with $HDI_{95\%}$ intervals to determine whether meaningful differences existed in the data. The ROPE for this chapter was set in line with Kruschke's (2018) recommendation to use half the typical cut-off for a small effect. Therefore, for these analyses I used a ROPE of ±0.1 (based on effect size conventions, Cohen's d small effect = 0.2; Cohen, 2013).

In this thesis, the ROPEs and $HDI_{95\%}$ intervals were used to make decisions about whether there was (or was not) evidence for meaningful effects based on the posterior data. When the first two examples of decision rules listed above arose (Figure 2.1 Panes A and B), we had strong evidence to either support a meaningful effect (reject the null hypothesis) or support that no effect existed (accept the null hypothesis) respectively. However, when there was not strong enough evidence to support either of these conclusions (as explained using the third decision rule), we reported the balance of evidence to determine whether the findings were in favour of the null (greatest proportion of the posterior fell within the ROPE), the alternate hypothesis (greatest proportion of the posterior fell outside of the ROPE noting the direction), or equivocal evidence. This second step of interpretation provides useful information to be able to distinguish between whether there was equivocal evidence for and against the null (inconclusive findings), or whether there was some evidence favouring one conclusion over the other, however with insufficient evidence to strongly support this conclusion.

Finally, software was used to generate statistical analyses and related content. Specifically, R software (R Core Team, 2016) was used for all statistical analysis. Models were fit using STAN (Carpenter et al., 2017) via the brms R package (Bürkner, 2017; Bürkner, 2018) save for Chapter 5 where JAGS (Plummer, 2016) was used via the runjags package (Denwood, 2016). All figures created throughout the thesis were produced using the ggplot (Wickham, 2009) and cowplot (Wilkie, 2017) packages.

CHAPTER 3: Do Social Resources Moderate Social Disadvantage Effects on Cognition in Older Adults? Evidence From Longitudinal and Cross-Sectional Data

3.1. Introduction

Accumulating research evidence indicates that older adults with greater social resources perform better on cognitive tasks (Kuiper et al., 2016). Yet less is known about how social resources interact with other factors believed to contribute to cognitive reserve, to predict levels or rates of change in cognitive functioning over time (Windsor et al., 2020). Past research has introduced the notion that cognitive reserve may moderate the relationship between social engagement and cognition (Hertzog et al., 2008). Cognitive reserve is a theory used to explain the repeated finding that brain pathology does not always manifest in clinically observable signs or symptoms of disease (Stern, 2002). The cognitive reserve hypothesis proposes that higher levels of exposure to education, complexity of occupation, and participation in cognitively stimulating leisure activities can provide a buffer to the effects of pathology (Opdebeeck et al., 2016). It has also been suggested that social activity engagement contributes to cognitive reserve (Marioni et al., 2012). Therefore, the present study was concerned with examining whether social resources could provide a compensatory function, helping to preserve levels of cognitive performance (assessed via measures of letter and category fluency and processing speed) in the presence of low levels of education.

We extended the existing literature using two datasets to answer our research questions. First, we used 13-year longitudinal data from the Australian Longitudinal Study of Ageing (ALSA; Luszcz et al., 2007). We aimed to determine whether associations between education, a commonly used proxy measure of cognitive reserve (Opdebeeck et al., 2016), and initial letter fluency or speed performance were weaker for those who reported a) higher levels of social activity engagement, b) lower levels of loneliness, and c) a combination of both. Such findings would indicate that social activity and/or a lower level of loneliness, respectively, are important for maintaining better cognition in older adults with fewer educational opportunities. Second, we used cross-sectional data from the Engagement, Lifestyle and Meaning Study (ELMS). Specifically, this dataset allowed us to consider interactions of education with multiple different types of social resources in predicting category fluency. These included indices of network structure (network size and contact frequency), network function (support from friends, family and neighbours), and network quality (Fiori et al., 2007). Finally, utilising ELMS data also enabled us to examine whether associations of social resources and category fluency remained evident after statistically controlling for broader engagement with life (Life Engagement Test (LET); Scheier et al., 2006). Independent associations of social network resources with category fluency would suggest that social interactions could offer something unique as a protective factor for cognition above and beyond being more generally engaged with personally meaningful activities (and thus potentially exposed to cognitively enriching activities, see Hertzog et al., 2008).

3.1.1. Conceptualisation of Social Resources

There is considerable variability in the way social resources have been conceptualised and measured throughout the literature. These differences in conceptualisation and operationalisation may underlie some inconsistencies in the previous findings concerned with social resources and cognition (Kelly et al., 2017). Previously scholars have delineated qualitatively distinct aspects of social networks in terms of their structure, function, and quality (Fiori et al., 2007). Structure relates to objective measures of social networks (e.g., marital status, total network size, the frequency of contact with networks, and participation in social activities and organisations). Function and quality focus on more subjective or qualitative aspects of social networks. Whereas function relates to perceived levels of support and resources provided by network members, quality focuses on subjective relationship experiences (e.g., pleasant exchanges vs. tensions). Here, we draw on different conceptual mechanisms to explain how each of these characteristics of social relationships could have positive implications for cognitive functioning in older adulthood.

Social network size is the most commonly used measure of social resources (Hughes et al., 2008), and many studies have shown associations of social network size with cognitive performance (e.g., Kuiper et al., 2016). One plausible mechanism explaining the importance of social networks for cognitive health is the *Use it or Lose it* hypothesis (Hultsch et al., 1999). This theory suggests that the brain is analogous to a muscle, and that engagement in life activity (i.e., physical, social and/or intellectual activity) stimulates the brain, helping to preserve the cognitive system. In contrast, disuse of the 'muscle' as evidenced by a lack of activity may hasten cognitive decline. Regarding social network structure, it has been argued that a larger network size provides a more diverse range of support resources (Thoits, 2011), and greater potential for engagement with life (Berkman et al., 2000). Thus, greater structural network resources may facilitate greater opportunities for intellectual stimulation that in turn contribute to preserved cognition.

Evidence also points to aspects of network function and quality having possible implications for cognitive health (Kuiper et al., 2016). Some studies have demonstrated that quality measures of social resources (e.g., lower levels of perceived quality of social support and functional support) are stronger predictors of dementia risk than structural social resources (e.g., social network size; Amieva et al., 2010). One plausible mechanism explaining associations of social support (which broadly captures aspects of both network function and quality) with cognitive health is the *Stress-Buffering hypothesis* (Cohen & Wills, 1985). This theory suggests that functional aspects of relationships, such as subjective feelings of social support and integration, may play an important role in cognition by aiding reduction in frequency and intensity of stressful situations. In turn, social support can help to reduce stress-induced deleterious physiological responses in the brain (e.g., the production of detrimental stress hormones such as cortisol) which have been associated with cognitive decline and the development of Alzheimer's Disease (Fratiglioni et al., 2000; Kuiper et al., 2016). Therefore, greater quality and functional social resources may help to reduce detrimental amounts of stress over the lifespan which in turn contribute to better preserved cognition in later life.

In the present study we aimed to extend previous investigations by considering the combined effects of different social network attributes as predictors of cognition, as well as examining the interplay of social resources with education on cognition. In the subsequent sections, we review theoretical evidence that provides a basis for predicting why our measures of social network quantity (social activity engagement) and quality (loneliness) might interact with education to predict cognitive performance, before outlining our specific aims and hypotheses.

3.1.2. Social Activity Engagement, Education, and Cognitive Reserve

The cognitive enrichment hypothesis (Hertzog et al., 2008) provides a broad basis for predicting the potential of social resources in compensating for low levels of education in the development of cognitive reserve. The fundamental premise of this hypothesis is consistent with the *Use it or Lose It hypothesis,* positing that engagement in cognitively stimulating lifestyle activities offer opportunity for mental exercise with the capacity to maintain or improve cognitive abilities. Importantly, this perspective recognises the scope for possible improvements in functioning in older adulthood, within biological limits (Hertzog et al., 2008), as a result of mental, cognitive, physical, and social activity engagement. Based on this premise, we were specifically interested in whether social activity engagement interacts with education, a widely recognised contributor to cognitive reserve that has consistently been associated with better cognitive performance in older adults (Gerstorf et al., 2006). Of particular interest is whether social activity engagement may be an alternate way to develop and reap the benefits of cognitive reserve for those who have had less opportunity to build cognitive reserve through education. Early social disadvantage (as implied by low education) can ultimately contribute to poorer cognition if socio-economic status does not improve from childhood to adulthood (Lyu & Burr, 2016). Thus, identifying potential moderators of this effect might strengthen intervention efforts aimed at promoting cognitive health in the population.

Few studies have examined interactions among different factors thought to contribute to cognitive reserve. Previous work reporting on data from the English Longitudinal Study of Ageing (Shankar et al., 2013) demonstrated findings consistent with the compensatory role of social activity engagement proposed above, where older adults with lower education but higher levels of social resources showed less pronounced reductions in cognitive performance over time than those with lower education and fewer social resources. Windsor et al. (2020) was the first study we are aware of to directly examine whether social resources fulfill a compensatory role in promoting cognitive reserve. However, Windsor et al.'s analysis of Berlin Aging Study (BASE) data showed that although network size was positively associated with category fluency performance, education did not interact with network size to predict fluency. In the present study we make use of methodological advantages available through use of Australian Longitudinal

Study of Ageing (ALSA) data to undertake a more comprehensive test of Windsor's (2020) Compensatory Reserve hypothesis.

A key component that distinguishes our study to Windsor et al. (2020) is the use of a structural social resource measure that more directly assesses engagement in potentially enriching activity (Hertzog et al., 2008) as opposed to a general measure of network size. Although Windsor et al. (2020) did not find evidence for their compensatory reserve hypothesis using their measure of network size, other BASE findings have found promising results that showed changes in social participation (as opposed to network size) predicted subsequent changes in processing speed (Lövdén et al., 2005). However, interactions with education were not tested as part of this earlier study. We suspect Lövdén et al.'s (2005) measure of social activity participation to be a stronger predictor than network size given that having a large network does not guarantee engagement with that network in ways that contribute to cognitive enrichment, whereas a measure of activity engagement better aligns with the central premise of the enrichment hypothesis. A similar measure of activity engagement was available in ALSA and was used in the current analysis to assess possible interactions with education.

3.1.3. Loneliness, Education, and Cognitive Reserve

In addition to focussing on activity engagement, we also consider how loneliness, an indicator of (lack of) social network quality, interacts with education to predict cognitive health. Loneliness is an increasing concern among older adults (Ong et al., 2016). Weiss (1973) suggested that conceptually there are two aspects of loneliness. Whereas social loneliness is more closely aligned to lack of opportunity for participation by limited or no access to friends or family, emotional loneliness typically refers to perceptions of emotional support and absence of close companionship which generally occurs following separation, divorce, or death of a loved one. Given that there is a substantial conceptual overlap between the social facet of loneliness and our measure of social activity participation, we used a measure of loneliness that captured the emotional facet.

Loneliness has been associated with cognitive decline (Boss et al., 2015; Zhong et al., 2017) and dementia risk (Wilson et al., 2007). Boss et al. (2015) suggest an array of possible mechanisms underlying the association between loneliness and impaired cognition, including both biological (i.e., prolonged activation of the hypothalamus–pituitary–adrenal (HPA) axis and inflammation) and psychological factors (i.e., increased stress, rumination of negative thoughts, and decreased positive affect). As we might expect, lack of quantitative social resources have been considered a risk factor for loneliness, and social connection appears to reduce feelings of emotional loneliness (e.g., Green et al., 2001; Pinquart, 2003; Shankar et al., 2013; van Tilburg, 1990). However, some research has also shown that social isolation does not always result in higher perceptions of loneliness. Rokach (2012), for example, suggests that it is the subjective perception of the situation that induces loneliness; specifically, the match or mismatch between the amount of contact that is desired compared to the amount of contact available. Therefore, this highlights the importance of considering loneliness in addition to social activity engagement, given that it is possible for someone to be socially engaged but at the same time perceive themselves to be lonely.

In the present study, we also consider interactions of education with loneliness in the prediction of initial letter fluency. We were interested in whether those with less education but also lower levels of loneliness exhibit less pronounced reductions in cognitive performance relative to those both lonely and with lower education, similar to Shankar et al.'s (2013) preliminary findings. We consider the stress-buffering hypothesis described above a plausible mechanism that could underlie such a link. Specifically, we argue that those who are not lonely are better placed to develop cognitive reserve when they have limited educational opportunities as they are more likely to have emotionally close others to draw on as supports, buffering stress-related declines in cognitive functioning. Such findings would demonstrate that not feeling lonely is an important mechanism of social engagement driving benefits of cognitive health and would provide support for a protective compensatory role of social connection in the context of low education. Finally, we extend on the work of Windsor et al. (2020) by testing not only interactions of education and social resources, but also a three-way interaction of education, social activity engagement, and loneliness to determine whether it is the case that people who might be best positioned to develop reserve through the accumulation of social resources are those who are engaged in activity (thereby being exposed to enriching activities and producing gains for the cognitive system) and also not lonely (thereby being better placed to manage stress and avoid the potential ill-effects of chronic HPA activation).

3.1.4. The Current Study

The present study focussed on two measures of cognitive performance. First, we used the initial letter and semantic category fluency tasks from the ALSA and ELMS datasets respectively. With reference to the goals of the present study, a number of previous investigations have demonstrated positive associations between social resources and fluency performance (e.g., Bourassa et al., 2017; Brown et al., 2012; James et al., 2011; Krueger et al., 2009; Miceli et al., 2019; Mortimer et al., 2012), and fluency has also been associated with short-term improvements in performance resulting from social interaction (Ybarra & Winkielman, 2012). Second, previous work has shown processing speed to be a strong indicator of cognitive decline (Lindenberger et al., 1993), and an education x emotional loneliness interaction emerged to predict processing speed using data from the Berlin Ageing Study (Windsor et al., 2020). Therefore, we also included the Digit Symbol Substitution Test (DSST; Wechsler, 1981) as a measure of processing speed which was available in the ALSA dataset.

Our primary analysis makes use of data from ALSA, where participants completed measures capturing individual differences in social activity engagement and loneliness at five time points over a 13-year period. Our aim was to examine the effect of interactions of education (our proxy measure of cognitive reserve) with a) social activity engagement, b) loneliness, and c) a combination of both, on fluency and processing speed. Findings of such interactions would contribute evidence toward evaluation of Windsor et al.'s (2020) compensatory reserve hypothesis, which suggests that social resources could play a compensatory role in buffering the effects of ageing on cognition among those with limited educational opportunities. We focus on the potentially different roles of our social resource variables as moderators of associations between education and initial letter fluency performance. Although Windsor et al. (2020) did not find consistent support for the compensatory reserve hypothesis in their preliminary investigation, we expect our measure of social activity engagement to be a stronger predictor of fluency performance in the context of low education as we argue this measure is more closely aligned with theories such as Use it or Lose it and the enrichment hypothesis. Further, as lack of emotional support could increase vulnerability to physiological stress response (Kuiper et al., 2016), we also expect to see an interaction of loneliness and education in reducing the level and rate of decline in cognition by mechanism of the stress-buffering hypothesis. Finally, we further extend previous investigations by testing interactions of education, social activity engagement, and loneliness to examine whether people who might be best positioned to develop cognitive reserve are those who are engaged in social activity and also have lower levels of loneliness.

Therefore, the highest-order term included in our models that was of direct relevance to our research questions was the four-way interaction of education x social activity engagement x loneliness x time.

1. It was predicted that steeper declines in cognitive performance (initial letter fluency and processing speed) over time among those with lower education would be less pronounced among those who reported higher levels of activity engagement and who were not lonely.

Second, to assess the replicability of education x social resources interactions at the between-person level, we conducted additional parallel analyses using cross-sectional data from the ELMS where we focussed on interactions of education with (a) social network size and frequency of contact; (b) perceived support from friends, family and neighbours; and (c) loneliness, to determine whether structure, function, or quality-based measures of social resources were better predictors of fluency performance. Similar to the analyses described above for ALSA, the analysis of the cross-sectional ELMS was concerned with whether poorer category fluency performance among those with lower education would be offset by social resources. Here it was predicted that:

2. The category fluency performance divide between those with higher and lower education would be less pronounced among those with greater social resources.

Finally, an additional value of utilising the ELMS data was the ability to examine whether social resources are associated with category fluency independently of more general engagement with life. The enrichment hypothesis provides a basis to emphasise the importance of everyday engagement with life activities on cognitive health. Past research has found support that an active lifestyle in late life, including individual or combined engagement in physical, mental, and social activities, has positive implications on cognition. For example, Paillard-Borg et al. (2009) used longitudinal data to explore whether an active lifestyle protects against dementia and found that physical, mental, and social aspects of an active lifestyle were related to a lower risk of developing dementia. Another experimental study conducted by Carlson et al. (2008) examining a short-term community-based program in a social setting found that increased cognitive and physical activity had positive implications on memory and executive functions. Although social engagement was a prominent component of such interventions, it was not directly examined as a factor independent of broader engagement with life. This is important, as some older adults may maintain a sense of engagement and purpose into later life through more solitary pursuits, and sense of purpose per se has also been associated with better cognitive performance (Windsor et al., 2015). Thus, we aimed to determine whether such social resources examined in the ELMS predicted fluency performance independently of broader assessments of engagement with life (i.e., the extent to which people perceived their everyday activities as meaningful). Such a finding would suggest there may be something more unique to social interactions as a protective factor to cognitive functioning beyond being engaged with life in a more general sense. Specifically, if network structure is the key driver of fluency improvement through Use it or Lose it processes, then we might expect that social engagement would be conflated with an intellectually engaged lifestyle more generally, and that controlling for engagement with life might substantially weaken links between network structure and cognition. On the other hand, if functional network aspects are protective due to stress buffering effects, this mechanism is more conceptually distinct from leading an intellectually engaged lifestyle, and therefore we might expect any protective effects of functional and/or quality aspects of networks to be attenuated to a lesser degree when controlling for engagement with life. It was therefore predicted that:

3. A meaningful relationship between structure and category fluency would no longer exist once we statistically controlled for engagement with life.
4. Buffering effects of network function on the education-fluency relationship (see Hypothesis 2) would remain positively associated with category fluency once we statistically controlled for engagement with life.

3.2. Method

3.2.1. Australian Longitudinal Study of Ageing (ALSA)

Participants and Procedure

The study sample was drawn from the Australian Longitudinal Study of Aging (ALSA; Luszcz et al., 2007, 2020). The complete original ALSA sample (*n* = 2087) consisted of 1477 participants who were drawn randomly from the South Australian electoral roll and 610 participants who were cohabitants of the primary sample (e.g., part of a couple or coresident) aged over 65 years. A unique couple identification number was recorded to distinguish participants who did and did not also have responses from another person within the same household. Although twelve waves of data were collected over a 22-year period (Luszcz et al., 2016), the current study primarily used data from Waves 6, 7, 9, 11, and 12, as the cognitive measures of interest were available at these waves.

The analytic sample included 474 older adults who were aged between 73 and 99 years (*M* = 82.61 years (*SD* = 4.78), *female* = 40.08%) at baseline (Wave 6 of the original ALSA). The outcome measures included in the current analyses were collected at Wave 6 (Time 1, September 2000 to February 2001), Wave 7 (Time 2, *M* = 3.06 (*SD* = 0.17) years after baseline; *n* = 325), Wave 9 (Time 3, *M* = 7.31 (*SD* = 0.20) years after baseline; *n* = 153), Wave 11 (Time 4, *M* = 9.61 (*SD* = 0.13) years after baseline; *n* = 119), and Wave 12 (Time 5, *M* = 12.43 (*SD* = 0.12) years after baseline; *n* = 68). We only included participants who had complete data on all predictor and covariates (i.e., social activity, loneliness, education, age, sex, number of comorbidities, and depression variables), who responded to at least one of the cognitive measures at baseline (i.e., initial letter fluency and/or processing speed), and who did not have possible dementia at baseline (as determined by the MMSE).

From this sample, there were 471 participants who completed the fluency measure at least once, and 194 participants who completed the speed measure at least once. Comparisons revealed that the fluency sample showed differences of -0.58 *SD* for social activity engagement, 0.02% more loneliness, -0.12 *SD* for education, 0.19 *SD* for age, 0.07% more males, -0.01 *SD* for comorbidities, and 0.01 *SD* for depressive affect compared to the speed sample. Finally, we also compared participants who reported relatively more fluency data points (three or more waves, *n* = 153) than those who provided data for only one or two waves (*n* = 321). Attrition analysis revealed that participants who remained in the study for three or more waves showed differences of: 0.55 *SD* for social activity engagement, 0.04% less lonely, -0.12 *SD* for education, -0.74 *SD* for age, 0.07% more females, -0.18 *SD* for comorbidities, and -0.07 *SD* for depressive affect relative to those who dropped out after one or two waves. All other descriptive information and bivariate correlations are presented in Table 3.1 for the initial letter fluency sample and Table 3.2 for the processing speed sample.

Table 3.1

ALSA – Initial Letter Fluency Descriptive Statistics and Bivariate Correlation Coefficients at Baseline

		Mean *(SD)*	*Range*	1	2	3	4	5	6	7
1.	Initial Letter Fluency	18.53 (7.72)	3 – 47	--						
2.	Social Activity Engagement	1.15 (0.60)	0 – 2.75	0.14	--					
3.	Lonely	0.10	0 – 1	-0.08	-0.09	--				
4.	Education	9.66 (2.64)	4 – 20	0.21	0.07	-0.01	--			
5.	Age	82.58 (4.82)	73 – 99	-0.12	-0.19	0.07	0.02	--		
6.	Female	0.41	0 – 1	-0.01	-0.16	0.01	0.02	0.18	--	
7.	Depressive affect	0.28 (0.34)	0 – 1.83	-0.04	-0.04	0.43	-0.05	-0.05	-0.16	--
8.	Count of comorbidities	4.22 (2.61)	0 – 10	0.05	-0.05	0.11	0.04	0.07	-0.05	0.22

Note. For categorical variables (lonely and female) *point biserial coefficients* are reported. For the correlation between the two categorical variables *phi coefficient* is reported. Values of categorical variables in the Mean column reflect proportions of individuals who were lonely and who were female.

Table 3.2

ALSA – Processing Speed Descriptive Statistics and Bivariate Correlation Coefficients at Baseline

		Mean *(SD)*	*Range*	1	2	3	4	5	6	7
1.	Processing Speed	32.01	7 – 62	--						
2.	Social Activity Engagement	1.63	1.25 – 2.75	0.02	--					
3.	Lonely	0.09	0 – 1	-0.13	-0.01	--				
4.	Education	10.21	5 – 20	0.05	0.03	0.03	--			
5.	Age	81.62	73 – 93	-0.35	0.07	-0.07	0.09	--		
6.	Female	0.33	0 – 1	0.00	0.05	-0.12	0.13	0.04	--	
7.	Depressive affect	0.27	0 – 1.67	-0.12	0.03	0.52	-0.13	-0.09	-0.20	--
8.	Count of comorbidities	4.26	0 – 10	-0.07	0.01	0.14	0.02	0.06	-0.10	0.22

Note. For categorical variables (lonely and female) *point biserial coefficients* are reported. For the correlation between the two categorical variables *phi coefficient* is reported. Values of categorical variables in the Mean column reflect proportions of individuals who were lonely and who were female.

Measures

Social Activity Engagement.

Social activity was assessed at all five waves. We used four items (similar to Bielak et al., 2014) from the Adelaide Activities Profile (AAP; Clark & Bond, 1995) which captured the frequency of participation in different types of social activities over a 3-month period. The items were: a) 'How often have you invited people to your home?', b) 'How many telephone calls have you made to friends or family?', c) 'How often have you participated in social activities at a centre such as a club, a church, or a community centre?', and d) 'How often have you participated in an outdoor social activity?'. Four-point scale responses differed for each item as they were designed to be sensitive to the frequency of each activity. For example, the response options available for 'how often have you invited people to your home' ranged from 1 (less than once a fortnight) to 4 (more than once a week), where responses to how many telephone calls made ranged from 1 (none) to 4 (over 10 calls a week) (see Appendix A for all response options). Item scores were averaged to create a single score for social activity engagement at each wave. Mean replacement was used if responses were missing for one of the four items. A fixed between-person measure of social activity engagement was created by taking the person mean of social activity scores across all available timepoints.

Loneliness.

Loneliness was also measured at each wave. In keeping with previous studies (e.g., Courtin & Knapp, 2017; Menec et al., 2019; Wagner et al., 2013), we used a single item from the Centre of Epidemiological Studies – Depression Scale (CES-D; Radloff, 1977; Appendix B) to measure loneliness. Participants were asked to indicate on a 4-point Likert scale how often they felt lonely over the past week. To create a fixed, categorical measure of loneliness, the mean score across all time points was taken. These scores were subsequently dichotomised into 'not lonely' (based on a mean score between 0 and 1.50) or 'lonely' (based on a mean score of 1.60 to 3).

Education.

Education was measured using a single item asking participants how many years of formal schooling they had completed.

Initial Letter Fluency.

We used the Initial Letter Fluency Test (Benton, 1969; Ruff et al., 1996) as a time-varying dependent measure. This task requires participants to generate as many words as possible beginning with a specific letter. Two 60-second trials were completed for letters 'f' and 'a'. A single score was calculated at each wave by summing correct responses for those who completed both items. Higher scores indicated better initial letter fluency performance.

Processing Speed.

We used the Digit Symbol Substitution Test (DSST; Wechsler, 1981) as our time-varying measure of processing speed. Participants were presented with a coding key pairing numbers 1 – 9 with unique symbols. They were presented with a randomly ordered set of numbers and given 90 seconds to transcribe as many symbols as possible that corresponded to the numbers. The symbols were available for reference throughout the task. The final score for each wave was the number of correctly substituted symbols completed within a 90-second period (i.e., total score minus error score). Higher scores indicated better processing speed.

Covariates.

We statistically controlled for chronological age at baseline, sex, count of comorbidities, and depressive affect. Count of comorbidities was recorded on a scale of 0 (no comorbidities) to

10 (10 or more comorbidities). Seven items from the CES-D (i.e., blues, depression, failure, fearful, crying, and sadness; Appendix B) have been shown to be a reliable measure of depressive affect in older adulthood (Hertzog et al., 1990). Excluding the loneliness item (as we used this item as our loneliness measure), six items were summed to create a single depressive affect score for each wave. Mean replacement was used for those missing data on two of the six items. Possible scores ranged from 0 – 18 with higher scores indicating more depressive affect. A fixed measure of depressive affect was then created using the mean across all available timepoints. Finally, global cognitive ability was measured at each wave using the Mini Mental State Exam (MMSE; Folstein et al., 1975). In keeping with previous studies (Anstey & Luszcz, 2002; Bielak et al., 2014; Windsor et al., 2015), we used a cut-off score of 23 or below (out of 30) to indicate possible dementia. The analytical sample did not include anyone who met the cognitive impairment cut-off at baseline.

3.2.2. Engagement, Lifestyle and Meaning Study (ELMS)

Participants and Procedure

A social research company recruited and administered telephone surveys to a random selection of adults from listed landline telephone numbers. Participants were 65 years or older living within the City of Onkaparinga metropolitan area in Adelaide, South Australia. Calls were only made once to each number, and call backs were arranged if requested by the participant. If more than one person was eligible to participate per home, the interviewer asked to interview the person in the home who had a birthday most recently. The total sample (n = 432) ranged in age from 65 to 103 (M = 76.66, SD = 7.02, *female* = 54.60%). However, the analytic sample only included participants who had complete data on all predictor, covariate, and outcome variables (i.e., were not missing on education, structure, function, quality, engagement with life, age, sex, psychological wellbeing, physical health, or category fluency) (*n* = 289, *age range:* 65 – 103 years, *M* = 76.60 (*SD* = 7.05), *female* = 52.9%). All other descriptive information and bivariate correlations are presented in Table 3.3.

Table 3.3

ELMS – Category Fluency Descriptive Statistics and Bivariate Correlations

		Mean *(SD)*	*Range*	1	2	3	4	5	6	7	8	9
1.	Category fluency	39.39 (10.58)	3 – 73	--								
2.	Education	12.6 (2.64)	8 – 18.50	0.25	--							
3.	Structure	--	--	0.13	0.11	--						
4.	Function	4.24 (0.65)	2 – 5	0.11	0.02	0.09	--					
5.	Quality	6.77 (1.66)	2 – 10	-0.01	0.01	0.09	0.09	--				
6.	Engagement with life	25.3 (2.77)	14 – 30	0.29	0.25	0.17	0.30	0.14	--			
7.	Age	76.6 (7.05)	65 – 103	-0.34	-0.29	-0.11	0.11	0.04	-0.21	--		
8.	Female	0.53	0 – 1	0.25	-0.23	0.06	0.11	0.02	-0.07	0.02	--	
9.	Psychological wellbeing	16.39 (1.79)	8 – 20	0.16	0.04	0.02	0.27	0.11	0.45	-0.08	-0.04	--
10.	Physical health	13.86 (2.99)	7 – 20	0.22	0.19	0.17	0.27	0.12	0.41	-0.18	-0.13	0.34

Note. Structure was a standardised variable therefore descriptive statistics were not relevant. For categorical variable 'female' *point biserial coefficients* are reported. Value of Mean column reflects proportions of individuals who were female.

Measures

Social Network Characteristics.

Network Quality. Network quality was assessed using the sum of two items from the Older Persons Quality of Life scale (OPQOL; Bowling, 2009; Bowling & Stenner, 2011). The items were: a) 'I would like more companionship with others', and b) 'I would like more people to enjoy life with', in line with loadings of these items onto a 'loneliness' factor (Mares et al., 2016). Responses to the items are provided on 5-point scales ranging from 1 (strongly agree) to 5 (strongly disagree). Higher scores indicate stronger disagreement with the statements, and therefore higher levels of perceived social network quality.

Network Structure. Network structure was measured by network size and network contact frequency. Specifically, network size was measured using three separate items asking participants the number of children, relatives (e.g., siblings, cousins), and friends they considered as having a close relationship with. The three items were summed to create a measure of total network size. Network contact frequency was assessed on a 6-point scale ranging from 1 (less than once a year) to 6 (3 or more times per week) asking participants how often they met up, spoke on the phone, and sent letters or emails to (a) children, (b) relatives, and (c) friends. The nine scales were summed to create a measure of network contact frequency, where higher scores indicated greater frequency. Network size and network contact frequency were first transformed to Z-scores before being summed to create a composite measure of network structure.

Network Function. To assess network function, we used a single item rated on a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree) from the OPQOL: 'My family, friends or neighbours would help me if needed.' Higher scores on this item indicated better function of social networks.

Education.

In line with Studies in Australia (2021) information on types of education (an Australian based private company run by education experts), education categories were converted into the following years of education: a) 'primary school only' was transformed to 8 years of education (including Kindergarten), b) 'high school only' was transformed from Years '8' to '12' to 9 to 13 years of education respectively, c) 'trade' assumed 11 years of schooling (e.g., up to Year 10; SA GOV, 2019) plus a mean of 1.25 years of the trade totalling 12.25 years of education, d) ‘diploma’ assumed 13 years of schooling (e.g., up to Year 12) plus a mean of 1.5 years of the diploma totalling 14.5 years of education, e) ‘undergraduate’ assumed 13 years of schooling plus 3 years of university totalling 16 years of education, and f) ‘postgraduate’ assumed 13 years of schooling, 3 years of undergraduate studies, plus a mean of 2.5 years of further postgraduate university study, totalling 18.5 years of education.

Category Fluency.

The Semantic Category fluency test (Acevedo et al., 2000) required participants to name as many animals as possible within 60 seconds. This was then repeated for two other categories: fruits and vegetables consecutively. The mean number of words produced across the three categories was calculated as the final measure. Higher scores indicated better semantic category fluency performance.

Engagement with Life.

Engagement with life was assessed by summing six items from the Life Engagement Test (LET: Scheier et al., 2006). Participants were asked to choose a rating of 1 (strongly disagree) to 5 (strongly agree) in terms of the following items: a) ‘To me, the things I do are all worthwhile’, b) ‘Most of what I do seems trivial and unimportant to me’, c) ‘I value my activities a lot’, d) ‘I don’t care very much about the things I do,’ e) ‘I have lots of reasons for living’, and f) ‘There is not enough purpose in my life’. Items b, d, and f were reverse coded prior to summing all six items for a total score. Higher scores indicated more engagement with life.

Covariates.

We statistically controlled for age, sex, psychological wellbeing, and physical health. Psychological wellbeing was measured using the OPQOL psychological and emotional wellbeing subscale (Bowling, 2009; Bowling & Stenner, 2011). Specifically, responses to the four items: a) 'I take life as it comes and make the best of things', b) 'I feel lucky compared to most people', c) 'I tend to look on the bright side', and d) 'if my health limits social/leisure activities, then I will compensate and find something else I can do' were summed to create a psychological wellbeing variable. Higher scores indicated better psychological wellbeing. Physical health was measured using the OPQOL health subscale (Bowling, 2009; Bowling & Stenner, 2011). The following four items: a) 'I have a lot of physical energy', b) 'pain affects my wellbeing' (reversed), c) 'health restricts me looking after myself or my home' (reversed), and d) 'I am healthy enough to get out and about' were summed to create a single score for physical health. Higher scores indicated better physical health.

3.3. Statistical Analysis

The data from ALSA were analysed using three level Bayesian multilevel growth models. Couples were added at the highest level of the model and retained for both fluency ($SD_{(intercept)}$ = 0.35, $HDI_{95\%}$ = [0.04, 0.57]) and speed analyses ($SD_{(intercept)}$ = 0.27, $HDI_{95\%}$ = [0.01, 0.62]). To account for random effects, we allowed the intercept and linear person mean centred time (see Ghisletta & Lindenberger, 2004; quadratic time was also modelled) to vary across couples (Level 3) and across individuals nested within couples (Level 2).

To determine the relative importance of our predictor variables, we analysed the model which included the highest order interaction (education x social activity engagement x loneliness x time), plus lower order cross-product terms. Between-person age (calculated as age at baseline plus mean time in study across all measurements), sex, count of comorbidities, and depressive affect were added to the model as covariates. To aid in interpretability of effect sizes, and to enable comparisons of the relative importance of different predictor variables within the

Bayesian framework (Kruschke, 2018), all continuous variables were standardised using the grand mean and standard deviations calculated across all assessments with the data in long form.

For consistency with previous studies, our primary analyses excluded participants who had mild cognitive impairment or dementia at baseline to reduce the possible influence of reverse causality (Stoykova et al., 2011; Windsor et al., 2020). Additionally, we conducted post-hoc analyses where we reported results with the exclusion of participants who were classified as having possible cognitive impairment at any assessment based on the MMSE cut-off to control for possible incipient dementia. This resulted in retainment of 304 of 341 total assessments from T2 - T5 for speed outcomes, and retainment of 853 of 1065 assessments from T2 - T5 for fluency outcomes.

Finally, we analysed the cross-sectional ELMS data using Bayesian regression models. Each social resource variable (structure, function, quality) was analysed in separate higher order models that included cross-products to test relevant interactions among the predictor variables. Covariates (e.g., age, sex, psychological wellbeing, and physical health) were included in each model. The models were also re-run with the inclusion of engagement with life to test Hypothesis 4.

We used a Bayesian estimation approach to analyse and interpret our data. The region of practical equivalence (ROPE) was set to ±0.05 in line with Kruschke's recommendations for correlational analyses with standardized data (Kruschke, 2018; Makowski et al., 2019). Interpretation of results were based on the highest density intervals (HDI) in relation to the ROPE. Specifically, 1) if the HDI fell completely within the ROPE, we accepted the null hypothesis, 2) if the HDI fell completely outside the ROPE, we accepted the alternate hypothesis, and 3) any other combination of the HDI and ROPE resulted in inconclusive evidence to make either decision with 95% confidence. We additionally reported the proportion of the HDI interval that lay within the ROPE ($P_{(within\ ROPE)}$) or outside the ROPE in the predicted direction ($P_{(meaningful)}$) to aid interpretation. We considered any balance of evidence over 80% as being suggestive of a true effect.

3.4. Results

The most important results for our research question utilising ALSA data were whether time, education, and different types of social resource variables (social activity engagement and loneliness) predicted individual differences in fluency and speed outcomes as represented by the model intercepts, or rates of change in the cognitive outcomes as represented by their linear slopes. Further, to determine whether social resources can play a compensatory role in buffering the effects of ageing in cognition for those with limited educational opportunities, we tested whether interactions between education and social resource variables (social activity engagement and loneliness) predicted cognitive performance (intercepts and slopes) for fluency and processing speed. Analysis of ELMS data allowed us to test for replicability of interactions of additional social network resources (structure, function, and quality) with education in the prediction of category fluency performance. This dataset also allowed us to consider whether social resources predicted category fluency performance independently of more general engagement with life. The findings for ALSA initial letter fluency, ALSA processing speed, and ELMS category fluency are reported in separate sections below.

3.4.1. ALSA – Initial Letter Fluency

We first report the main effects for initial letter fluency performance (see Table 3.4 for all ALSA – initial letter fluency inferential statistics). Parameter estimates indicated that the evidence was too disbursed to draw meaningful conclusions about the reliability of associations between social activity engagement and the intercept (i.e., refer to the probability column in Table 3.4 which indicates the proportion of the HDI that fell below, within, and above the ROPE limits). Contrary to expectations, although we could not exclude the possibility that fluency performance declined on average over time with 95% confidence ($P_{(meaningful)}$ = 16.8%), there was evidence to suggest no reliable linear effect of time-in-study ($P_{(within\ ROPE)}$ = 83.2%) (B = -0.06, $HDI_{95\%}$ = [-0.13, 0.02]). Further, although we could not exclude a negligible effect with 95% confidence for education at the intercept ($P_{(within\ ROPE)}$ = 7.18%), there was clear evidence to suggest a positive association ($P_{(meaningful)}$ = 92.7%) (B = 0.15, $HDI_{95\%}$ = [0.02, 0.28]). Similarly, for the association of loneliness with the intercept, although we could not exclude a negligible effect ($P_{(within\ ROPE)}$ = 18.9%), there was non-negligible evidence to suggest a negative association ($P_{(meaningful)}$ = 78.5%) (B = -0.12, $HDI_{95\%}$ = [-0.29, 0.05]). These latter findings were consistent with expectations, indicating that those who had more years of education, and those who were less lonely, performed better on fluency.

Contrary to expectations, no interactions emerged between education with social activity engagement (B = -0.05, $HDI_{95\%}$ = [-0.19, 0.08], $P_{(meaningful)}$ = 6.01%), or a combination of social activity engagement and loneliness (B = 0.02, $HDI_{95\%}$ = [-0.11, 0.15], $P_{(within\ ROPE)}$ = 0.33%) in the prediction of levels or rates of change in initial letter fluency performance. The education x loneliness interaction was trending in the expected direction, however the evidence was weak (B = -0.07, $HDI_{95\%}$ = [-0.20, 0.06], $P_{(meaningful)}$ = 61.5%). Taken as a whole, the results did not provide evidence in support of social resources moderating the relationship between education and fluency performance. Further, there was evidence supporting the null hypothesis in relation to interactions of time in study with education, social activity engagement, and loneliness (i.e., greater than 80% certainty that the HDI fell completely within the ROPE limits). These findings showed that the rate of change in fluency performance over time did not differ as a function of levels of education, social activity engagement, or loneliness. Finally, we did not find evidence of a four-way interaction ($P_{(within\ ROPE)}$ = 75.2%).

Although no evidence emerged for the compensatory reserve hypothesis, for completeness, we conducted post-hoc analyses excluding observations for those participants who had possible incipient dementia at any time point based on their MMSE scores. The main effect of loneliness on the intercept was no longer meaningful once these participants were excluded ($P_{(meaningful)}$ = 51.90%) (B = -0.06, $HDI_{95\%}$ = [-0.27, 0.16]). Otherwise, no other differences existed between the two datasets. Findings of the post hoc analyses are reported in Appendix C.

Table 3.4

ALSA Model Including Social Activity, Loneliness, and Education as Predictors of Initial Letter Fluency Trajectories Among Those Without Probable Dementia at Baseline (n = 471)

	Intercept			Linear slope			Quadratic slope		
Parameter	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE
Fixed effects									
Intercept/slope	-0.14	[-0.31, 0.03]		-0.06	[-0.13, 0.02]	[0.57, 0.43, 0.00]	-0.03	[-0.07, 0.00]	[0.17, 0.83, 0.00][a]
Covariates									
Age at baseline	-0.04	[-0.12, 0.03]		-0.00	[-0.08, 0.08]				
Female	0.03	[-0.06, 0.11]		-0.00	[-0.04, 0.03]				
Count of comorbidities	0.06	[-0.02, 0.15]		0.01	[-0.03, 0.04]				
Depressive affect	-0.02	[-0.11, 0.07]		-0.02	[-0.06, 0.02]				
Main predictors									
Education	0.15	[0.02, 0.28]	[0.00, 0.07, 0.93]*	0.01	[-0.08, 0.09]	[0.11, 0.73, 0.17]			
Social activity engagement	0.06	[-0.08, 0.21]	[0.06, 0.37, 0.58]	-0.00	[-0.08, 0.08]	[0.10, 0.80, 0.10][a]			
Lonely	-0.12	[-0.29, 0.05]	[0.79, 0.19, 0.03]	0.01	[-0.07, 0.09]	[0.06, 0.78, 0.16]			
Education x social activity engagement	0.02	[-0.11, 0.15]	[0.52, 0.42, 0.06]	0.01	[-0.07, 0.09]	[0.07, 0.75, 0.19]			
Education x lonely	-0.07	[-0.20, 0.06]	[0.62, 0.35, 0.04]	0.04	[-0.04, 0.13]	[0.02, 0.54, 0.44]			
Social activity engagement x lonely	-0.06	[-0.20, 0.08]	[0.57, 0.37, 0.06]	-0.02	[-0.10, 0.05]	[0.26, 0.72, 0.03]			
Education x social activity engagement x lonely	0.02	[-0.11, 0.15]	[0.15, 0.53, 0.33]	0.01	[-0.07, 0.09]	[0.07, 0.75, 0.17]			
Random effects									
Level 3 (couple)									
Intercept (SD)	0.35	[0.04, 0.57]							

Slope (SD)	0.06	[0.00, 0.12]
Intercept-slope correlation	0.12	[-0.90, 0.94]
Level 2 (individual)		
Intercept (SD)	0.74	[0.61, 0.86]**
Slope (SD)	0.05	[0.00, 0.12]
Intercept-slope correlation	0.19	[-0.78, 0.93]
Residual	0.46	[0.43, 0.49]**

Note. [a] 80% certainty of HDI falling within the ROPE. [b] HDI fell completely within the ROPE. [*] 80% certainty of HDI falling outside the ROPE. [**] HDI fell completely outside the ROPE.

3.4.2. ALSA – Processing Speed

Results of the ALSA analysis that included processing speed as the dependent variable are reported in Table 3.5. Although we could not exclude a negligible effect with 95% confidence ($P_{(within\ ROPE)}$ = 10.70%), there was evidence to support a negative main effect of time ($P_{(meaningful)}$ = 85.80%) (B = -0.19, $HDI_{95\%}$ = [-0.45, 0.07]). Similarly, although we could not exclude a negligible effect ($P_{(within\ ROPE)}$ = 11.00%), there was also evidence to support a loneliness main effect ($P_{(meaningful)}$ = 83.10%) (B = -0.20, $HDI_{95\%}$ = [-0.52, 0.12]), and a social activity engagement main effect ($P_{(meaningful)}$ = 73.8%) (B = 0.16, $HDI_{95\%}$ = [-0.18, 0.50]). These findings were consistent with expectations, indicating that over time processing speed performance declines, and that those who are lonely and less socially engaged perform worse in processing speed. The evidence was too disbursed to draw meaningful conclusions about an education main effect on processing speed.

A non-negligibly sized four-way interaction of education x social activity engagement x loneliness x time emerged (B = -0.33, $HDI_{95\%}$ = [-1.07, 0.41], $P_{(meaningful)}$ = 77.20%). The nature of this interaction is displayed in “slope-on-a-rope” form in Figure 3.1 (with probabilities associated with each slope presented in Table 3.6). The *x*-axis in this figure represents the *slope* of processing speed performance, which is indicative of changes in processing speed over time; the estimated slopes for different possible combinations of high or low education, social activity, and loneliness (one SD above or below the mean) are reflected in the different categories displayed on the y-axis. It can be observed that the participants whose speed performance declined the most rapidly over the study interval were those who were lonely, had lower levels of education, and lower levels of social activity engagement ($P_{(meaningful)}$ = 87.30%).

To determine whether this group meaningfully differed from all other combinations of education, social activity engagement, and loneliness levels, we conducted pairwise comparisons that compared the slope for time for those who were lonely, had low social engagement, and low education with the slopes for all other combinations. Figure 3.2 shows a graphical representation of these comparisons. The pairwise comparisons revealed that the most vulnerable group had a meaningfully faster rate of decline compared to all other combinations (see Table 3.7 for probability of estimates falling below, within, or above the ROPE). Some evidence for the compensatory reserve hypothesis emerged, where the vulnerable group meaningfully declined in processing speed at a faster rate compared to those who had low education, were not lonely, and higher levels of social activity participation ($P_{(meaningful)}$ = 84.50%).

Post-hoc analyses were conducted that excluded participants who fell below the MMSE cut-off at subsequent assessment sessions to control for possible incipient dementia (see Table 3.8). Once these observations were excluded, the four-way interaction was no longer meaningful (B = 0.04, $HDI_{95\%}$ = [-0.92, 1.02]) and the evidence was too disbursed to make judgements on trends (refer to Table 3.8 for probability estimates). Education and loneliness main effects also became non-meaningful. However, although we could not exclude a negligible effect with 95% confidence ($P_{(within\ ROPE)}$ = 9.80%), there was evidence to support a meaningful three-way interaction of education x social activity engagement x loneliness in predicting the intercept ($P_{(meaningful)}$ = 79.70%) (B = 0.24, $HDI_{95\%}$ = [-0.22, 0.70]). The nature of the interaction is shown in Figure 3.3. The *x*-axis in the figure represents predicted levels of processing speed performance; the *y*-axis in the figure represents different combinations of high or low social activity and loneliness (one SD above or below the mean); the top panel represents those with high levels of education and the bottom panel represents those with low levels of education. It can be observed that among those with higher education, speed performance appeared notably poorer among those who were also lonely and had low levels of social activity engagement. Similarly poor performance among those lonely and less socially active was not observed among those with lower levels of education.

Table 3.5

ALSA Model Including Social Activity, Loneliness, and Education as Predictors of Processing Speed Trajectories Among Those Without Probable Dementia at Baseline (n = 194)

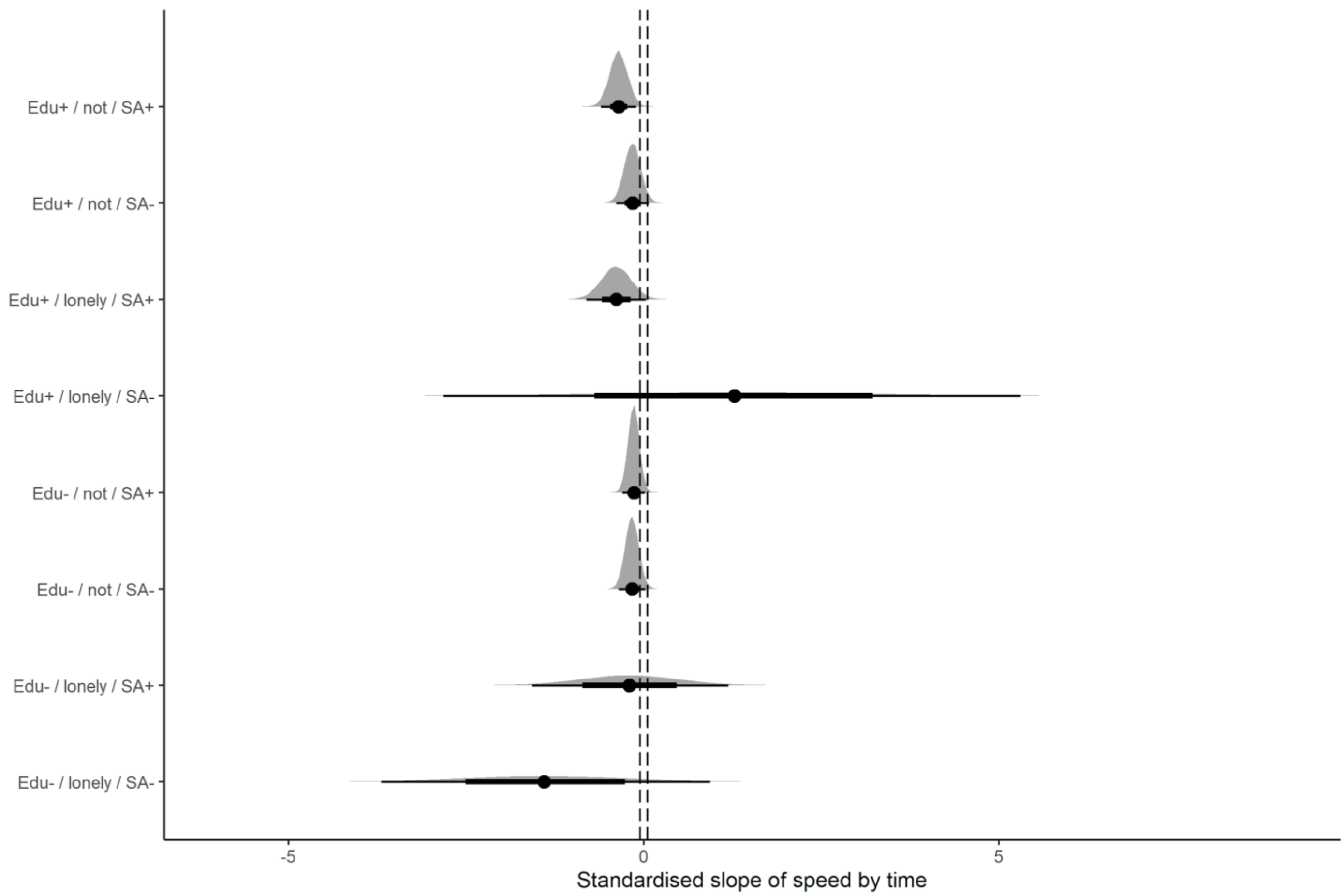
	Intercept			Linear slope			Quadratic slope		
Parameter	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE
Fixed effects									
Intercept/slope	-0.29	[-0.60, 0.02]		-0.19	[-0.45, 0.07]	[0.86, 0.11, 0.04]*	-0.00	[-0.10, 0.10]	[0.18, 0.67, 0.15]
Covariates									
Age at baseline	-0.17	[-0.29, -0.05]**		-0.11	[-0.24, 0.02]				
Female	-0.07	[-0.21, 0.06]		-0.01	[-0.10, 0.09]				
Count of comorbidities	0.05	[-0.08, 0.18]		-0.01	[-0.11, 0.08]				
Depressive affect	-0.11	[-0.26, 0.05]		0.03	[-0.10, 0.16]				
Main predictors									
Education	-0.01	[-0.60, 0.02]	[0.38, 0.32, 0.30]	0.28	[-0.58, 1.14]	[0.22, 0.07, 0.71]			
Social activity engagement	0.16	[-0.18, 0.50]	[0.11, 0.15, 0.74]	-0.08	[-0.46, 0.30]	[0.56, 0.18, 0.25]			
Lonely	-0.20	[-0.52, 0.12]	[0.83, 0.11, 0.06]*	0.01	[-0.25, 0.28]	[0.32, 0.29, 0.40]			
Education x social activity engagement	0.18	[-0.27, 0.64]	[0.16, 0.13, 0.72]	-0.38	[-1.12, 0.36]	[0.81, 0.06, 0.13]*			
Education x lonely	-0.06	[-0.30, 0.17]	[0.55, 0.29, 0.17]	0.34	[-0.52, 1.19]	[0.19, 0.07, 0.75]			
Social activity engagement x lonely	0.11	[-0.23, 0.45]	[0.17, 0.19, 0.64]	-0.04	[-0.42, 0.36]	[0.48, 0.19, 0.33]			
Education x social activity engagement x lonely	0.23	[-0.22, 0.69]	[0.11, 0.10, 0.79]	-0.33	[-1.07, 0.41]	[0.77, 0.07, 0.16]			
Random effects									
Level 3 (couple)									

Intercept (SD)	0.27	[0.01, 0.62]
Slope (SD)	0.08	[0.00, 0.21]
Intercept-slope correlation	0.01	[-0.94, 0.94]
Level 2 (individual)		
Intercept (SD)	0.62	[0.34, 0.80]**
Slope (SD)	0.08	[0.00, 0.20]
Intercept-slope correlation	0.32	[-0.81, 0.97]
Residual	0.67	[0.59, 0.76]**

Note. [a] 80% certainty of HDI falling within the ROPE. [b] HDI fell completely within the ROPE. * 80% certainty of HDI falling outside the ROPE. ** HDI fell completely outside the ROPE.

Figure 3.1

Graphical Representation of the Four-Way Interaction (Education x Lonely x Social Activity Engagement x Time) for Processing Speed



Note. The *x*-axis represents the slope of processing speed performance over time. The *y*-axis lists all combinations of high (+1 SD) or low (-1 SD) levels of education, loneliness, and social activity. The vertical dotted line represents the ROPE boundaries (±0.05). Distributions indicate HDIs (larger dispersions reflect greater uncertainty in the estimates).

Table 3.6

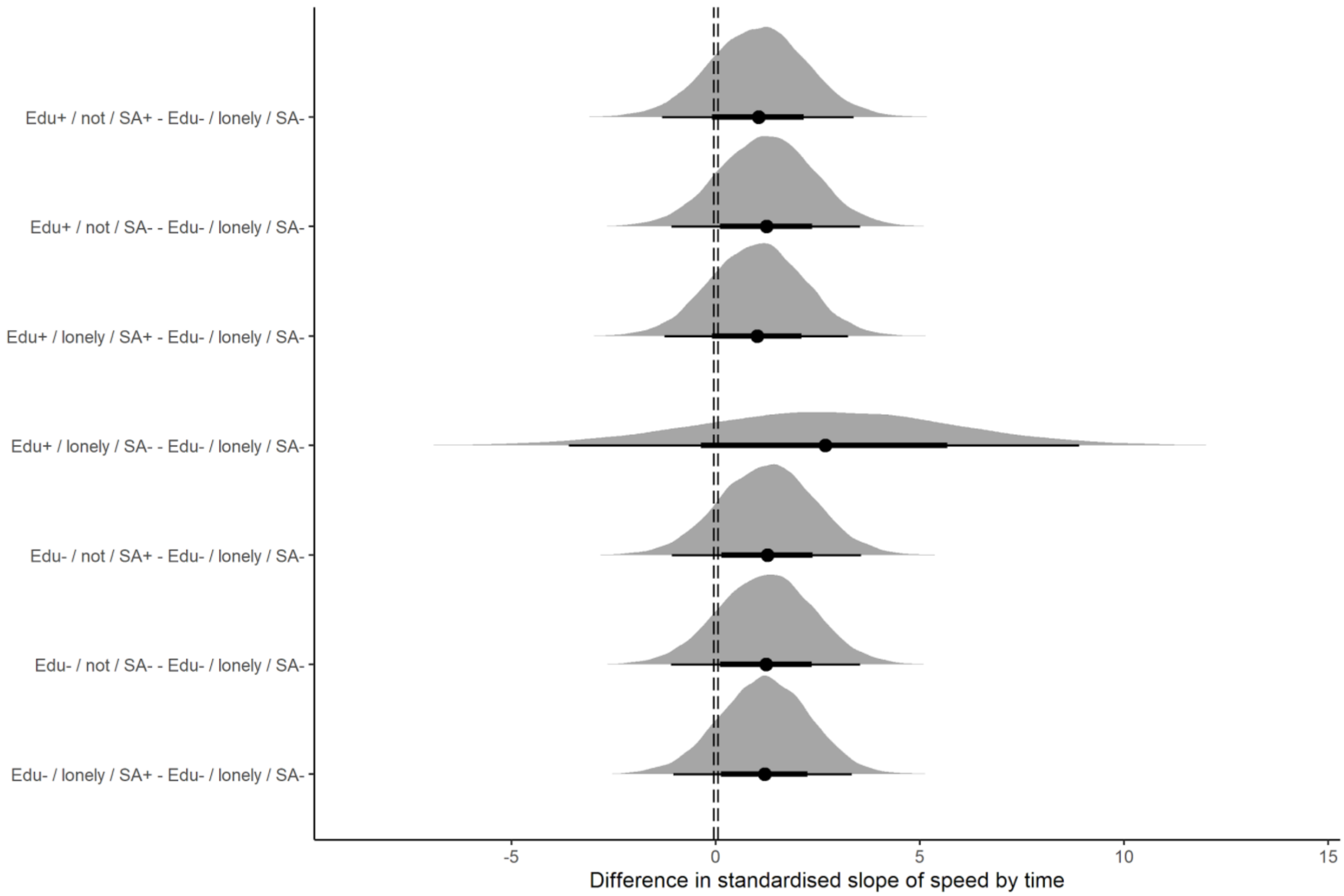
Probability That the True Effect Fell Below, Within, or Above the ROPE for All Combinations of High and Low Education, Loneliness, and Social Activity (from The Four-Way Interaction Slopes)

	Prob. [below, within, above] the ROPE
Low education, lonely, low social activity	[0.87, 0.02, 0.11]*
Low education, lonely, high social activity	[0.59, 0.06, 0.36]
Low education, not lonely, low social activity	[0.88, 0.11, 0.02]*
Low education, not lonely, high social activity	[0.88, 0.12, 0.01]*
High education, lonely, low social activity	[0.26, 0.02, 0.73]
High education, lonely, high social activity	[0.94, 0.04, 0.02]*
High education, not lonely, low social activity	[0.82, 0.13, 0.04]*
High education, not lonely, high social activity	[0.99, 0.01, 0.00]*

Note. * 80% certainty of HDI falling outside the ROPE.

Figure 3.2

Graphical Representation of the Post-Hoc Four-Way Slope Differences When Compared to the Most Vulnerable Group Combination (Low Education, Lonely, Low Social Activity)



Note. The *x*-axis represents the slope of processing speed performance over time. The *y*-axis lists all combinations of pairwise comparisons between the low education, lonely, and low social activity combination (i.e., the most vulnerable group) with all other combinations of education, loneliness, and social activity engagement (i.e., non-vulnerable group slope - vulnerable group slope). The vertical dotted line represents the ROPE boundaries (±0.05). Distributions indicate HDIs (larger dispersions reflect greater uncertainty in the estimates).

Table 3.7

Post-Hoc Analyses of the Four-Way Slope Differences When Compared to the Most Vulnerable Group Combination (Low Education, Lonely, Low Social Activity)

	Prob. [below, within, above] the ROPE
Low education, lonely, high social activity	[0.14, 0.02, 0.85]*
Low education, not lonely, low social activity	[0.14, 0.02, 0.84]*
Low education, not lonely, high social activity	[0.14, 0.02, 0.85]*
High education, lonely, low social activity	[0.20, 0.01, 0.80]*
High education, lonely, high social activity	[0.18, 0.03, 0.79]
High education, not lonely, low social activity	[0.14, 0.02, 0.84]*
High education, not lonely, high social activity	[0.18, 0.02, 0.80]*

Note. * 80% certainty of HDI falling outside the ROPE.

Table 3.8

ALSA Model Including Social Activity, Loneliness, and Education as Predictors of Processing Speed Trajectories Among Those Without Probable Dementia at All Timepoints (n = 179)

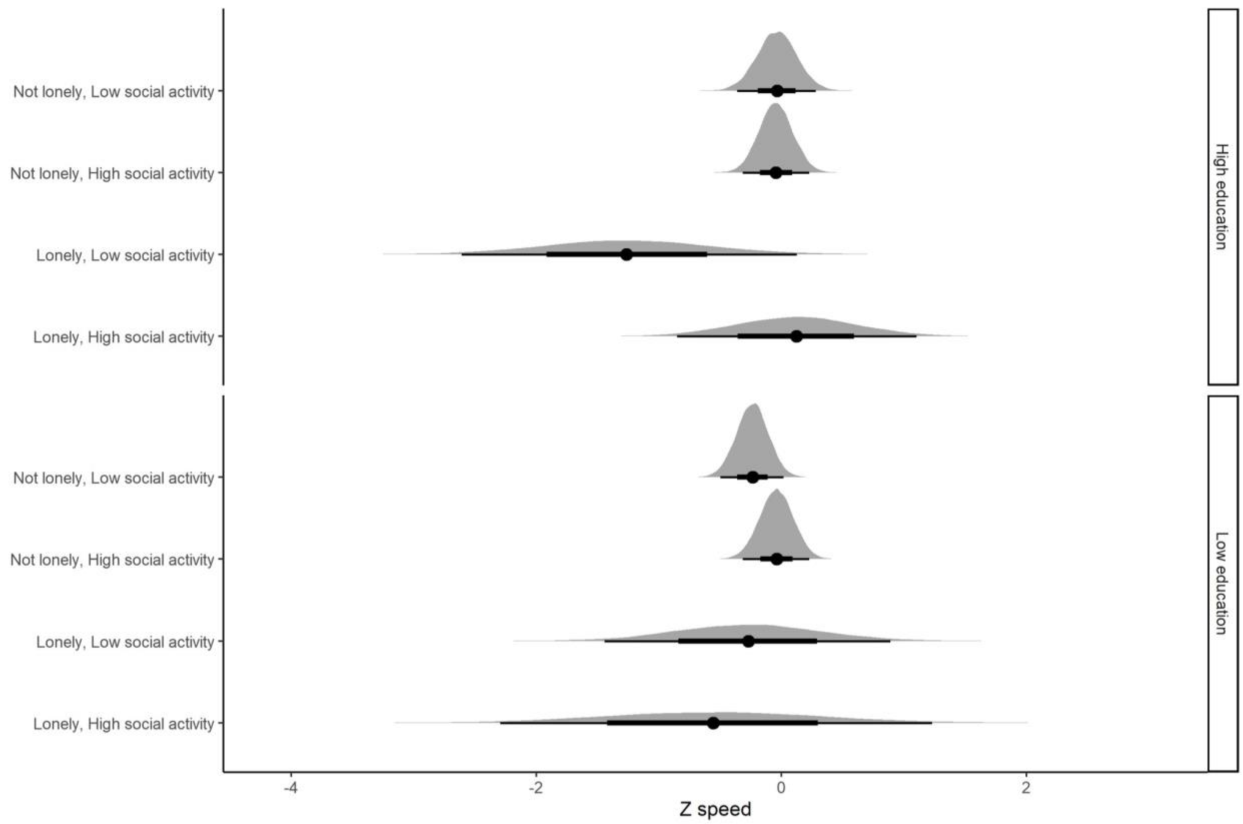
	Intercept			Linear slope			Quadratic slope		
Parameter	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE
Fixed effects									
Intercept/slope	-0.21	[-0.56, 0.13]		-0.03	[-0.40, 0.34]	[0.47, 0.20, 0.33]	0.01	[-0.10, 0.12]	[0.15, 0.63, 0.22]
Covariates									
Age at baseline	-0.14	[-0.27, -0.01]		-0.09	[-0.22, 0.04]				
Female	-0.07	[-0.22, 0.08]		-0.03	[-0.12, 0.07]				
Count of comorbidities	0.03	[-0.11, 0.17]		-0.04	[-0.14, 0.06]				
Depressive affect	-0.13	[-0.30, 0.04]		0.06	[-0.08, 0.20]				
Main predictors									
Education	-0.03	[-0.28, 0.21]	[0.45, 0.30, 0.25]	-0.02	[-1.08, 1.00]	[0.48, 0.08, 0.45]			
Social activity engagement	0.18	[-0.22, 0.58]	[0.13, 0.13, 0.74]	-0.29	[-0.78, 0.20]	[0.84, 0.08, 0.08]*			
Lonely	-0.09	[-0.44, 0.25]	[0.59, 0.19, 0.22]	0.14	[-0.24, 0.52]	[0.16, 0.16, 0.68]			
Education x social activity engagement	0.20	[-0.27, 0.65]	[0.14, 0.12, 0.74]	-0.00	[-0.97, 0.97]	[0.46, 0.08, 0.46]			
Education x lonely	-0.07	[-0.31, 0.17]	[0.56, 0.28, 0.16]	0.00	[-1.04, 1.03]	[0.46, 0.08, 0.47]			
Social activity engagement x lonely	0.11	[-0.29, 0.51]	[0.22, 0.17, 0.61]	-0.24	[-0.73, 0.25]	[0.77, 0.10, 0.12]			
Education x social activity engagement x lonely	0.24	[-0.22, 0.70]	[0.11, 0.10, 0.80]*	0.04	[-0.92, 1.02]	[0.43, 0.08, 0.49]			
Random effects									
Level 3 (couple)									
Intercept (SD)	0.29	[0.01, 0.65]							

Slope (SD)	0.07	[0.00, 0.19]
Intercept-slope correlation	-0.05	[-0.95, 0.94]
Level 2 (individual)		
Intercept (SD)	0.65	[0.36, 0.84]**
Slope (SD)	0.06	[0.00, 0.18]
Intercept-slope correlation	0.16	[-0.90, 0.96]
Residual	0.67	[0.59, 0.77]**

Note. [a] 80% certainty of HDI falling within the ROPE. [b] HDI fell completely within the ROPE. [*] 80% certainty of HDI falling outside the ROPE. [**] HDI fell completely outside the ROPE.

Figure 3.3

Graphical Representation of the Post-Hoc Three-Way Interaction (Education x Lonely x Social Activity Engagement) for Processing Speed



Note. The x-axis represents point estimates of processing speed performance (higher score = better performance). The y-axis lists all combinations of high (+1 SD) or low (-1 SD) levels of loneliness and social activity. The top panel reflects those with high (+ 1 SD) levels of education, and the bottom panel reflects those with low (-1 SD) levels of education. Distributions indicate HDIs (larger dispersions reflect greater uncertainty in the estimates).

3.4.3. ELMS – Category Fluency

Our next series of analyses were undertaken to further examine possible interactions of education with different measures of social network resources as predictors of category fluency using data from the cross-sectional ELMS study. An initial model showed that engagement with life (B = 0.18, $HDI_{95\%}$ = [0.07, 0.30]) and education (B = 0.22, $HDI_{95\%}$ = [0.11, 0.33]) were both meaningful predictors of category fluency performance controlling for the covariates. Among the covariates, age (B = -0.31, $HDI_{95\%}$ = [-0.42, -0.21]) physical health (B = 0.17, $HDI_{95\%}$ = [0.06, 0.28]) and sex (B = 0.29, $HDI_{95\%}$ = [0.18, 0.39]) were meaningful predictors of category fluency performance. Psychological wellbeing trended in the same direction, where although we could not exclude a negligible effect ($P_{(within\ ROPE)}$ = 23.3%), the balance of evidence was in favour of a meaningful effect (B = 0.09, $HDI_{95\%}$ = [-0.02, 0.20], $P_{(meaningful)}$ = 76.0%). These findings were consistent with expectations, indicating that those with higher levels of education, who were more engaged with life, were younger, had better physical health, had better psychological wellbeing, and were female showed better performance on the category fluency task.

In terms of the main predictor variables, structure, function, and quality social resource measures were not meaningful predictors of category fluency performance (see Tables 3.9, 3.10, and 3.11 for highest order models for structure, function, and quality respectively). Further, no interactions emerged between education or age with structure (B = 0.02, $HDI_{95\%}$ = [-0.11, 0.15], $P_{(within\ ROPE)}$ = 53.60%), function (B = -0.02, $HDI_{95\%}$ = [-0.14, 0.10], $P_{(within\ ROPE)}$ = 57.00%), or quality (B =-0.06 , $HDI_{95\%}$ = [-0.19, 0.08], $P_{(within\ ROPE)}$ = 40.10%) social resources. These findings did not support the hypothesis that social resources would moderate the relationship between education and category fluency.

To address our final research question regarding effects of social resources independent of broader engagement with life, the higher order models were re-run controlling for engagement with life. These models were primarily exploratory given that we did not observe associations of social resources with fluency. The results confirmed that both engagement with life (structure: $B = 0.15$, $HDI_{95\%} = [0.02, 0.28]$; function: $B = 0.15$, $HDI_{95\%} = [0.03, 0.28]$; quality: $B = 0.15$, $HDI_{95\%} = [0.03, 0.26]$) and education (structure: $B = 0.20$, $HDI_{95\%} = [0.09, 0.31]$; function: $B = 0.20$, $HDI_{95\%} = [0.09, 0,31]$; quality: $B = 0.21$, $HDI_{95\%} = [0.09, 0.32]$) remained meaningful predictors even when social resources variables were included in the models.

Table 3.9

ELMS Model of Education x Network Structure x Age as Predictors of Category Fluency Performance

Parameter	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE
Intercept	-0.01	[-0.11, 0.10]	
Covariates			
Female	0.33	[0.23, 0.44]**	
Psychological wellbeing	0.10	[0.00, 0.21]	
Physical health	0.14	[0.03, 0.25]	
Main predictors			
Age	-0.24	[-0.25, -0.13]**	[1.00, 0.00, 0.00]
Education	0.22	[0.11, 0.33]**	[0.00, 0.00, 1.00]
Structure	0.05	[-0.06, 0.16]	[0.04, 0.46, 0.50]
Education x network structure	-0.06	[-0.18, 0.05]	[0.60, 0.38, 0.03]
Education x age	0.05	[-0.07, 0.16]	[0.06, 0.47, 0.48]
Network structure x age	-0.07	[-0.18, 0.05]	[0.60, 0.38, 0.02]
Education x network structure x age	0.02	[-0.11, 0.15]	[0.14, 0.54, 0.32]

Note. [a] 80% certainty of HDI falling within the ROPE. [b] HDI fell completely within the ROPE.

[*] 80% certainty of HDI falling outside the ROPE. [**] HDI fell completely outside the ROPE.

Table 3.10

ELMS Model of Education x Network Function x Age as Predictors of Category Fluency Performance

Parameter	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE
Intercept	-0.00	[-0.11, 0.11]	
Covariates			
Female	0.33	[0.23, 0.44]**	
Psychological wellbeing	0.10	[-0.01, 0.20]	
Physical health	0.14	[0.03, 0.25]	
Main predictors			
Age	-0.24	[-0.35, -0.13]**	[1.00, 0.00, 0.00]
Education	0.23	[0.11, 0.33]**	[0.00, 0.00, 1.00]
Function	0.00	[-0.11, 0.11]	[0.18, 0.62, 0.20]
Education x network function	0.04	[-0.07, 0.14]	[0.05, 0.55, 0.41]
Education x age	0.05	[-0.06, 0.17]	[0.04, 0.44, 0.52]
Network function x age	0.02	[-0.09, 0.13]	[0.09, 0.59, 0.32]
Education x network function x age	-0.02	[-0.14, 0.10]	[0.30, 0.57, 0.14]

Note. [a] 80% certainty of HDI falling within the ROPE. [b] HDI fell completely within the ROPE.

[*] 80% certainty of HDI falling outside the ROPE. [**] HDI fell completely outside the ROPE.

Table 3.11

ELMS Model of Education x Network Quality x Age as Predictors of Category Fluency Performance

Parameter	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE
Intercept	-0.00	[-0.11, 0.10]	
Covariates			
Female	0.33	[0.23, 0.43]**	
Psychological wellbeing	0.10	[-0.01, 0.21]	
Physical health	0.15	[0.04, 0.25]	
Main predictors			
Age	-0.24	[-0.35, -0.13]**	[1.00, 0.00, 0.00]
Education	0.23	[0.11, 0.34]**	[0.00, 0.00, 1.00]
Quality	-0.06	[-0.17, 0.06]	[0.55, 0.42, 0.03]
Education x network quality	0.04	[-0.08, 0.17]	[0.06, 0.49, 0.45]
Education x age	0.04	[-0.07, 0.16]	[0.06, 0.50, 0.44]
Network quality x age	0.04	[-0.07, 0.15]	[0.07, 0.52, 0.41]
Education x network quality x age	-0.06	[-0.19, 0.08]	[0.54, 0.40, 0.06]

Note. [a] 80% certainty of HDI falling within the ROPE. [b] HDI fell completely within the ROPE. * 80% certainty of HDI falling outside the ROPE. ** HDI fell completely outside the ROPE.

3.5. Discussion

The major goal of the present study was to examine whether social resources appeared to play a compensatory role in buffering the effects of ageing on cognition among those with limited educational opportunities. To answer our research question, we analysed five-waves of longitudinal data over a 13-year period from ALSA participants. We considered key individual differences including sex, age, comorbidities, and depressive symptoms. Importantly, we also controlled for possible reverse causality by excluding participants who had probable dementia at baseline, and by including follow-up analyses where we excluded participants classified as having possible dementia at follow-up assessments. Further, we conducted additional analyses using ELMS to consider interactions of education with multiple different types of social resources (i.e., structure, function, quality) in predicting category fluency. Finally, analysis of ELMS allowed us to consider whether associations of social resources and cognition were or were not independent of general engagement with life.

The independent associations of our social resource variables (social activity participation and loneliness) with cognition based on our analysis of ALSA were partially consistent with our expectations and the wider literature. Specifically, our findings revealed that higher social activity engagement was weakly associated with overall better performance on tests of processing speed. This finding was consistent with models of cognitive ageing that suggests social activity is a cognitively stimulating lifestyle activity that encourages mental exercise and in turn improves cognition (e.g., Hertzog et al., 2008). However, this finding was not replicated in the initial letter fluency findings. Further, the ALSA results showed that loneliness was associated with worse performance on tests of initial letter fluency and processing speed. This finding was broadly consistent with past research that suggests loneliness negatively impacts cognition by way of deleterious biological (i.e., cortisol secretion) and psychological (i.e., increased stress and rumination, and decreased positive affect) mechanisms (Boss et al., 2015). Together, these findings suggest that not experiencing loneliness could have a role to play in maintaining cognitive functioning in older adulthood. However, the lack of consistency in findings across the two cognitive outcome measures in ALSA, and the fact that social network associations with category fluency were not replicated in ELMS raises questions as to the robustness of social engagement-cognition associations.

Although we did find some (albeit inconsistent) support for associations of quantity (i.e., social activity engagement) and quality (i.e., emotional loneliness) social resources with levels of cognition in our analysis of ALSA, we consider some reasons for why these associations were not replicated in ELMS. First, we suspect the reason we found our structural resource variable to predict fluency performance in the ALSA findings (i.e., social activity engagement variable) but not in the ELMS, was the difference between the measures used. Specifically, the type of structural variable used in ELMS (i.e., number and frequency of contact with close networks) was based on the notion that having a larger network size provides greater opportunity for engagement with stimulating activity with these networks, which in turn would contribute to preserved cognition (Berkman et al., 2000). One of our aims in the present study was to extend on the findings of Windsor et al (2020) by using a variable that more directly captured engagement in social activity. The fact that we found some associations using the activity measure, but not the measure of network size supports the possibility that measurement limitations may have contributed to Windsor et al. (2020) not finding direct support for their compensatory reserve hypothesis. This speculation is supported by the ELMS finding of associations between general engagement with life and category fluency performance, where our engagement with life variable targeted engagement in meaningful activities, which in many cases may include a social component. Second, an additional difference in how social resources were measured was that they were only assessed at one time point in the cross-sectional dataset, whereas social resources were assessed at multiple timepoints in the longitudinal dataset. This gave us the ability to create an average score for each participant across multiple assessments, which may have provided a more reliable index compared to a one-off assessment as was the case in ELMS.

Although we speculate that the lack of consistency between social resource and cognition associations in our study can be explained by differences in social resource measures across our two datasets, we also consider that the wider literature also shows inconsistencies in findings of social-cognition associations. Specifically, where many studies have reported a relationship between structural social resources (i.e., network size and network contact frequency) and cognition (see meta-analysis summary by Kuiper et al., 2016), there have been other studies that have not found associations between structural or functional social resources on cognition (e.g., Aartsen et al., 2002; Albert et al., 1995; Bassuk et al., 1999). There are several possible reasons underlying these discrepancies in the literature. First, although Kuiper et al.'s (2016) systematic review and meta-analysis ultimately supported associations of social resources and cognitive performance, they acknowledged that the heterogeneity of study designs made it difficult to draw firm conclusions about the strength of the associations and thus the relative importance of the different relationship aspects (i.e., structure versus function). Second, the pooled odds ratio (and confidence interval) estimates reported in this meta-analysis for both (a) poor structural social relationships and cognitive decline (OR = 1.08, CI = [1.05, 1.11]) and (b) poor functional social relationships and cognitive decline (OR = 1.15, CI = [1.00, 1.32]) were equivalent to a small effect size (see Chen et al., 2010).

It has also been suggested that the size of effects representing associations of social resources with cognition may have been overestimated due to publication bias issues. Specifically, Kuiper et al. (2016) referred to exploratory studies who did not report relationships between social resource variables with cognitive abilities because no effect was found (contributing to the ongoing filing drawer crisis; Rosenthal, 1979). A final explanation we offer for the lack of social-cognitive associations from our ELMS results is our use of Bayesian estimation, in contrast to the majority of gerontological research where frequentist approaches have been applied. It has been demonstrated that although Bayesian and frequentist approaches generally agree about which hypothesis is best supported by the data (alternative or null hypothesis), the strength of the support (or lack of) differs (Brydges & Bielak, 2020), with Bayesian analyses often being more conservative in estimating evidence in favour of an effect than Frequentist approaches (Wetzels et al., 2011). Given that the evidence is not compelling in the literature (i.e., small effects), it may be that our use of Bayesian estimation did not allow us to overestimate the evidence in favour of an effect in an area where effect sizes are generally small.

An additional aim of the study was to use our cross-sectional ELMS data to determine whether social resources offer something unique as a protective factor for cognition above and beyond being engaged with life in a more general sense. Our findings of general engagement with life based on the cross-sectional ELMS analysis were supportive of the wider literature (e.g., Hultsch et al., 1999; Small et al., 2012; Stine-Morrow et al., 2007) with scores on the life engagement test positively associated with category fluency performance. This suggests that meaningful activity in general (regardless of whether it is social in nature) may contribute to improvements in cognition. However, there were no associations of network structure, function, or quality resources with category fluency (before or after including engagement with life in the model). It therefore remains unclear whether structural social network benefits observed for cognition are due to conceptually similar processes to those associated with intellectual engagement more generally (i.e., use it or lose it; Hultsch et al., 1999). Future research may benefit in using more fine-grained social resource measures (i.e., similar to our social activity engagement measure in ALSA) to re-test similar questions in order to tap into the underlying mechanisms explaining a social-cognition relationship.

3.5.1. Social Resources, Education, and Trajectories of Cognitive Functioning in Later Life

Of key interest to the present study was whether social resources could act as a buffer for cognition for those who had low educational attainment. We found some support for this theory. Specifically, the nature of the four-way interaction found in the ALSA processing speed findings (displayed in Figure 3.1) indicated that the most vulnerable group of older adults (in terms of decline in processing speed over time) were those who had low education, were lonely, and had low levels of social activity participation. There was a meaningfully slower rate of decline in processing speed over time for those who had low education but were *not* lonely and had *high* social activity participation. This finding was consistent with the notion that social activity engagement and not feeling lonely could act as a buffer to cognitive decline in the context of those with low educational attainment in line with the compensatory reserve hypothesis (Windsor et al., 2020). These findings are consistent with previous work by Murayama et al.

(2019) who found that having a strong "district-level" social network buffered the relationship between low education and cognitive impairment.

With the opportunity to exclude participants who developed incipient dementia over the course of the study, we were able to investigate the interactions of social resources with education and time with a minimisation of reverse causality bias. The findings from these post-hoc analyses placed a strong caveat on the aforementioned findings. Specifically, the fact that the four-way interaction no longer existed once this sample was excluded indicates that these participants were driving the within-person changes captured by the interaction. This means that it is equally plausible that reverse causality can explain these findings. For instance, those participants who developed dementia as the study progressed may have not been cognitively able to continue with their usual social engagements and may have felt more isolated as a result of their illness (Victor et al., 2020). Thus, these findings should be interpreted with caution.

Although the four-way interaction was no longer meaningful after participants who developed dementia over the study period were excluded from the analyses, the meaningful three-way interaction of education x social activity engagement x loneliness was retained. The unexpected pattern (displayed in Figure 3.3) that emerged indicated that processing speed performance was particularly poor for those who had high levels of education and had the high vulnerability combination of being both lonely, and having low levels of social activity engagement. It is unclear why these findings were observed for those with higher levels of education who might be expected to be better 'protected' on account of cognitive reserve (Stern, 2002), and not among those with lower education. One possible explanation is reverse causality. It may be the case that those with higher levels of education are more likely to routinely engage in more cognitively demanding activities as facilitators of social interaction (e.g., playing bridge, book clubs, etc.). Thus, as their cognitive ability begins to show more noticeable declines, this might make it more difficult to remain engaged in such activities, resulting in reduced activity engagement and loneliness. In contrast, those with lower education may be better able to maintain social connections and activities in the face of some cognitive losses if those connections are not as centred around intellectually challenging activities. It is also possible that the results represent a chance finding, as the data were relatively sparse for those with the combination of high levels of education, low levels of social activity engagement, and were lonely.

3.5.2. Strengths, Limitations, and Outlook

The primary purpose of this study was to extend the existing knowledge of how social resources contribute to the maintenance of cognition in later life. First, given the inconsistency of findings across studies, we are not confident that social activity engagement independently contributes to cognitive test performance. Second, our findings did not provide consistent evidence in support of a compensatory role of social resources in protecting against educational disadvantage. However, we did find some evidence of a non-negligible effect in the form of a complex four-way interaction in the ALSA processing speed findings, where social activity engagement and loneliness together appeared to play a protective role in maintaining processing speed over time for people who had low educational attainment. These findings suggest that further examination of the combined effects of social disadvantage and social resources in older adults appears warranted.

A major strength of our study was the utilisation of Bayesian analyses. Most previous studies observing whether relationships exist between social resources, cognition, and social disadvantage variables have adopted a frequentist approach. Using a Bayesian approach allowed us to not only draw conclusions about how certain we are that a true effect exists, but also to determine how certain we are that a true effect does not exist. For example, for many time x social resource interactions for initial letter fluency performance (see Table 3.4), the evidence was favouring the null hypothesis (i.e., the likelihood was over 80% that the true estimate fell within our prior appointed negligible range). Specifically, as opposed to finding $p > 0.05$ and stating failure to reject the null, we were able to demonstrate a greater certainty of accepting the null. For example, initial letter fluency performance did not change over time regardless of social activity engagement levels.

We acknowledge several limitations to our study. Firstly, although a benefit of the longitudinal design was to capture changes across longer time periods, we acknowledge that the generalisability of the participants providing the most longitudinal data points likely represent a positively biased minority of the sample. Second, we were not able to use the complete set of data provided by the Australian Longitudinal Study of Ageing as the key social and cognitive variables of interest were not available at all waves. Third, as our design was correlational in nature there are several non-competing explanations for our results that cannot be ruled out. Specifically, although in ALSA we have taken measures to reduce the possibility of finding a reverse causality effect (i.e., excluding participants with probable dementia for our main analyses), it is possible that those who are more cognitively engaged seek out stimulating activities that include social engagement. This was supported by the findings after controlling for time-varying probable dementia status in follow-up analyses. Similarly, the findings arising from the ELMS analysis could indicate that people report higher engagement with life because they are more cognitively able. Indeed, a bi-directional relationship where cognitive ability and engagement with life work interdependently to support each other seems eminently plausible.

There may also be other third factor variables which can explain the relationship between social resources and cognition that were not accounted for in our analysis. For example, those who have a natural predisposition to engaging in intellectually stimulating activities are more likely to find themselves in social situations, and the mental stimulation may be potentially maintaining cognition (Curtis et al., 2015). Finally, more reliable, accurate measures of activity engagement than were available in the current studies could be used. For example, our measure of social activity engagement in ALSA only asked participants to consider four specific areas of social engagement (inviting others to their home, making telephone calls to friends and family, participating in social activities at a centre, and participating in outdoor social activities) and various additional contexts for social activity exist (e.g., social events with friends or family such as parties or dinners, working or volunteering, and physical activity group classes). In addition, participants were asked about activity during "the past month" which may be a non-reliable estimation of actual activity level that is subject to recall bias. For more reliable estimates, future research might employ the use of daily-diary measures (e.g., Bielak et al., 2019). For example, Bielak (2017) created a composite measure with items loading on different activity domains, to assess daily covariation of activity engagement and cognition. Similarly, our loneliness measure (although it has been used in previous work, e.g., Courtin & Knapp, 2017; Menec et al., 2019; Wagner et al., 2013), may not be as reliable as established loneliness measures (e.g., see Veazie et al., 2019 for a review of the most common instruments used to measure social isolation).

To sum up, our findings showed non-negligible (but weak) evidence for the compensatory reserve hypothesis. Specifically, the findings suggested that high social activity engagement and not feeling lonely was protective of decline in processing speed ability over time among people who had low levels of education. However, given that this interaction was no longer meaningful after excluding observations for people with incipient dementia, we are careful to attribute too much weight to these findings. It is encouraged that future research tests similar questions using more fine-grained social resource (activity and support) measures to determine whether these findings can be replicated. Such research is necessary to continue to develop an understanding of how social resources might play an important function in maintaining cognition in socially disadvantaged older adults.

CHAPTER 4: Do Older Adults' Daily Social Activities Relate to Fluctuations in Daily Perceptual Speed Performance? A Diary Study

4.1. Introduction

We commonly hear anecdotal remarks about people feeling sharper or slower on a given day based on what activities were or were not engaged in. Across longer, or 'macro' time scales (see Ram & Gerstorf, 2009), accumulating research evidence supports the notion that activity engagement is related to cognition in older adulthood. For example, both cross-sectional and longitudinal studies have demonstrated that older adults who engage in more social, cognitive, and physical activities have better cognitive outcomes relative to those who engage in activities less frequently (Kuiper et al., 2016). Past research has suggested a range of possible mechanisms explaining why activity might benefit cognition. Postulated mechanisms explaining long-term changes in cognition focus on biological processes that are likely driven by neurological changes. For example, the cognitive reserve hypothesis proposes that engaging in cognitively demanding activity, including social interactions, could provide cognitive stimulation which builds cognitive reserve over time (biological studies have found evidence of angiogenesis, synaptogenesis, and neurogenesis; Fratiglioni et al., 2000) and ultimately may produce resilience to cognitive decline even in the face of neuropathology (Hultsch et al., 1999; Stern, 2002; Stine-Morrow et al., 2021). The stress-buffering hypothesis also suggests that social interactions may play a protective role in reducing stress-related deleterious responses in the brain (e.g., excessive or dysregulated cortisol secretion) as social support can help reduce stress (Kelly et al., 2017). Such biological mechanisms are likely slow-acting and have been described in the literature to manifest over years or decades (Bielak et al., 2019).

Less is known about how social interactions relate to fluctuations in cognitive function across shorter time scales. Some scholars have pointed to shorter-term psychological processes linking greater activity engagement to better cognition. For example, greater engagement with social networks have been shown to enhance emotional wellbeing, improve quality of life, and reduce stress (Bielak, 2010). Such psychosocial variables (e.g., emotional support and self-efficacy) have been shown to be linked to better cognitive performance in older age (Zahodne et al., 2019). Additionally, immediate boosts in positive affect (Ashby et al., 1999; Isen, 1999) or motivation (Chiew & Braver, 2011; Pessoa, 2009), which can result from social interactions, have been shown to relate to improvements in short-term cognitive performance (Weizenbaum et al., 2020). In general, the proposed mechanisms outlined in the literature differ when considering how longer-term cognitive changes as opposed to daily fluctuations in cognition might be determined by social activity engagement. However, it is also possible that changes in routine activity causes short-term gains in cognitive performance, which over time could have cumulative longer-term protective implications for cognition (Bielak et al., 2019).

The current study examined whether cognitive performance among older adults on a given day was related to the type of activity that was engaged in that day (i.e., 'micro' time scale). We were particularly interested in whether daily *social* activity engagement (social-private and social-unfamiliar activity) covaried with cognitive performance. In addition to social activity domains, we also assessed daily covariation between general activity domains (information, cognitive, physical, games, and television activities) and cognition, consistent with previous daily studies (Allard et al., 2014; Bielak et al., 2019; Phillips et al., 2016; Whitbourne et al., 2008). We also examined whether cognitive performance on a given day was related to social interaction quality, by examining associations of enjoyment levels of daily pleasant social exchanges, or severity levels of stressful social exchanges, with daily cognition. Evidence for coupling of social exchange quality with cognitive performance could indicate that the affective component of social relationships is implicated in short-term mechanisms linking social engagement with cognition (Fredrickson, 2001, 2004). Finally, we were interested in whether a stronger association between greater occasion-specific enjoyment levels and better cognitive performance existed for those who reported experiencing lower enjoyment levels of positive exchanges in general (i.e., acute boosts in cognition due to the novelty of experiencing a positive interaction). Similarly, we were interested in whether a person's average severity of negative exchange levels moderated the predicted relationship between greater severity levels of daily negative social exchanges and worse cognitive performance.

4.1.1. Social Activity and Cognition

Research examining specific activity domain associations with cognitive outcomes at the daily level has been scarce, and findings have been mixed. To date we are only aware of a small number of studies evaluating different types of activity-cognition relationships at the daily level (e.g., Allard et al., 2014; Bielak et al., 2019; Neupert et al., 2006; Phillips et al., 2016; Whitbourne et al., 2008; Zhaoyang et al., 2021). In terms of broader activity engagement, the most consistent finding across these studies (aside from Whitbourne et al., 2008) was that engaging in different levels of routine physical activity does not appear to be associated with changes in daily cognitive performance (Allard et al., 2014; Bielak et al., 2019; Phillips et al., 2016). There were some findings of covariation of other activity and cognitive domains (e.g., Allard et al., 2014 found time-lagged associations of daily intellectual activities with daily semantic memory performance), however these findings were less consistent across studies.

More closely aligned to the social focus of the present study, a limited number of studies have evaluated within-person associations of social activity in particular with changes in daily cognitive outcomes. Bielak (2019) examined a wide range of daily activities, and found that daily social-private activities (i.e., socialising with close others was most highly endorsed in this factor) were more consistently (and positively) associated with day-to-day fluctuations in cognition than any other activity domain. Specifically, analysis of within-person associations showed that on days when social-private activity was higher, participants performed better on tests of perceptual speed and memory. Daily social-unfamiliar activities (i.e., meeting someone new) was also positively associated with Word Recognition performance but not with other cognitive outcomes. Further, a recent study by Zhaoyang et al. (2021) used an ecological momentary assessment approach where participants completed surveys on social interactions and mobile cognitive assessments five times a day. Within-person analyses revealed that having more daily social interactions was associated with better cognitive functioning on the same day and across the subsequent two days. They also extended previous work by capturing affective features of social engagement, where they found a positive association between pleasant social situations with cognitive functioning at the daily level. These two studies provide preliminary evidence of a positive relationship between social resources and cognition at the daily level.

Of the small number of studies that have examined associations of social activity with cognitive performance across micro- time scales, not all have shown consistent results. Most notably, a study by Allard et al. (2014) did not reveal evidence in support of daily covariation between social activities and semantic memory performance. However, we suggest three possible explanations for the discrepancy in these findings compared to Bielak et al. (2019) and Zhaoyang et al. (2021). First, Allard et al. (2014) created an ecological momentary assessment study that sent out five surveys regarding activity and social company, and randomly administered mobile cognitive assessments at two of the five time points per day. If a social activity occurred after the last cognitive assessment for the day, this risked the chance of the association being missed (if daily social activity precedes daily cognitive change). Whereas, as Zhaoyang et al. (2021) assessed cognition at each timepoint in the day, this ensured events were appropriately sequenced in time. Similarly, Bielak et al. (2019) included appropriately sequenced assessments, where cognitive measures were completed once per day *after* the reported activity engagement surveys. Second, Allard et al. (2014) did not differentiate between types of social exchanges like the other two studies did, which could have confounded their results (given that Bielak et al. found social-private activities were a stronger predictor of cognition than social-unfamiliar activities). Finally, the sample size was substantially smaller in Allard et al. (n = 60) than the two other studies (n = 146 and n = 312 respectively for Bielak et al., 2019b and Zhaoyang et al. 2021), and therefore may have been underpowered. Thus, although inconsistencies and limited current research evidence regarding daily social activities and daily cognition exists, the positive results from the more recent studies mean that this represents a promising area for research.

In the present study, our available data and assessments were similar to those reported in Bielak et al. (2019). Specifically, our data allowed for differentiation of ‘private’ and ‘unfamiliar’ social activity domains. Daily activities assessed also preceded cognitive assessments. We expected our replication of previous daily diary studies to reveal positive covariation of social activity engagement with cognition. Finally, we extended previous work by examining associations of quality of social exchanges with daily cognition by not only focussing on positive interactions (like Zhaoyang et al., 2021), but also negative interactions (i.e., enjoyment levels of positive social exchanges and severity levels of negative social exchanges). Because social activity can produce positive or negative affect, we explored whether reporting different enjoyment and perceived severity (a proxy for negative affect) levels of positive or negative daily social encounters respectively was associated with better, or worse daily cognitive test performance.

4.1.2. The Positive and Negative Affective Components of Social Exchanges and Cognition

Little is known about possible beneficial effects of day-to-day positive social encounters in later life on short-term fluctuations in cognitive test performance. Frederickson's broaden and build theory provides an initial basis for postulating mechanisms that could underlie links between positive social exchanges and short-term boosts in cognitive performance. This theory proposes a relationship between positive emotions and intellectual resources, such that positive emotions broaden an individual's scope for attention and in turn promote improvement in cognition (Fredrickson, 1998, 2001, 2004). This theory has been supported by multiple studies showing that positive affect can improve performance on various cognitive tasks (Bryan et al., 1996; Bryan & Bryan, 1991; Isen, 1987, 1999; Isen & Means, 1983; Masters et al., 1979), and is broadly consistent with research from the cognitive ageing literature pointing to positive associations of supportive social exchanges with cognition (e.g., Windsor et al., 2014). Given some experimental work has shown immediate effects of social interactions positive in nature (although affect was not directly manipulated) on cognitive performance (e.g., Ybarra et al., 2008, 2011), and based on the findings of Zhaoyang et al. (2021) reported above, we also expected to find positive within-person daily coupling of positive social interactions (enjoyment ratings) with cognitive test performance. In light of associations of positive social network attributes with cognitive performance reported in previous cross-sectional and long-term longitudinal studies (e.g., Kuiper et al., 2016; See Chapters 1 and 3) we also expected to find that engaging in positive social exchanges would be associated with overall better cognitive test performance at the between-person level.

In contrast, negative social exchanges have been thought to have a detrimental effect on cognitive outcomes, particularly in the context of cognitive decline in older adulthood (Wilson et al., 2015). Such associations are often explained by stress induced physiological changes that have the potential to impact cognition (e.g., increased cortisol levels and more rapid progression of plaque build-up in the arteries), as a consequence of having limited support networks to help through stressful day-to-day and larger scale life events. There have been a small number of studies investigating the relationship between negative social exchanges and cognitive ageing using cross-sectional and longitudinal study designs, with evidence to support the notion that negative social exchanges are related to worse cognitive outcomes (Tun et al., 2013; Wilson et al., 2015; though not all studies in this area have produced consistent findings, for example, see Seeman et al., 2001; Windsor et al., 2014).

The mechanisms explaining short-term within-person associations of negative exchanges with cognition are different to those that might be invoked to account for the cumulative long-term effects of bio-psychosocial processes that unfold over decades. One example of a short-term mechanism that could underlie links between negative social exchanges and cognitive performance has been referred to as *cognitive interference*. Specifically, researchers have found that experiencing stress reduces performance on cognitive tasks, and that this may in part be due to rumination about the stressor making it difficult to focus on the cognitive task at hand (Stawski et al., 2006). As rumination is a known depressive feature, this premise fits with the well-established findings that low wellbeing or depressive symptoms are associated with poorer cognitive outcomes in older adults (e.g., Thomas & O'Brien, 2008). There has been evidence of intraindividual coupling of daily stress and cognition (Sliwinski et al., 2006) and experimental work showing that acute stress can be highly disruptive for working memory (Luethi et al., 2009). Most closely related to the social aspect of the present study, Neupert et al. (2006) found that on days when older adults experienced interpersonal stressors with friends and family, they were more likely to report memory failures. Taking these findings together, and recognising negative social exchanges as a commonly experienced and significant source of stress (Rook et al., 2012), we predicted that more severe daily negative social exchanges would be associated with poorer daily cognitive test performance.

4.1.3. Does a Person's Average Level of Positive/Negative Social Exchanges Moderate the Relationship Between Daily Positive/Negative Social Exchanges and Cognition?

Finally, we aimed to extend the literature by considering the possibility that the *novelty* of the social exchange, or the extent to which it is, or is not consistent with more typical social experiences, plays a role in determining the degree of association with cognitive performance. It is possible that one's typical experience of social exchanges (both positive and negative) may contribute to the variability in the effects of occasion-specific social exchanges on cognition, and may even help to explain why some studies have failed to find associations of social network quality with cognition (e.g., Albert et al., 1995; Bassuk et al., 1999). In the present study, the possible moderating role of more typical social exchange experiences assessed at the between-person level on associations of daily social exchanges with cognition was examined (i.e., BP X WP interactions).

Justification for our focus on the cross-level interactions can be derived from emerging work in the health neuroscience field (Erickson et al., 2014). In line with the premise that health benefits of physical activity may be more pronounced for less healthy, or less active individuals (Stenling et al., 2021), there has recently been a push in this field to take more stable, enduring characteristics into account when designing and interpreting the effects of interventions on cognition (Stillman & Erickson, 2018). For instance, one study found that within-person physical activity (i.e., occasion-specific deviations from the participants own mean activity levels) had stronger positive associations with cognition for individuals who had lower average levels of physical activity (Stenling et al., 2021). More closely aligned to the affect focus of the present study, another daily study found that those who had a greater sense of purpose at baseline experienced less of an increase in daily positive affect after experiencing a positive event (i.e., between-person sense of purpose moderated the within-person association between daily positive events and daily positive affect) (Hill et al., 2020). This finding that higher levels of positivity at baseline may reduce responsivity to positive events in daily life is in line with our proposed premise of *novelty* of a social experience being a potentially important contextual factor in determining whether that social encounter has implications for cognitive test performance on the same day. Finally, a recent study found that the average levels of positive social interactions (between-person) moderated the positive relationship between daily positive social exchanges and same-day cognition (within-person) (Zhaoyang et al., 2021). Specifically, stronger associations of daily positive exchanges with cognitive test performance were evident among those who reported less frequent positive exchanges in general. We therefore expected that people who typically experience less frequent positive social exchanges are more likely to reap the acute cognitive benefits (possibly via broaden-and-build processes) from a positive social exchange on a given day than someone who more regularly experience positive social exchanges. Finally, we extend on previous studies by also considering BP X WP interactions for negative social exchanges. Specifically, we expected daily associations of negative social exchanges with poorer cognitive performance (possibly as a result of cognitive interference) to be stronger among those who generally experience negative social exchanges less frequently.

4.1.4. Current Study

The present study used Transitions in Later Life Study (TRAILLS) data, where older adults provided daily online measures of activity engagement (social-private, social-unfamiliar, cognitive, information, physical, games, and television) and cognition (processing speed was assessed via correct response time on a symbol search task) for seven days across a two-week period. As the activity engagement items were completed in relation to the day that passed prior to undergoing the cognitive tests, this temporal ordering provided some general support for possible causal links between daily activity engagement and cognition where daily covariation was observed. Our study extended that of Bielak et al. (Bielak et al., 2019) who used a similar design to test daily coupling of a variety of routine activity domains with cognitive outcomes. Consistent with their study, we aimed to evaluate whether 1) any differences existed between types of activities on baseline cognitive performance (between-person differences), and 2) whether engaging in different types of daily activities covaried with daily variability in cognitive outcomes (within-person differences). Although the main focus of the present study was to consider the between- and within-person fluctuations separately, we also looked at the BP X WP interactions for activity engagement for completeness. Based on the Bielak et al. findings:

1. We expected social activity to be negatively associated with the intercept for performance on correct response time (between-person analyses). This would indicate that greater social activity engagement is associated with faster reaction time overall.

2. We expected social activity to negatively covary with correct response time (within-person analyses). This would indicate faster reaction times on days when participants had engaged in social activity.

Second, our extension of Bielak et al.'s (2019) study tested whether the affective valence ascribed to a social exchange on a given day (i.e., enjoyment ratings associated with perceived positive social exchanges, and severity ratings associated with perceived negative social exchanges) was differentially associated with day-to-day cognition (similar to Zhaoyang et al., 2021). When considering the valence of social exchange quality at the daily level and how it relates to cognition, we predicted that:

3. Enjoyment ratings of positive social exchanges would negatively covary with correct response time daily.
4. Severity ratings of negative social exchanges would positively covary with correct response time daily.

Finally, we were interested in cross-level interactions (i.e., BP x WP) to examine contextual effects of more typical relationship quality on daily social experiences and cognitive test performance. Specifically, our final research question concerned whether between-person levels of enjoyment/severity of positive/negative social exchanges respectively moderated the relationships between daily enjoyment/severity scores and daily processing speed at the within-person level (i.e., occasion-specific deviations from the participant's own mean). We expected that:

5. Those with greater severity of negative exchanges ratings (at the between-person level) would show weaker positive within-person associations of daily severity of negative exchanges scores with digit span performance.

6. Those with greater enjoyment of positive exchanges ratings (at the between-person level) would show weaker negative within-person associations of daily enjoyment of positive exchanges scores with digit span performance.

4.2. Method

4.2.1. Participants and Procedure

The data used in the current analysis were collected in 2010 as part of the TRAILLS (Curtis et al., 2015). Participants living in Australia aged 50 years or older were recruited via an email invitation that was sent to all members of a non-profit organisation (National Seniors Australia). This resulted in recruitment of a convenience sample of 239 adults aged between 51 and 84 years. All aspects of the study were completed online by participants using a home computer. At baseline, participants completed questions regarding basic demographic information, and their mental and physical health. They also completed up to 7 daily diary questionnaires assessing a variety of types of activity engagement (social, cognitive, informative, physical, games, and television), social measures (enjoyment and severity ratings respectively for a positive or negative social interaction experienced on a given day) and cognitive performance (symbol search correct response time). Participants were asked to complete the 7 daily questionnaires at approximately the same time each day in the evening, within two-weeks of the baseline assessment.

Given that the main focus of the present study was to investigate whether engaging in certain activities on a given day related to fluctuations in cognition, all analyses were reported using the activity sample (unless otherwise stated). Participants were included in the activity sample (n = 147; age M = 61.62, SD = 5.74; *female* = 58.50%) if they completed all covariate measures (e.g., age, gender, education, health, and depressive symptoms), at least one day of complete data on all activity measures and the processing speed task (175 complete assessments). However, to best use the available daily data for the social measures, we analysed separate samples to answer our research questions about whether engagement in positive and negative social exchanges on a given day relate to cognitive performance on that given day. Specifically, participants were included in the positive interactions sample (n = 114) if they completed all covariate measures, gave a positive interaction enjoyment score on at least one day, and completed the cognitive task on at least one day. Similarly, participants were included in the negative interaction sample (n = 167) if they completed all covariate measures, responded to the negative interaction severity score on at least one day, and completed the speed task on at least one day. For all samples, to preserve an appropriate degree of time elapsed between assessments, data were excluded for a given assessment if it took place less than 18 hours following the preceding assessment. On average, participants in the activity, positive, and negative samples completed 4.75, 3.66, and 4.98 daily assessments respectively (out of a maximum 7 days). Further, for activity, positive, and negative samples, 45.1%, 21.6%, and 51.7% of the respective samples completed 6 or more assessments. Descriptive information on key study variables are presented in Table 4.1.

Table 4.1

Descriptive Information and Bivariate Correlations on Key Study Variables

	Mean *(SD)*	*Range*	Correlations 1	2	3	4	5	6	7
Daily assessments on activity variables[a]									
1. Social-private	6.36 (3.92)	0 – 32	--						
2. Social-unfamiliar	3.49 (2.41)	0 – 16	0.06	--					
3. Information	5.74 (2.31)	0 – 24	-0.02	0.12	--				
4. Cognitive	5.41 (2.87)	0 – 16	0.12	0.21	0.29	--			
5. Games	0.78 (1.58)	0 – 8	-0.07	0.14	0.25	0.28	--		
6. Television	3.56 (1.58)	0 – 8	0.07	0.03	0.07	-0.20	-0.06	--	
7. Physical	8.95 (6.75)	0 – 48	0.19	0.20	0.02	0.10	0.07	0.05	--
Daily assessments on social exchanges									
Severity of negative exchange[b]	4.22 (1.69)	1 – 7							
Enjoyment of positive exchange[c]	5.21 (1.07)	1 – 7							

Note. [a]Daily activities were aggregated at the person level. All activity aggregates (and correlations) were calculated using the 'activity' sample. [b]Daily severity of negative exchange aggregates were created using the 'negative' sample. Descriptive statistics were calculated from the person-means of the participants who endorsed having at least one negative interaction. [c]Daily enjoyment of positive exchange aggregates were created using the 'positive' sample. Descriptive statistics were calculated from the person-means of the participants who endorsed having at least one positive interaction.

4.2.2. Measures

Daily Measures

Activity Characteristics Questionnaire.

Participants were asked to indicate how much time they spent doing certain activities in the past 24 hours. Response options included: no time at all (0); some time but less than 15 minutes (1); between 15 and 30 minutes (2); between 31 minutes and 1 hour (3); 1 to 2 hours (4); 2 to 4 hours (5); 4 to 8 hours (6); 8 to 12 hours (7); or more than 12 hours (8). Items were grouped into activity categories based closely (save for five items not included in the study) on the Activity Characteristics questionnaire (ACQ) created by Bielak (2017) which has previously been used in a daily-diary study (Bielak et al., 2019). The seven activity categories were created by taking the sum of the following items: 1) *social private* (interacting with close family and/or friends; attending cultural events; doing an activity that requires you to create something; doing things that were outside of your typical routine), 2) *social unfamiliar* (interacting with people you are not close with; meeting new people), 3) *cognitive* (actively reading; writing), 4) *information* (organising or planning; in conversations or meetings that focussed on solving a problem; leading, coaching, or mentoring others), 5) *games* (taking part in sports, games, or leisure activities that require the use of particular strategies), 6) *television* (watching television or videos), and 7) *physical activity.* Three *physical* activity items (engaging in vigorous-intensity; medium-intensity; mild-intensity activity or exercise) were combined to form one physical variable using Bielak et al.'s (2017) equation "mild exercise + (2 x moderate exercise) + (3 x vigorous exercise)", based on the presumption that light intensity exercise is approximately 1/3 of the intensity of vigorous exercise, and half the intensity of moderate exercise.

Enjoyment of Positive Interaction.

Daily positive social interactions were assessed using a binary variable that captured whether participants endorsed the positive event option of experiencing a ‘positive social interaction with one or more people’ on a given day. If the positive social interaction item was endorsed, participants were asked to rate their enjoyment of the positive social interaction when it occurred on a scale of 1 (not at all) to 7 (extremely). If participants did not report having a positive social interaction that day, they were given an enjoyment score of 0.

Severity of Negative Interaction.

Daily negative social interactions were assessed using a binary variable that captured whether participants did or did not endorse the stressful event option of having experienced an ‘argument, disagreement, or conflict’ on a given day. If the negative social interaction item was endorsed, participants were subsequently asked to rate how stressful or unpleasant the negative social interaction was when it occurred on a scale of 1 (not at all) to 7 (extremely). If participants did not endorse the item, they were given a severity score of 0.

Symbol Search.

A symbol search task was used to assess speed of processing daily. The task was an adaptation of the WAIS-IV digit-symbol coding task, several variants of which have been used in daily-diary and ecological momentary assessment studies (Thomas & O’Brien, 2008). A pair of symbols appeared at the bottom of the computer screen and five symbols appeared at the top of the screen. Participants were instructed to press the ‘m’ key if one of the symbols at the bottom of the screen matched any of the symbols at the top of the screen. They were instructed to press the ‘z’ key if there were no matches. There were 40 trials of this task. The dependent variable was average correct response time (in milliseconds) across the trials. Higher scores (longer response time) indicated worse performance. Previous studies using similar online tools have typically trimmed the slowest responses (Bielak et al., 2019). Thus, we trimmed the slowest 2 percent of responses.

Baseline measures

Covariates.

We statistically controlled for the baseline covariates age, gender, total years of education, global self-rated health, and depression (similar to Bielak et al., 2019). Global self-rated health was assessed using the item: 'In general would you say your health is 'poor' (1), 'fair' (2), 'good' (3), 'very good' (4), or 'excellent' (5)? To assess depression, we summed the 7 depression domain items from the Depression, Anxiety, and Stress Scale (DASS-21; Henry & Crawford, 2005) (see Appendix D). Possible item responses were 'did not apply to me at all' (1), 'applied to me to some degree or some of the time' (2), 'applied to me a considerable degree, or a good part of the time' (3), or 'applied to me very much, or most of the time' (4).

4.2.3. Data Preparation

All daily activity, positive interaction enjoyment, and negative interaction severity factors were disaggregated into between-persons and within-persons scores: The between-person score was obtained by calculating each individual's average score across all available assessments (creating a person-specific mean). The within-person score was obtained by subtracting each individual's day-specific score from their average to obtain deviations from their person-specific mean. All covariates were centred (i.e., score minus the grand mean). Finally, all continuous predictor (e.g., daily measures and covariates) and outcome variables (symbol search correct response time) were transformed into *z*-scores using the grand *M* and *SD* (*z*-scores were re-calculated for each sample used).

4.3. Statistical Analysis

Bayesian multilevel modelling was used to analyse the TRAILLS data. All models included the time-invariant covariates of age, gender, total years of education, global self-rated health, and depressive symptoms. We also included the time-varying covariate time (session) and the quadratic (session-squared) in the model. The activity, positive interaction enjoyment, and the negative interaction severity variables were entered into the models as their corresponding between- and within-person components. The between-person components were modelled as time-invariant predictors of cognitive level, allowing investigation of whether between-person differences in that activity was associated with processing speed. The within-person components were modelled as time-varying predictors, allowing examination of covariation between daily activity (and daily enjoyment/severity ratings of positive and negative social exchanges respectively) and daily processing speed.

The region of practical equivalence (ROPE) was set to ±0.05 (Kruschke, 2018; Makowski et al., 2019). Interpretation of results were based on the highest density intervals (HDI) in relation to the ROPE. Specifically, 1) if the HDI fell completely within the ROPE, we accepted the null hypothesis, 2) if the HDI fell completely outside the ROPE, we accepted the alternate hypothesis, and 3) any other combination of the HDI and ROPE resulted in inconclusive evidence to make either decision with 95% confidence. We additionally reported the proportion of the HDI interval that lay within the ROPE ($P_{(within\ ROPE)}$) or outside the ROPE in the predicted direction ($P_{(meaningful)}$) to aid interpretation. We considered any balance of evidence over 80% suggestive of a true effect.

4.4. Results

We initially examined whether different types of activity engagement were related to the intercept for processing speed (between-person analyses), or whether any covariation between activity and processing speed existed at the daily level (within-person analyses). Second, to determine whether the affective valence of a social exchange can explain changes in processing speed, we tested whether person-centred enjoyment (positive) and severity (negative) of social exchanges were related to processing speed (between-person analyses), and whether daily enjoyment (positive) and severity (negative) social exchanges covaried with processing speed performance (within-person analyses). Finally, to consider whether daily covariation of positive/negative social events with processing speed was dependent on baseline levels of positive/negative exchanges, we examined whether cross-level interactions (BP X WP) existed between person-centred enjoyment/severity of social exchanges and daily enjoyment/severity of social exchanges. The symbol response time findings are reported below (lower scores indicate better performance). All results are reported in Table 4.2.

4.4.1. Associations of average daily activities with levels of processing speed (BP effects)

Focussing first on the covariates, age ($B = 0.27$, $HDI_{95\%} = [0.14, 0.40]$, $P_{(meaningful)} = 100.00\%$), session ($B = -0.94$, $HDI_{95\%} = [-1.05, -0.83]$, $P_{(meaningful)} = 100.00\%$), and session-squared ($B = 0.53$, $HDI_{95\%} = [0.42, 0.64]$, $P_{(meaningful)} = 100.00\%$) were all meaningful predictors of symbol response time performance. Specifically, these findings suggested that older participants had slower response times. Further, the linear and quadratic session effects indicated that as the study period went on, response times became faster at an accelerated rate which is indicative of a practice effect. None of the other covariates gender, depression, education, or health were meaningfully associated with processing speed.

In terms of the between-person analyses of activity engagement and affective social exchanges with symbol search performance, the evidence was too disbursed to draw meaningful conclusions about social private, social unfamiliar, games, television, cognitive, or physical activity main effects, and severity of negative social exchanges or enjoyment of positive exchanges main effects (refer to the probabilities column in Table 4.2 which indicates the proportion of the HDI that fell below, within, and above the ROPE limits).

However, although we could not exclude a negligible effect with 95% confidence for an association of information with symbol search correct response time ($P_{(within\ ROPE)}$ = 25.80%), there was a weak trend in the evidence to suggest a positive association existed ($P_{(meaningful)}$ = 73.60%, B = 0.09, $HDI_{95\%}$ = [-0.02, 0.20]). The direction of this finding was inconsistent with expectations, indicating that those who spent more average time engaging in 'information' type activities (e.g., organising or planning; in conversations or meetings that focussed on solving a problem; and leading, coaching, or mentoring others) had higher (slower) average symbol search correct response time.

4.4.2. Associations of daily activities and social exchange quality with processing speed (WP effects)

Within-person (WP) associations of the activity domains with processing speed are summarised in Table 4.2. Table 4.2 also shows WP associations of social exchange quality indicators (enjoyment and severity ratings) with processing speed. Contrary to expectations, no daily covariation was evident between any of the activity, enjoyment, or severity ratings and symbol search performance. In fact, all activities (save for physical) and enjoyment of positive exchanges showed strong evidence in favour of the null where all HDI intervals fell completely within the ROPE. Although we could not exclude a meaningful effect with 95% confidence for physical activity engagement ($P_{(meaningful)}$ = 12.7%) or severity of negative exchanges ($P_{(meaningful)}$ = 2.96%), the balance of evidence was in favour of the null effect (see probability estimates in Table 4.2). These findings suggested that the type of activity engaged in on a given day was not related to symbol search performance that same day. The findings also suggested that engaging in a social exchange (positive or negative) also was not related to symbol search performance on that same day.

4.4.3. Did average levels (BP effects) of daily measures moderate the relationship between daily measures and cognitive performance on the same day (WP effects) (i.e., cross-level interactions)?

The cross-level interactions between the WP and BP effects of the same feature of activity or affective social exchange were added into the models to predict same day performance (summarised in Table 4.2). The results indicated no meaningful cross-level interactions for any activity domain or affective social exchange type. Instead, all activities (save for information) and severity of negative exchanges showed strong evidence in favour of the null where all HDI intervals fell completely within the ROPE. Although we could not exclude a meaningful effect with 95% confidence for informational activity engagement ($P_{(meaningful)}$ = 5.76%) or enjoyment of positive exchanges ($P_{(meaningful)}$ = 11.60%), the balance of evidence was in favour of the null effect (see probability estimates in Table 4.2). Thus, the between-person and within-person findings reported earlier do not change when taking their interactions into consideration.

Table 4.2

Summary of the Between-Person, Within-Person, and Cross-Level Interaction (BP X WP) Effects of Daily Activities and Social Affective Features on Daily Processing Speed Performance

Parameter	Est.	$HDI_{95\%}$	Prob. [below, within, above] the ROPE
Activity domains			
Social-private			
BP	-0.00	[-0.12, 0.11]	[0.21. 0.60, 0.19]
WP	0.01	[-0.03, 0.04]	[0.00, 0.99, 0.01][b]
BP X WP	0.02	[-0.02, 0.05]	[0.00, 0.96, 0.04][b]
Intercept (SD)	0.75	[0.66, 0.84]	
Residual	0.46	[0.44, 0.49]	
Social-unfamiliar			
BP	0.03	[-0.08, 0.16]	[0.08, 0.52, 0.40]
WP	0.00	[-0.03, 0.04]	[0.00, 1.00, 0.00][b]
BP X WP	-0.00	[-0.03, 0.03]	[0.00, 1.00, 0.00][b]
Intercept (SD)	0.75	[0.66, 0.84]	
Residual	0.46	[0.44, 0.49]	
Information			
BP	0.09	[-0.02, 0.20]	[0.01, 0.26, 0.74]
WP	-0.00	[-0.04, 0.03]	[0.00, 1.00, 0.00][b]
BP X WP	-0.02	[-0.06, 0.01]	[0.06, 0.94, 0.00][a]
Intercept (SD)	0.74	[0.66, 0.84]	
Residual	0.46	[0.44, 0.49]	
Cognitive			
BP	0.07	[-0.04, 0.18]	[0.01, 0.35, 0.64]
WP	-0.00	[-0.04, 0.03]	[0.00, 1.00, 0.00][b]
BP X WP	0.01	[-0.02, 0.04]	[0.00, 0.99, 0.01][b]
Intercept (SD)	0.74	[0.66, 0.84]	
Residual			
Games			
BP	0.03	[-0.08, 0.13]	[0.08, 0.59, 0.33]
WP	0.01	[-0.04, 0.05]	[0.01, 0.96, 0.03][b]
BP X WP	-0.02	[-0.05, 0.01]	[0.02, 0.98, 0.00][b]
Intercept (SD)	0.75	[0.66, 0.84]	
Residual	0.46	[0.44, 0.49]	
Television			
BP	-0.02	[-0.13, 0.10]	[0.29, 0.58, 0.13]
WP	0.01	[-0.03, 0.04]	[0.00, 0.99, 0.01][b]
BP X WP	-0.01	[-0.04, 0.03]	[0.01, 0.99, 0.00][b]
Intercept (SD)	0.75	[0.66, 0.84]	
Residual	0.46	[0.44, 0.49]	
Physical			
BP	0.01	[-0.11, 0.13]	[0.16, 0.59, 0.25]
WP	-0.03	[-0.06, 0.00]	[0.13, 0.87, 0.00][a]
BP X WP	0.00	[-0.04, 0.04]	[0.00, 0.99, 0.01][b]
Intercept (SD)	0.75	[0.66, 0.84]	
Residual	0.46	[0.44, 0.49]	
Affective social exchanges			
Enjoyment of positive exchanges			
BP	0.05	[-0.06, 0.17]	[0.04, 0.46, 0.50]
WP	0.02	[-0.02, 0.05]	[0.00, 0.96, 0.04][b]
BP X WP	-0.02	[-0.07, 0.03]	[0.12, 0.88, 0.00][a]
Intercept (SD)	0.72	[0.63, 0.81]	
Residual	0.41	[0.39, 0.44]	
Severity of negative exchanges			
BP	-0.01	[-0.12, 0.11]	[0.25, 0.60, 0.16]
WP	0.00	[-0.05, 0.06]	[0.03, 0.93, 0.04][a]
BP X WP	0.00	[-0.02, 0.03]	[0.00, 1.00, 0.00][b]
Intercept (SD)	0.75	[0.67, 0.84]	
Residual	0.46	[0.44, 0.49]	

Note. [a] 80% chance of ROPE falling within the HDI. [b] HDI fell completely within the ROPE. All models were adjusted for the covariates: age (years), gender (female = -1, male = 1), education (years), depression, health, linear trend (study day), and quadratic trend (study day^2), using each respective sample (activity, positive, and negative) run in individual models.

4.5. Discussion

The present study used baseline and daily variables from the TRAILLS daily diary dataset to evaluate whether older adults' cognitive performance on a given day was related to what activities they engaged in that same day. Contrary to our predictions, no within-person associations between daily activities and daily speed performance were found. A trend for an association of between-person information activity with symbol search performance was evident, but in the opposite direction to what might be expected (i.e., higher average levels of information activity was associated with slower processing speed). We also assessed whether the affective valence of a social exchange (i.e., how enjoyable a positive social exchange or severe a negative social exchange was rated) was associated with cognition. However, daily social events (enjoyment or severity ratings) were not found to be associated with cognition at the within- or between-person level. Finally, we considered cross-level interactions (i.e., WP X BP) to examine whether average levels of enjoyment of positive exchanges/severity of negative exchanges moderated the relationship between daily enjoyment/severity levels (i.e., we examined whether the *novelty* of the positive/negative exchange impacted the strength of the daily covariation of the positive/negative exchange and cognition). No meaningful cross-level interactions were found.

One possible explanation for why we did not find any activity-cognition relationships is that processing speed may be less sensitive to the effects of activity engagement than other cognitive domains. There have been inconsistencies in the literature about which cognitive domains derive the most benefit from activity participation (Bielak, 2010). Where there have been some results suggesting that activity engagement positively affects perceptual speed (Bielak et al., 2019; Ghisletta et al., 2006), other studies have found speed to be less consistently associated with activity engagement (e.g., Windsor et al., 2020; Ybarra et al., 2011) Ybarra et al.

(2008) described the resource priming theory as a mechanism that could explain why social activities in particular relate to better cognitive performance. Specifically, they suggest that engaging in a social exchange briefly exercises executive functioning processes (i.e., the ability for both parties to pay attention to each other, hold the topic of conversation in mind, and inhibit irrelevant or inappropriate behaviour) which boosts subsequent mental performance on tasks tapping *similar* cognitive resources (i.e., executive functions rather than processing speed). Similarly, many studies have demonstrated larger 'near' transfer effects than 'far' transfer effects when 'training' cognitive functioning (e.g., see meta-analysis by Karbach & Verhaeghen, 2014). This fits with the premise that different activity domains impact cognitive domains differently (Bielak, 2010). It is important that future research examining activity-cognition associations consider a range of cognitive domains as outcome variables to gain a more complete understanding of possible differential effects. Given the lack of findings in the present study, future micro-longitudinal work might focus on executive functioning measures as a means of testing notions of resource priming in settings with strong ecological validity.

Another possible reason for the discrepancy between our findings and those of the few published micro-longitudinal studies in the area is the *filing drawer problem*. There have not been many published studies investigating social activity-cognition links across daily or momentary time scales. It could be the case that other researchers have analysed data asking related research questions with a similar lack of findings, with these studies remaining unpublished.

4.5.1. Activity and Cognition

The main focus of the present study was to determine whether the daily activities people engaged in -in particular social activities- were related to daily fluctuations in cognition.

Contrary to expectations, our results demonstrated evidence against covariation of all daily activities and daily processing speed performance. Not only did our Bayesian analyses indicate that fluctuations in all assessed activity domains (social-private, social-unfamiliar, information, cognitive, physical, games, or television) across the week did not correspond with changes in daily cognitive performance, the evidence favoured the null for covariation of all activity domains with speed (save for physical, which trended in this same direction).

We were particularly interested in whether engaging in *social* activities on a given day was related to fluctuations in cognition. Our findings differed to previous work that has found a social activity-cognition link. For example, Bielak et al. (2019) found that engaging in daily social-private activities were more consistently associated with daily cognitive levels than any other type of activity, with participants who engaged in social-private activities on a given day also responding faster and performing better on episodic and working memory tests relative to their average on that same day. However, our findings suggest with high levels of certainty that there was no relationship for both social-private and social-unfamiliar activities with speed performance at the daily or between-person levels. Our findings instead align with those of Allard et al. (2014), who did not find daily covariation of social activities with cognitive outcomes. Considering our results in the context of the previous work, it may be that daily social-cognition coupling effects are subtle and not easily replicated across different samples.

The consideration of different time scales is important for understanding the complexities of the social-cognition relationship. Our findings do not support a relationship between social activity engagement and cognition at the daily level. However, past research has demonstrated relationships between social activity and cognition on different timescales. Namely, acute (Ybarra et al., 2008, 2011), cross-sectional, and longitudinal (Kuiper et al., 2016) relationships of social activity and cognition have been investigated. The mechanisms used to describe acute changes in cognitive performance vary from resource priming ideas to short-term changes in affect and/or motivation (Ybarra et al., 2008). On the other hand, cross-sectional and longitudinal relationships of social activity and cognition are often described in the literature to reflect longer-term effects in the brain such as the development of cognitive reserve (Stern, 2002). We speculate that daily measures of the social-cognition relationship might fit somewhere between these acute and longitudinal findings making it difficult to observe fluctuations at this level. Specifically, it might be the case that the time-period between engaging in activities and completing cognitive tasks at the daily level (i.e., at the end of the day) could be too widely spaced apart to observe covariation in the same way that immediate changes in cognition (for example stemming from a positive emotional response evoked by a stimulating social exchange) can be captured using moment-to-moment assessments (e.g., Zhaoyang et al., 2021). Such an explanation is consistent with the possibility that, although we did not observe daily associations, accumulation of short-term activities that exercise cognitive resources (in line with theories such as the enrichment hypothesis and/or use it or lose it) may underlie the longer-term relationships between social engagement and cognition that have been reported in numerous studies (Kuiper et al., 2016).

Finally, we found a trend for an association of information activity and processing speed performance at the between-person level. This finding however was not in the predicted direction. Instead, the pattern of results indicated that those who in general spent more time in the day coaching or mentoring others, or in conversations or meetings that focussed on solving a problem, had worse overall cognitive performance. It is possible that short-term engagement in these scenarios might have produced some negative emotion (e.g., presenting to an audience might produce worry or fear). Although these were not observed at the daily level, perhaps the accumulation of these negative emotions produced a longer-term stress response in the brain known to negatively impact cognition. Stress has been shown to decrease working memory performance in the past (Luethi et al., 2009). However, this is speculation and not supported by our negative exchange within- or between-person findings. Given these points, and that the confidence in a true effect was less than 80%, it may be that this was a chance finding. Another possibility is that the results were confounded by unobserved individual difference factors. For example, those maintaining greater social responsibilities into later life (as implied by the information activity items) might be more conscientious and as a result approached the symbol task more carefully and methodically, producing slower times overall.

4.5.2. Affective Social Exchanges and Cognition

We also did not find a meaningful association of positive or negative social exchanges at the between- or within-person level with cognition. This is in contrast to emerging evidence in the area. For example, Zhaoyang et al. (2021) who looked specifically at features of social interactions found that when people experienced a higher number of social exchanges on a given day, they had better cognitive performance on that same day. Our study differs as it looked at the levels of enjoyment rather than the frequency of social interactions on a given day. Consistent with Ybarra et al.'s (2008) notion of resource priming, perhaps the need to adapt one's perspective or engage working memory processes across the negotiation of different social contexts is more important for priming the operation of cognitive systems than experiencing an enjoyable interaction with a potentially familiar network member.

In terms of our findings for negative social exchanges at the daily level, one limitation is likely to have been limited by statistical power as only 11 participants reported experiencing negative social exchanges on more than one day. As ours is the first study that we are aware of to consider within-person covariation of severity of negative social exchanges with cognition, there may be value in future studies continuing to assess these relationships using a larger number of assessments.

4.5.3. Strengths, Limitations, and Future Directions

Our study included a number of notable innovations. First, utilising day-to-day assessment methods is an ecologically valid way to capture covariation of activity domains (particularly in a social context) with cognitive outcomes. One limitation of this approach, however, is that the online environment is not as well controlled as that of lab-based assessments. This potentially created more noise in the data and made the speed measure less sensitive than would have been the case with better standardised administration.

An additional strength of our study was our use of Bayesian analyses. Bayesian inference can determine whether we should accept the alternate hypothesis or the null hypothesis. This differs from frequentist analyses which use a statistical cut-off to reflect a failure to reject the null hypothesis, but does not provide information as to how likely the null hypothesis is to hold true (i.e., to make claims that no relationship exists between the variables of interest). In our findings, it was the case that the null hypothesis could be accepted for most daily activity domains with processing speed performance. This finding was particularly important when considering past findings who failed to reject the null hypothesis for covariation of certain activity domains with cognition (e.g., physical activity; Allard et al., 2014; Bielak et al., 2019; Phillips et al., 2016). In contrast, the findings from our study suggests, with some confidence, that there was no meaningful relationship between all different daily activities (save for physical, which was trending in the same direction) with processing speed.

Considering our findings within the broader context of research on social engagement and cognition points to a complex relationship where associations may vary according to cognitive domains and assessments made using different time scales. Specifically, although activity engagement and the affective quality of social exchanges may not reliably predict fluctuations in speed performance at the daily level, it remains possible that more momentary boosts to cognition arising from social exchanges contribute to cognitive performance in the longer-term, consistent with the enrichment perspective (Hertzog et al., 2008).

CHAPTER 5: Is Perspective-Taking a Mechanism Underlying Acute Social Interaction Benefits on Executive Functioning in Young Adults? An Experimental Study

5.1. Introduction

Consider the act of two people engaging in a simple exchange of views. There are many attention and cognition related processes typically involved in such a social interaction. For instance, both parties will generally pay attention to each other, maintain in memory the topic of the conversation, consider each other's perspectives, and infer each other's beliefs and desires, while inhibiting irrelevant or inappropriate behaviour, or internal or external distracting stimuli (Kane & Engle, 2002; Ybarra et al., 2011). Many of these processes depend on cognitive resources referred to as executive functions. Executive functioning is classified in terms of inhibitory control, working memory, and cognitive flexibility (Diamond & Ling, 2016). The integrated operation of these processes underlies the ability for people to process information by manipulating and maintaining tasks, plans, and goals. These are all important skills required for social engagement (Ybarra & Winkielman, 2012).

In addition to social engagement, executive functioning also plays a fundamental role in enabling various aspects of human endeavours. For example, Diamond and Ling (2016) review an abundance of literature demonstrating links between higher levels of executive functioning and happiness, obtaining and maintaining jobs and relationships, refraining from substance abuse, and avoiding incarceration. Further, poor executive functioning is a symptom of different types of dementias (i.e., Alzheimer's disease and vascular dementia; Yuspeh et al., 2002), and screening tools for neurodegenerative diseases and other cognitive impairments often include measures of executive functioning (i.e., Standardised Mini Mental State Exam (SMMSE), Molloy & Standish, 1997; Montreal Cognitive Assessment (MoCA), Nasreddine et al., 2005).

Research has begun to change the way the malleability of executive functioning is viewed. Where an individual's capacity for executive functioning has tended to be regarded as a relatively stable predictor of different outcomes in adulthood (as reflected in the Diamond & Ling, 2016 review) declining from middle age onwards (Kuiper et al., 2016), there has more recently been a movement towards studying the capacity to positively influence executive functioning through extended interventions on lifestyle and behavioural changes targeting working memory and attention (e.g., Jaeggi et al., 2008; Rueda et al., 2005), and short-term meditative interventions (e.g., Berman et al., 2008; Tang & Posner, 2009). Of central interest to the present study is evidence that social engagement might also have positive benefits on executive functioning performance (Myhre et al., 2017; Ybarra et al., 2008). To further advance our understanding of the role of social interaction on short-term changes in executive functioning, the current study used an experimental design to (a) replicate and extend past findings of positive effects of social interaction on executive functioning, and to (b) examine perspective-taking as a possible mechanism underlying this effect.

5.1.1. The Relationship Between Social Resources and Cognition

The majority of studies to date examining the relationship between social resources and cognition have been correlational, with many conducted within the context of larger longitudinal studies of aging (Bourassa et al., 2017; Fabrigoule et al., 1995; Fratiglioni et al., 2000; Ihle et al., 2019; Kuiper et al., 2016; Stoykova et al., 2011). Measures of social resources (e.g., individual differences of social network size or social support) are typically based on self-reports. Such study designs make it difficult to interpret the results given possible reverse-causality effects (i.e., the possibility that poorer cognition may be the cause as opposed to the consequence of less social interaction; Kuiper et al., 2016). However, most studies examining this relationship exclude participants who have mild cognitive impairment or dementia to reduce the possible influence of reverse causality (Kuiper et al., 2016). In general, cognitive ageing studies support positive associations of social resources with levels of cognitive functioning including executive functions (e.g., Bassuk et al., 1999; Fratiglioni et al., 2000; Seeman et al., 2001; Wilson et al., 2007) and some studies have also pointed to slower rates of decline in cognition among participants with greater social engagement (Fabrigoule et al., 1995) or who are less socially isolated or sad (Diamond & Ling, 2016). A meta-analysis showed that lower levels of both structural (i.e., size of social network and frequency of contact) and functional (i.e., quality of support) aspects of social relationships, or a combination of both, were associated with faster rates of cognitive decline (Kuiper et al., 2016). A smaller subset of research has been devoted to understanding the relationship between social resources and changes in measures of executive functioning specifically, as opposed to broader cognitive functioning. Overall, the literature points to a relatively reliable positive association between social engagement and executive functioning ability (e.g., Bourassa et al., 2017; Ihle et al., 2019; Kelly et al., 2017; Sims et al., 2011; Tun et al., 2013).

Relatively few studies have used experimental designs to assess whether social interactions are associated with short term changes in cognitive performance, including executive functioning. The first study to our knowledge supporting a causal link found that participants engaging in a social interaction significantly outperformed those in the control condition who watched television on a post-intervention reading span task ($d = 0.75$) and a post-intervention template matching processing speed task ($d = 0.67$). No significant differences were found between those who engaged socially to those engaging in intellectually stimulating activities for the same amount of time (d = 0.01) (Ybarra et al., 2008). As there were no pre-intervention measures of cognition taken, it is unclear whether an improvement in executive functioning or speed was made as a result of social engagement. The mechanism underlying this acute social interaction benefit on cognition was attributed to 'resource priming'. Ybarra et al. (2008) posit a process akin to warming up muscles prior to physical exertion, where social interactions that depend on cognitive inference generation 'exercise' the use of executive functions and subsequently contribute to enhanced performance. One other experimental study capturing short-term changes found significant improvements in the updating executive functioning domain (measured using a composite score from the Letter Memory and Keep Track tests) as a result of engaging in online social interactions via Facebook when compared to a control condition (Myhre et al., 2017). However, processing speed and other areas of cognitive function (e.g., shifting, inhibition, and processing speed measured using the Global-Local and Letter Number tasks, the Stroop and Simon tasks, and the Trail Making Test – Trail A respectively), did not appear to improve for the Facebook group.

Other studies have included social interaction indirectly as part of intervention programs targeted at increasing cognitive functioning. For example, Carlson et al. (2008) conducted a short-term randomised controlled trial of an everyday activity intervention to boost cognitive health. Participants were randomly allocated to the "Experience Corps" program, a voluntary senior service assisting primary school children with reading achievement, library support, and classroom behaviour. This program targeted memory and components of executive functioning, as well as being highly socially engaging. Executive functioning was measured using the Trail Making Test and the Rey-Osterrieth Complex Figure Test. When compared to a randomised-control condition, the intervention condition demonstrated clinically meaningful improvements in executive function and memory among those with borderline to impaired executive function at baseline. Although this study did not directly examine the impact of social interaction on executive function, social interaction was a key component of the intervention condition. In line with resource priming theory, the researchers suggested that their intervention program targeted working memory, mental flexibility, and components of executive functioning skills, which in turn resulted in improvements in memory and executive functioning performance. Similarly, another study created a team-based intervention program for older adults called the "Senior Odyssey" to test whether social and intellectual engagement buffers age-related cognitive declines (Cigolle et al., 2007; Stine-Morrow et al., 2007). Greater improvements in processing speed were evident for the experimental group than the control group, but no meaningful differences were found for working memory, inductive reasoning, or visuospatial processing. However, as there was no social group to compare to, it remains unclear whether the social aspect of the intervention contributed to changes in processing speed. Although social participation was not the key component of intervention in these studies, these results suggest that including a social component within an intervention may have positive effects on cognition.

In the previous sections of this thesis, I have drawn on literature from laboratory studies capturing short-term changes as well as micro-longitudinal and longitudinal cohort studies capturing long-term changes in social resources and cognition. We argue that engagement in intellectually stimulating activities including social exchanges that provoke short-term resource priming on a regular basis may contribute over time to longer-term benefits for cognitive functioning (e.g., shallower rates of normal cognitive decline). This idea is informed by the enrichment-hypothesis which argues that cognitive engagement through lifestyle choices offers opportunities for mental exercise and has the capacity to positively change the course of cognitive development (Hertzog et al., 2008). Although the extant literature points to a relatively consistent pattern of positive associations between social resources and cognition (Kuiper et al., 2016), and even a possible causal role of social engagement in producing short-term gains in executive functioning (Ybarra et al., 2008), little is known about the mechanisms underlying this association.

5.1.2. Possible Mechanisms Underlying a Social Interaction Benefit for Executive Functioning

There are several plausible mechanisms that could explain why people with greater social resources tend to perform better on tests of executive functioning. Aside from the aforementioned resource priming theory, it is also possible that social interaction produces positive affect (Ashby et al., 1999; Isen, 1999), enhanced motivation (Chiew & Braver, 2011; Pessoa, 2009), optimal levels of arousal (e.g., mild to moderate in the inverted-U) (McEwen, 2007; McEwen et al., 2016; Sapolsky, 2015; Seery et al., 2010) and even implicit stereotypes (Ambady et al., 2001) which have all been well documented in the literature to enhance cognitive test performance. An additional mechanism concerns the role of social engagement in enhancing cognitive reserve. Specifically, it has been suggested that engaging in social activities which require cognitive stimulation can help to build cognitive reserve (i.e., a greater capacity to effectively make use of alternative neural structures in the context of accumulating brain pathology) and therefore optimise cognitive performance (Kelly et al., 2017). Further, social resources, such as having networks of friends may promote engagement in intellectually engaging activity in old age which further contributes to cognitive reserve (Ihle et al., 2019). Our focus in the present study is on examining perspective-taking as a specific element of social interaction that could contribute to short term improvements in executive functioning performance.

A small number of studies conducted by Ybarra et al. (2011) have experimentally examined the resource priming hypothesis by manipulating perspective-taking within social interactions. Of note, all measures of executive functioning and processing speed described were conducted post-intervention with no pre-test baseline scores obtained from participants. This lack of pre-test data means that it cannot be ruled out that participants with better executive functioning skills were by chance randomly assigned to the experimental conditions. Ybarra et al.'s (2011) first study contrasted effects of social interactions that had a cooperative goal with social interactions that had a competitive goal. The Trail Making Test and a template matching task were administered post-intervention to assess executive functioning and processing speed respectively. They found that the cooperative group outperformed the control group (d = 0.73) and the competitive group (d = 0.91) on post-intervention executive functioning. There were no significant differences found in post-intervention processing speed between the conditions. The authors theorised that executive functioning was being exercised to a greater degree in the cooperative social interactions as this condition required participants to engage with one another, triggering processes such as 'mind reading' and 'perspective-taking'. On the other hand, competitive social interactions were speculated to cause participants to withdraw from such processes, and instead encouraged a focus on self-protection. To further test this theory, Ybarra et al. (2011) conducted a follow-up experiment where the competitive goal was structured to allow for perspective-taking processes. Participants assigned to the social interaction condition engaged in a lie-production lie-detection task, a competitive social interaction that elicited perspective-taking and mind-reading processes. Participant pairs created a list of lies and truths about themselves, taking turns to assess the veracity of the other person's statements. They found that the competitive social interaction group outperformed the control group (*d* = .91) and a brain games group (*d* = 0.60) on a post-intervention executive functioning measure of reading span. Again, no significant differences were found between conditions on a processing speed task. In line with their theory, Ybarra et al. (2011) concluded that if competitive social interactions are structured to involve perspective-taking processes, they can also produce subsequent boosts to executive functioning performance.

Although the studies described above provided evidence in general support of Ybarra et al.'s (2011) mind-reading and perspective-taking hypothesis, neither study directly measured these processes. Therefore, Ybarra et al. (2011) conducted a third study directly manipulating perspective-taking within the study design. Participants all completed the same competitive social interaction task, where they were given a description of a future-interaction that would occur (the Prisoner's Dilemma game), and then were given 10-minutes to 'get-to-know' their assigned partner. Participants in one condition were told to try to understand their assigned partner (inducing perspective-taking processes), where those in the other condition were told to prevent their assigned partner from taking their perspective (inducing withdrawal and avoidant strategies). Participants in the perspective-taking condition outperformed the perspective-taking prevention condition on the post-intervention executive functioning Trail Making Test (Trail B – Trail A). No differences between conditions were found for the speed measure (Trail A performance). These findings further contributed to the evidence that perspective-taking processes appear to produce acute gains in subsequent executive functioning performance.

Overall, each study described above provided preliminary evidence supporting performance gains from social interactions that encouraged mind-reading and perspective-taking processes, consistent with resource priming theory. However, it remains unclear whether other aspects of collaborative social interaction (e.g., arousal, affect, and motivation) also contributed to boosts in executive functioning, or whether the observed boosts in executive functioning were solely due to the perspective-taking processes induced by particular types of social interaction. If it is solely the perspective-taking processes that are driving this boost in executive functioning, then executive functioning benefits should also be observed when perspective-taking tasks are performed alone; that is *outside* the context of a social interaction.

5.1.3. Current Study

The current research provides further evidence in relation to the hypothesised central role of perspective-taking (Ybarra et al., 2011) in accounting for demonstrated short-term increases in executive functioning performance following a social interaction. Our aim (Study 1) was to determine whether cognitive benefits of perspective-taking are still observed when perspective-taking is performed alone as opposed to within a social interaction. To this end, we compared the executive functioning performance of young adult participant pairs before and after (a) engaging in perspective-taking within a social interaction (PT-social condition), (b) engaging in perspective-taking alone (PT-alone condition), and (c) not engaging in perspective-taking or a social interaction (control-alone condition). We further aimed to extend on the methods of Ybarra et al. (2008, 2011) by using a more rigorous experimental design to demonstrate boosts in executive functioning arising from social interaction and perspective taking. In contrast to the series of studies conducted by Ybarra et al. (2008, 2011) which did not include baseline measures of cognition; we included a pre-test measure of executive functioning to directly examine changes in executive functioning performance. Because social interactions have provided benefits for short-term cognition performance via mechanisms in addition to perspective taking such as positive affect (Ashby et al., 1999; Isen, 1999) and enhanced motivation (Chiew & Braver, 2011; Pessoa, 2009), we expected that those undertaking perspective taking as part of a social interaction would show superior performance to those undertaking perspective taking alone. The Connections Test (an alternative form of the Trail-Making Test; Salthouse, 2011) was used to measure executive functioning. The hypotheses for Study 1 were as follows:

1.1. If perspective taking boosts executive functioning, it was predicted that (i) for those who undertook perspective-taking alone, EF scores would be higher at post-test (indicating an improvement in performance) relative to pre-test (baseline). We further predicted that (ii) among participants in the two ‘alone’ conditions, those who engaged in perspective taking would show a greater difference in EF scores (i.e., post- minus pre-test) relative to those who did not engage in perspective taking.

1.2. If social interaction boosted executive functioning (over and above the effects of perspective taking), we predicted that (iii) for those who undertook perspective-taking in a social interaction, EF scores will be higher at post-test (indicating an improvement in performance) relative to pre-test (baseline). We further predicted that (iv) among participants in the two perspective taking conditions, those who engaged in a social interaction would show a greater difference in EF scores (i.e., post- minus pre-test) relative to those who did not take part in a social interaction.

5.2. Study 1

5.2.1. Method

Participants

We recruited 72 female first-year psychology students (*range* = 17 – 30 years, *M* = 19.25 years) in pairs (i.e., 36 dyads) through an advertisement on the Flinders University Research Participation System. The study was approved by the university's Social and Behavioural Research Ethics Committee and was pre-registered at osf.io/5vzsc. Three additional participants participated alone, as opposed to with an assigned partner, and were ultimately excluded from the final sample to ensure consistency in testing conditions. Participants received study credits for volunteering. The neutral title 'Film Analysis and Decision-Making study' was chosen to avoid any potential placebo effects that could arise from advertising the study as a possible enhancement of cognitive abilities (Foroughi et al., 2016).

Procedure and Materials

Participant pairs were randomly allocated to one of three conditions: *perspective-taking social interaction (PT-social), perspective-taking alone (PT-alone), or the active control condition (control-alone).* Participant pairs sat next to each other at a table, each with a computer in front of them. Participant pairs in the PT-social condition had nothing separating them, whereas those in the PT-alone and control-alone conditions were separated by a partition throughout the experiment.

Letters of introduction, information sheets and consent forms were provided to participant pairs on arrival. After giving informed consent, participants were asked to answer basic demographic questions about their age, gender, and language most commonly spoken.

Connections Test.

All participants were then given written and subsequently verbal instructions describing the Connections Test (Salthouse, 2011). The Connections Test requires participants to create a connecting path between ascending letters, numbers, or an alternating combination of both.

Successive targets are always in one of eight adjacent circles located above, below, to the left, to the right, or in one of the four diagonals adjacent to the target. Participants were instructed to do this as fast as they could without making any mistakes. Participant pairs were tested simultaneously, with participants given 20 seconds to complete each trial (i.e., a total administration time of 5 minutes 20 seconds at each pre- and post-test).

For the simple conditions, the numbers only condition consisted of targets from 1 to 49, and the letters only condition consisted of targets from A to Z, followed by the letters of A* to W* (the repeated asterisked letters are required as more than 26 targets are used per sheet). For the complex conditions, the numbers – letters condition consisted of the numbers 1 – 25 alternating with the letters from A to X, and the letters – numbers condition consisted of the letters from A to Y alternating with the numbers from 1 to 24. We created four different forms in each of the four conditions. Each given form consisted of the same sequence of movement directions in each of the four conditions. To ensure no added complexity was introduced for the letters condition, we ensured that all forms only allowed the connection of the letter once (e.g., B was an option to connect to A but B* was not).

Participants were given instructions on how to complete the Connections Test and then given a practice task (Appendix E). Participants completed one pack (i.e., 16 forms) at pre-test and one pack at post-test. Two packs were created and the order each participant pair received these packs was counterbalanced. Pack 1 used the same sequence detailed in Salthouse et al., (2000). Specifically: N1, L2, NL3, LN4, LN1, NL2, L3, N4, N2, L1, NL4, LN3, LN2, NL1, L4, N3 where the letters refer to the conditions (i.e., N = numbers, L = letters, NL = numbers-letters, and LN = letters-numbers) and the digits refer to the form. Pack 2 was in the order: L4, N3, LN2, NL1, NL4, LN3, N2, L1, L3, N4, LN1, NL2, NL3, LN4, N1, L2. The order of presentation in which participant pairs received the two different Connections Test sequences was counterbalanced (i.e., Order 1 = Pack 1 at pre-test and Pack 2 and post-test, Order 2 = vice versa). Participants completed 8 sets over the two packs.

The simple Connections Test conditions (numeric and alphabetic) measure processing speed, whereas the difference between alternating conditions (referred to here as the complex conditions), and simple conditions performance provides an index of executive functioning. The sum of all correct connections (highest possible score is 48) and the sum of all errors were recorded.

The Connections Test is a variant of the Trail Making Test (TMT; Reitan, 1958) used specifically for research (as opposed to clinical) purposes. The Connections Test addresses concerns of the TMT's different spatial arrangements of targets within and between Trail A (simple: numbers only) and Trail B (complex: alternating numerical and alphabetical sequence). Two main concerns include: (1) whether slower performance in Trail B than Trail A can alternatively be explained by larger distance between targets in Trails B, and (2) the motoric requirements associated with the unequal distance between targets (Salthouse et al., 2000). These possible confounds are addressed in the Connections Test by ensuring successive targets are always contingent to one another (for both simple and complex conditions) and only require simple short lines to connect targets.

Motivation.

Subsequent to completing the pre-test Connections Test, motivation was measured consistent with Ybarra et al., (2008, 2011), asking participants to rate how engaging, motivating and stimulating they found the Connections Test using a 5-point Likert-type scale from 0 (not at all) to 4 (a great deal).

Discrete emotions.

Emotion was assessed using Dillard and Shen's (2007) Self-Report Measure of Discrete Emotions using a 5-point Likert-type scale, where participants were asked to "indicate to what extent you are feeling this way right now" using ratings of 0 (none of this emotion) to 4 (a great deal of this emotion) on the following items (discrete emotions corresponding to items are listed in italics): *surprise* (surprised, startled, astonished), *anger* (irritated, angry, annoyed, aggravated), *fear* (fearful, afraid, scared), *sadness* (sad, dreary, dismal), *guilt* (guilty, ashamed), *happiness* (happy, elated, cheerful, joyful) and *contentment* (contented, peaceful, mellow, tranquil). A separate score was calculated for each discrete emotion by taking the average of their corresponding items, with higher scores indicating more of each emotion.

Film.

Dependent on condition, participants were given specific pre-film instructions (described in detail below) before they watched a 6-min affectively neutral film (wearing headphones). The stimulus was created by editing together four scenes from the movie *Paris, Texas* (Wenders, 1984). The composition of the scenes was designed to convey a story line that enabled participants to take the characters' perspectives, but at the same time to not elicit a strong positive, or negative emotional response. The film consisted of scenes establishing that the main character (Walt) finds his brother (Travis) walking through open countryside by a road after Travis had been missing for four years. Scenes depict relatively affectively neutral conversations between Walt and a largely non-communicative Travis as they drive through a rural landscape and Walt tries to understand where Travis has been. Eventually Travis expresses a wish to travel to Paris, Texas where he has purchased a vacant lot. Prior to commencing this study, we conducted a short pre-validation study asking participants about their emotional responses to the film which confirmed its neutral affect (see Appendix F for complete details of the pre-validation).

Subsequently, dependent on condition, participants were given specific question prompts about the film. All participants were given five minutes to provide “dot-point” responses to these prompts (see below for examples). We were not interested in performance on this task. We simply used this activity to encourage or inhibit perspective-taking. During this phase of the experiment the researcher left the room.

Perspective-taking (social interaction).

Those participant pairs allocated to the perspective-taking social interaction (PT-social) condition were given the following pre-film instructions based on Davis et al. (1987). Perspective-taking instructions were: “Please try to imagine how the characters are feeling and what they might be thinking. In particular, imagine you were in a situation like the one Walt (the brother driving the car) finds himself in. In your mind’s eye, try to visualise how Walt might feel, and what he might be thinking.” Once participants watched the film, they were given a list of prompts relating to the thoughts and feelings of the characters encouraging them to engage in perspective-taking. For example, “What might Walt be thinking when he first sees his brother, Travis? Why might Walt be thinking this?” To facilitate social interaction, participants were asked to work together to provide responses to the prompts.

Perspective-taking (alone).

Participant pairs allocated to the perspective-taking alone (PT-alone) condition were also asked to focus on the characters thoughts and feelings throughout the film, and subsequent to watching the film were given the same prompts to encourage perspective-taking. Participants were asked to work alone in providing responses to the prompts.

Control (alone).

The participant pairs allocated to the control-alone condition were provided with the following pre-film instructions, also based on Davis et al.'s (1987) environmental observation instructions: "Please make careful observations of the settings that the scenes take place in. In particular, observe closely the clothes that the characters are wearing, the era that the film appears to be set in, aspects of the landscape, and details of any buildings or motor vehicles that are shown." After participants watched the film, they were given prompts designed to direct attention away from the perspectives of the characters. For example, "How does the natural landscape (plants, the shape of the land, etc.) compare with the landscape in and around Adelaide?" Similar to the PT-alone condition, participants were asked to make dot-point responses to these prompts alone.

All conditions.

Next, regardless of condition, participants once again rated their motivation and emotions using the aforementioned scales. Then, participants completed the post-test connections task, comprising their second allocated sequence (16 forms). Finally, participants completed the manipulation and salience checks.

Manipulation Checks.

Similar to Davis et al. (1987) two items were included as checks to ensure perspective-taking was manipulated successfully. The item: "To what extent did you attempt to imagine the feelings, thoughts, and reactions of the characters in the film clip?" was included to measure participant's level of perspective-taking. Conversely, the item: "To what extent did you attempt to carefully observe the setting (e.g., props/scenery) in the film clip?" was included to reflect the extent to which participants observed other aspects of the film such as the environment, as instructed to the control condition. All conditions evaluated both items on a 9-point Likert type scale, ranging from 0 (not at all) to 8 (very much).

In addition, a salience measure was also included as a manipulation check. Participants were asked to respond to the following two items: "Please list the key words you would use to describe the feelings, thoughts, and reactions of the characters in the film clip" and "Please list the key words you would use to describe the setting (e.g., props/scenery) in the film clip." Number of words and time taken (in seconds) was recorded, and words/time ratio was calculated for the perspective-taking and environmental observation word sets. The log of the ratio was taken to avoid the distortion of differences inherent in ratio measures. Specifically, a one-unit change in the numerator [denominator] will produce a different change in the ratio depending on the value of the denominator [numerator], but an equivalent change in the log of the ratio. A higher perspective-taking ratio (i.e., listing more perspective-taking words in less time) for those in the perspective-taking conditions (combined) compared to those in the control-alone condition would further support effectiveness of the manipulation. Alternatively, we would expect the control-alone participants to have a relatively higher environmental observation ratio (i.e., be able to list more environmental observation words in less time) compared to the perspective-taking conditions (combined).

5.2.2. Data Analytic Approach

To examine perspective-taking as a possible mechanism underlying the effect of social interaction on executive functioning performance, we used a hierarchical Bayesian parameter estimation model, analogous to a mixed-effects version of a traditional analysis of variance (ANOVA). Specifically, the means for each participant in each cell of the design were calculated as a linear combination of all predictors (participant, dyad, condition, form, complexity, and set) reflecting the grand mean and the main and interaction effects from a full factorial cross of factors (condition, type and set). The outcome variable EF score was measured by the difference between the number of correct and error connections in the complex conditions minus the simple conditions on the Connections Test. We added a constant of 48 to the difference scores to remove negative numbers and better facilitate interpretation. Higher scores represent better EF performance.

In keeping with the movement towards *New Statistics* (Cumming, 2013; Kruschke & Liddell, 2018) that advocates for emphasis on reporting effect sizes as a more informative description of the findings with appropriate indices of uncertainty, we predominately rely on the Cohen's *d* estimates for all comparisons to determine whether meaningful differences exist in our data. Specifically, we use the cut-offs 0.2, 0.5, and 0.8 as a guide to represent small, moderate, and large effects respectively (Cohen, 2013). Bayesian 95% highest density intervals ($HDI_{95\%}$) (indicated in square brackets throughout the main text and relevant tables) represent the uncertainty in the estimates. Further, as it is rarely useful to compare exactly to zero as the criterion for no effect, we instead use a region of practical equivalence (ROPE) of ±0.1 as Cohen's *d* values within this interval are considered negligible (or equivalent to zero).

Our reporting of results was based on three possible scenarios drawn from the relationship between the HDI interval and the ROPE. First, if the HDI interval lay completely outside of the ROPE, then we concluded, with 95% certainty, that there was a meaningful effect (i.e., reject the null hypothesis). Second, if the HDI interval completely lay within the ROPE, then we concluded, with 95% confidence, that there was no meaningful difference (i.e., accept the null hypothesis). Finally, if the HDI interval fell partly outside the ROPE, or if the ROPE completely lay within the HDI, then we had inconclusive evidence to accept or reject the null hypothesis with 95% certainty. We additionally determined the proportion of the HDI interval that lay within the ROPE ($P_{(within\ ROPE)}$) or outside the ROPE in the predicted direction ($P_{(meaningful)}$) to aid interpretation of the results, considering anything over 80% to be indicative of a true effect.

Violin plots (Figures 5.1 – 5.5) were created to graphically display the results using R packages ggplot2 (Wickham, 2009) and cowplot (Wilkie, 2017). The wider the violin plot, the more credible the value. The point represents the mean, and the vertical line represents the 95% HDI interval. The ROPE is indicated by the two dashed lines. This data analytic approach is used to examine the overall data patterns for Studies 1 and 2.

Markov Chain Monte Carlo techniques programmed in R (R Core Team, 2016), rjags (Plummer, 2016) and runjags (Denwood, 2016) were run for all models to generate representative credible values from the joint posterior distribution on the model parameters. The six chains were burned in and checked for convergence graphically and statistically (Gelman & Rubin, 1992), and run long enough to ensure a minimum effective sample size of 10,000 for all location parameters (Kruschke, 2015). The mathematical formulations, including prior distributions, for all models are available in our pre-registration at osf.io/5vzsc.

5.2.3. Results and Discussion

Manipulation Checks

Given that our perspective-taking and environmental observation manipulations were adapted from Davis et al. (1987) we also used their manipulation check method (i.e., self-reported engagement). See Table 5.1 for all relevant statistics. As expected, participants in the PT-social condition meaningfully reported higher endorsement of the use of perspective-taking relative to their reported use of environmental observation ($P_{(meaningful)}$ = 99.8%). A similar pattern emerged for the PT-alone condition, where although we cannot exclude a negligible difference with 95% confidence ($P_{(within\ ROPE)}$ = 2.2%), there was moderate evidence for higher endorsement of perspective-taking than environmental observation ($P_{(meaningful)}$ = 97.4%). Also, in line with expectations, the control-alone condition meaningfully reported environmental observation more than they reported perspective taking with a large effect ($P_{(meaningful)}$ = 99.8%).

Table 5.1

Self-Reported Engagement Manipulation Check. Posterior Mean, Effect Size (Cohen's d), and ROPE Probabilities for Self-Reported Engagement With Perspective-Taking (PT), Environmental Observation (EO), and Their Difference (PT - EO) Across Conditions (PT-Social, PT-Alone, And Control-Alone)

Self-reported engagement	Perspective-taking (PT)	Environmental Observation (EO)	Difference (PT – EO)	*d* †	Prob. [below, within, above] the ROPE (±0.1)
Condition					
PT-social	7.43 [6.72, 8.16]	5.73 [5.04, 6.46]	-1.70 [-2.70, -0.69]	-0.95 [-1.52, -0.37]	[1.00, 0.00, 0.00]**
PT-alone	7.09 [6.37, 7.79]	5.92 [5.21, 6.62]	-1.17 [-2.15, -0.16]	-0.65 [-1.21, -0.09]	[0.97, 0.02, 0.00]*
Control-alone	5.72 [5.04, 6.40]	7.40 [6.71, 8.07]	1.68 [0.70, 2.66]	0.94 [0.38, 1.50]	[0.00, 0.00, 1.00]**

Note. $HDI_{95\%}$ are displayed in square brackets. † *d* reflects the effect size of the PT – EO difference in ratings of engagement based on the estimated means. Probability below the ROPE indicates a greater PT ratio for PT conditions. Probability above the ROPE indicates a greater EO ratio for control condition. * 80% certainty of HDI falling outside the ROPE. ** HDI fell completely outside the ROPE.

Analysis of the salience measures (refer to Table 5.2) did not produce results as clear as those of the self-reported engagement manipulation check reported above. Specifically, examination of differences in the perspective-taking ratio (i.e., the log of words divided by seconds) when comparing those who received the perspective-taking manipulation (PT-social and PT-alone conditions combined) to those who received the environmental observation manipulation (control-alone condition) revealed ambiguous evidence (i.e., the balance of evidence was highly disbursed). Similarly, there were ambiguous findings for differences in the environmental observation ratio between those who received the perspective-taking manipulation and the environmental observation manipulation.

Given that we have evidence of self-reported engagement with perspective-taking and the environmental observation in the predicted direction using methods consistent with Davis et al. (1987), we accept these findings as broadly supporting the success of our manipulation. However, the lack of corollary supporting evidence provided by analysis of the salience measures suggests that future studies might benefit from further refining similar approaches to the perspective-taking manipulation.

Table 5.2

Salience Measure Manipulation Check. Posterior Mean, Standard Deviation, Effect Size (Cohen's d), and ROPE Probabilities for Ratio (Perspective-Taking, Environmental Observation) And Manipulation (Perspective-Taking, Environmental Observation)

Manipulation	Perspective-taking (PT)	Environmental Observation (EO)	*d* †	Prob. [below, within, above] the ROPE (±0.1)
Perspective-taking ratio				
M	-2.07 [-2.18, -1.97]	-2.09 [-2.26, -1.92]	0.03 [-0.32, 0.38]	[0.23, 0.42, 0.35]
SD	0.35 [0.25, 0.45]	0.42 [0.29, 0.56]		
Environmental observation ratio				
M	-1.87 [-2.03, -1.71]	-1.80 [-2.01, -1.59]	-0.09 [-0.43, 0.25]	[0.48, 0.39, 0.13]
SD	0.54 [0.42, 0.66]	0.54 [0.39, 0.70]		

Note. $HDI_{95\%}$ are displayed in square brackets. † *d* reflects the effect size of the difference in ratio for the perspective-taking (PT) and environmental observation (EO) conditions based on the estimated means. Probability above the ROPE indicates a greater PT ratio for PT conditions. Probability below the ROPE indicates a greater EO ratio for control condition. * 80% certainty of HDI falling outside the ROPE. ** HDI fell completely outside the ROPE.

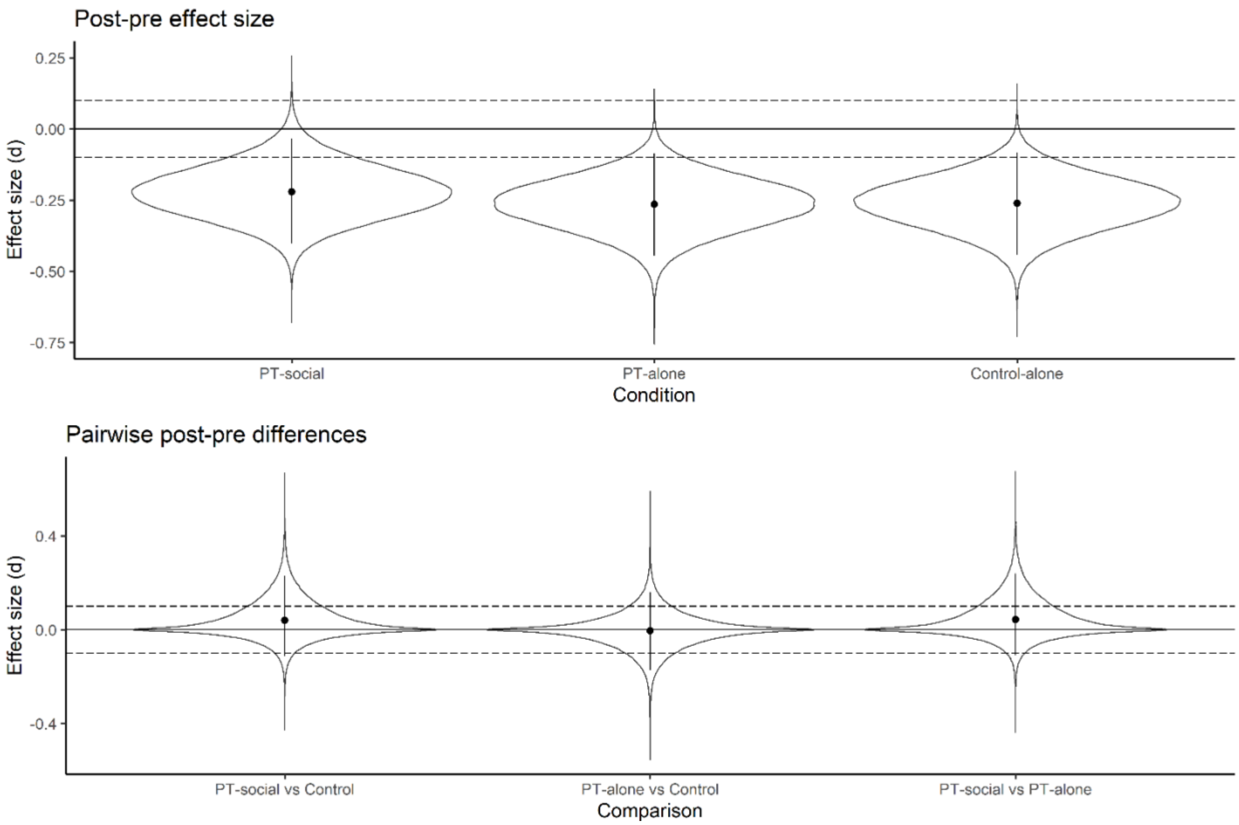
Condition Differences on EF Score

All statistics relevant to this section are presented in Table 5.3. To reiterate the effects of key interest in relation to our predictions; if acute improvements in executive functioning resulting from social interaction are primarily driven by perspective-taking, then similar improvements on EF score from baseline to post-test should be observed for both those engaging in perspective-taking as part of a social interaction (PT-social condition), and those engaging in perspective-taking alone (PT-alone condition). We would not expect to observe the same degree of improvement in EF performance among those who did not engage in perspective-taking (i.e., control-alone condition). We initially focussed on the pre- to post-test changes in each of the three conditions (PT-social, PT-alone, control-alone) on EF score performance (scored as complex minus simple performance on the Connections Test). Taken together, the findings did not provide support for the hypothesis that perspective-taking would benefit EF performance. Specifically, for the PT-alone condition, although we cannot exclude a negligible difference with 95% confidence ($P_{(within\ ROPE)}$ = 3.2%), there was clear evidence to suggest a small but meaningful decline in EF scores from baseline to post-test ($P_{(meaningful)}$ = 96.8%). This decrement however did not appear to be different in size compared to the control-alone condition who were not instructed to engage in perspective-taking (d = -0.00, $HDI_{95\%}$ = [-0.17, 0.16], $P_{(within\ ROPE)}$ = 82.7%). Taken together, the declining EF scores from pre-to-post test appear to represent practice effects in the form of a greater relative improvement in the simple task across trials, relative to improvement in the complex task (EF = complex - simple).

Further, recognising that processes of social engagement in addition to perspective taking (e.g., arousal, affect and motivation) might contribute to enhanced EF following a social interaction, we expected to see the greatest improvements in EF from pre- to post-test for those in the PT-social condition. However, although we cannot exclude a negligible difference with 95% confidence ($P_{(within\ ROPE)}$ = 9.8%), the findings did not support the hypothesis that social interaction would boost EF score. Contrary to predictions, results showed clear evidence of a decrease in EF score from baseline to post-test among those in PT-social condition ($P_{(meaningful)}$ = 90.1%). Given the likelihood of practice effects (see above), of key interest was whether the magnitude of change observed for the PT-social condition from pre- to post-test differed from that of PT-alone. The change from pre- to post-test for PT-social did not appear to be different in size compared to PT-alone (d = 0.04, $HDI_{95\%}$ = [-0.11, 0.24], $P_{(within\ ROPE)}$ = 76.5%). Changes in EF from pre- to post-test, and pairwise differences in changes across conditions are shown in Figure 5.1. The posterior estimates display a pattern of decrease in EF score over time for all conditions including the control with no evidence of any pairwise differences.

Figure 5.1

Plots of Posterior Estimates of Effect Size (d) for EF Pre- to Post-Test Changes, and Pairwise Differences in Changes Across Conditions (Study 1)



Note. This figure presents change in EF score for time (baseline – post-test) for each experimental condition (upper panel) and the pairwise differences between conditions (lower panel). For all plots representing change or group differences, the region of practical equivalence (±0.1) is represented by dashed lines.

Although we did not find evidence suggesting a clear benefit of social interaction on executive functioning, we also analysed changes in affect and motivation on an exploratory basis for completeness. To briefly summarise, the affect results indicated that for all conditions, anger, fear, guilt, happiness, and surprise appeared to decrease from baseline to post-test, whereas sadness appeared to increase over time for all conditions. The contentment findings were mixed, where an increase in contentment was apparent for the PT-social and control conditions, however a decrease in contentment was observed for the PT-alone condition. Further, all aspects assessed for motivation (i.e., global, engaging, stimulating, and motivating) appeared to decrease from baseline to post-test for all conditions. The complete statistics are reported in Appendix G.

Post hoc analyses

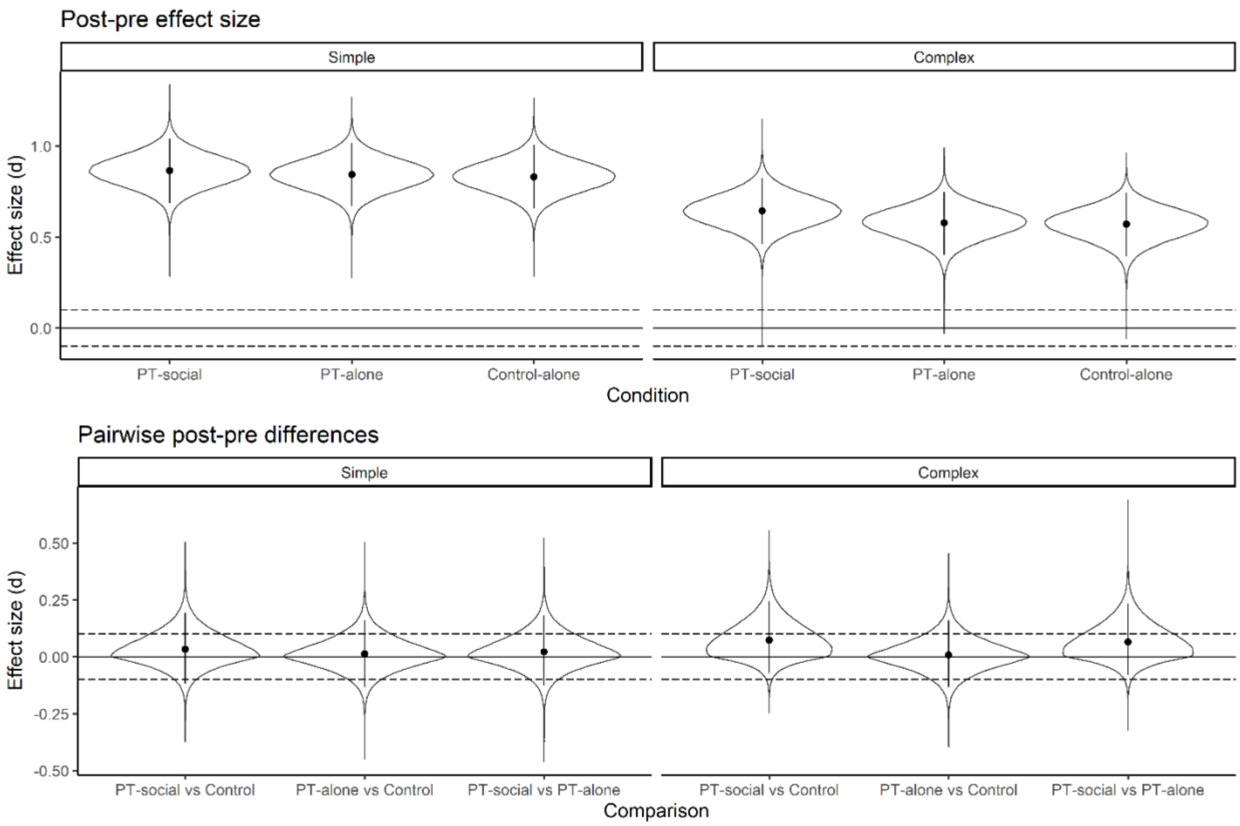
Our EF measure was derived from the Connections Test which produces simple scores as a reliable measure of processing speed, and complex scores which target cognitive switching processes (Salthouse et al., 2000). Given that the EF measure combines performance on both tasks, to further elucidate the pattern of findings we also considered each domain separately as outcome measures. Statistics relevant to this section are displayed in Table 5.3.

We found that for those in the PT-alone condition, simple scores meaningfully improved from baseline to post-test with a large effect, $d = 0.84$ ($P_{(meaningful)} = 100\%$), and complex scores also improved meaningfully with a moderate effect, $d = 0.58$ ($P_{(meaningful)} = 100\%$). An identical pattern of results emerged for those in the PT-social condition, where simple scores improved meaningfully with a large effect, $d = 0.86$ ($P_{(meaningful)} = 100\%$), and complex scores improved meaningfully with a moderate effect, $d = 0.64$ ($P_{(meaningful)} = 100\%$). Therefore, although both the perspective-taking (PT-social and alone) conditions had greater overall simple and complex scores at post-test compared with baseline, the amount of improvement was greater for the simple compared to the complex connections, explaining the overall EF score reduction from pre- to post-test (See Figure 5.2 for graphical representation). We also conducted parallel analyses for the control condition to determine what we should expect from a normal practice effect. Findings showed that similar to the perspective-taking conditions, simple Connections Test scores meaningfully improved from baseline to post-test with a large effect, $d = 0.83$ ($P_{(meaningful)} = 100\%$), and complex Connections Test scores also meaningfully improved however with a moderate effect, $d = 0.57$ ($P_{(meaningful)} = 100\%$), similar to perspective-taking conditions.

Taken as a whole, our main analysis of pre- and post-test EF scores, and our post-hoc analyses which considered separate dimensions of simple and complex connections scores did not provide support for our prediction that social interaction improves executive functioning, nor that perspective-taking is a mechanism underlying such an effect. Further, as both complex and simple score improvements were comparable to those observed in the control group, this suggests that the observed increases in all conditions are indicative of practice effects. However, as the control condition engaged in writing answers to prompts about the film, we speculate that we may have unintentionally introduced demand effects in our control group akin to an ‘intellectual activity’ type of condition that has been shown in previous research to boost cognitive performance (e.g., Ybarra et al., 2008). This issue is addressed in Study 2.

Figure 5.2

Plots of Posterior Estimates of Effect Size (d) for Simple and Complex Pre- to Post-Test Changes, and Pairwise Differences in Change Across Conditions (Study 1)



Note. This figure presents changes in time (baseline – post-test) for simple and complex Connections Test scores separately, for each experimental condition (upper panel) and the pairwise differences between conditions (lower panel).

Table 5.3

Posterior Mean, Effect Size (Cohen's d), and ROPE probabilities for All Combinations of Condition (PT-social, PT-alone, Control-alone) and Time (Baseline, Post-test, Difference) on Complexity (EF score, Simple, Complex) Scores

	Baseline (Time 1)	Post-test (Time 2)	Difference (Time 2 - Time 1)	*d* †	Prob. [below, within, above] the ROPE (±0.1)
EF score (Complex – Simple + 48)					
PT-social	28.18 [26.07, 30.28]	26.91 [24.78, 29.01]	-1.27 [-2.31, -0.19]	-0.22 [-0.40, -0.03]	[0.90, 0.10, 0.00]*
PT-alone	28.54 [26.41, 30.68]	27.02 [24.90, 29.18]	-1.52 [-2.55, -0.49]	-0.26 [-0.45, -0.09]	[0.97, 0.03, 0.00]*
Control-alone	28.01 [25.88, 30.15]	26.52 [24.38, 28.66]	-1.50 [-2.53, -0.48]	-0.26 [-0.44, -0.08]	[0.96, 0.04, 0.00]*
Simple					
PT-social	35.56 [31.38, 39.79]	40.52 [36.25, 44.68]	4.96 [3.96, 5.96]	0.86 [0.69, 1.04]	[0.00, 0.00, 1.00]**
PT-alone	34.29 [30.08, 38.38]	39.13 [34.99, 43.30]	4.84 [3.84, 5.80]	0.84 [0.67, 1.02]	[0.00, 0.00, 1.00]**
Control-alone	34.28 [30.08, 38.42]	39.06 [34.83, 43.17]	4.77 [3.78, 5.76]	0.83 [0.66, 1.01]	[0.00, 0.00, 1.00]**
Complex					
PT-social	15.74 [11.68, 20.05]	19.43 [15.27, 23.68]	3.69 [2.67, 4.72]	0.64 [0.46, 0.82]	[0.00, 0.00, 1.00]**
PT-alone	14.83 [10.73, 19.01]	18.15 [14.01, 22.33]	3.32 [2.33, 4.32]	0.58 [0.40, 0.75]	[0.00, 0.00, 1.00]**
Control-alone	14.30 [10.11, 18.44]	17.57 [13.35, 21.68]	3.28 [2.27, 4.26]	0.57 [0.40, 0.74]	[0.00, 0.00, 1.00]**

Note. $HDI_{95\%}$ are displayed in square brackets. † *d* reflects the effect size of the Time 2 minus Time 1 difference for the estimated means. Probability above the ROPE indicates greater EF score at Time 2 compared to Time 1. * 80% certainty of HDI falling outside the ROPE. ** HDI fell completely outside the ROPE.

5.3. Study 2

In Study 2, we aimed to address the finding that participants in the control condition improved on overall Connections Test scores to a similar extent to those in both perspective-taking conditions (social interaction and alone). We theorised that by asking our control condition to engage in answering prompts about the film, we unintentionally created a cognitively stimulating task akin to the type of 'brain game' condition that has been shown to result in acute improvements to performance on cognitive tasks similar to social interaction (Ybarra et al., 2008). Therefore, we ran an additional experiment where we compared performance of participants assigned to an active control condition (equivalent to the control condition described above) to performance of participants assigned to a more passive control condition. Participants in the passive control condition were not asked to engage in any analysis of the film content. We predicted that those in the 'active' control would show a greater difference in EF, simple, and complex connections scores (i.e., post- minus pre-test) relative to those in the 'passive' control.

5.3.1. Method

Participants

Similar to Study 1, a sample of 48 female psychology students (*range* = 17 – 28 years, *M* = 19.75 years) were recruited in pairs. Four additional participants who participated without a partner were excluded from the final sample. The sample size in Study 2 replicated the number of participants per condition in Study 1 (12 participant pairs per condition). Data collection stopped once we reached 24 pairs to ensure the sample size and testing conditions (e.g., testing in pairs as opposed to individuals) were equal for each condition.

Procedure and Materials

Participant pairs were randomly allocated to one of two control conditions: *active control condition* or the *passive control condition.* Our active control condition was an exact replica of the control-alone condition described in Study 1. The passive control condition replicated the control-alone condition with the exception of the following key differences: (1) The passive control pre-film instructions merely informed participants that they would be watching a film, unlike the control-alone condition who were asked to focus on the props and scenery of the film, and (2) following the film, participants in the passive control condition did not complete any dot-point responses to prompts, but instead were directed immediately to the post-test Connections Test.

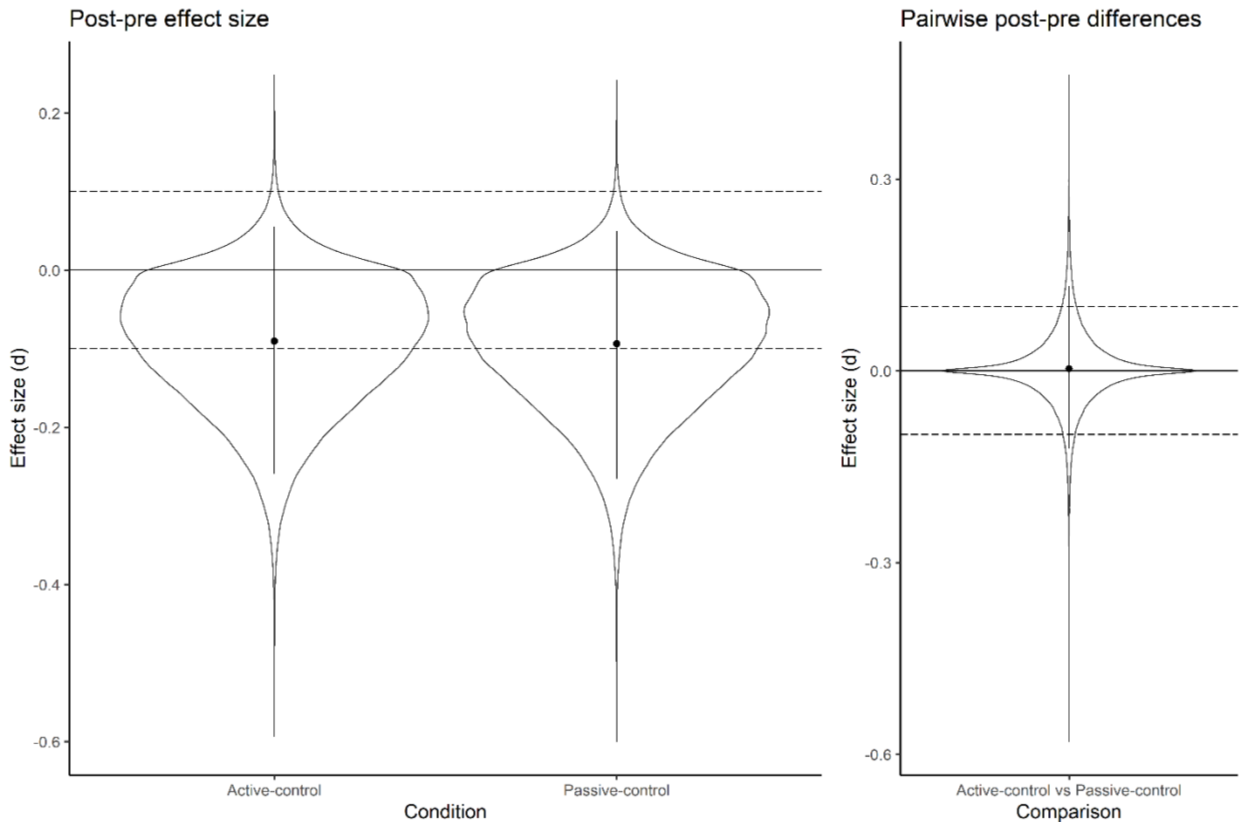
5.3.2. Results and Discussion

Condition Differences on EF Score

Relevant statistics can be found in Table 5.4 and graphical representations are displayed in Figure 5.3. The balance of evidence was too disbursed to support changes in EF scores from baseline to post-test for the passive control or the active control. However, contrary to expectations, the two control conditions did not appear to meaningfully differ in the magnitude of pre- to post-test change (d = -0.00, $HDI_{95\%}$ [-0.13, 0.12] = $P_{(within\ ROPE)}$ = 90.9%).

Figure 5.3

Plots of Posterior Estimates of Effect Size (d) for EF Pre- to Post-Test Changes, and Pairwise Differences in Changes Across Conditions (Study 2)



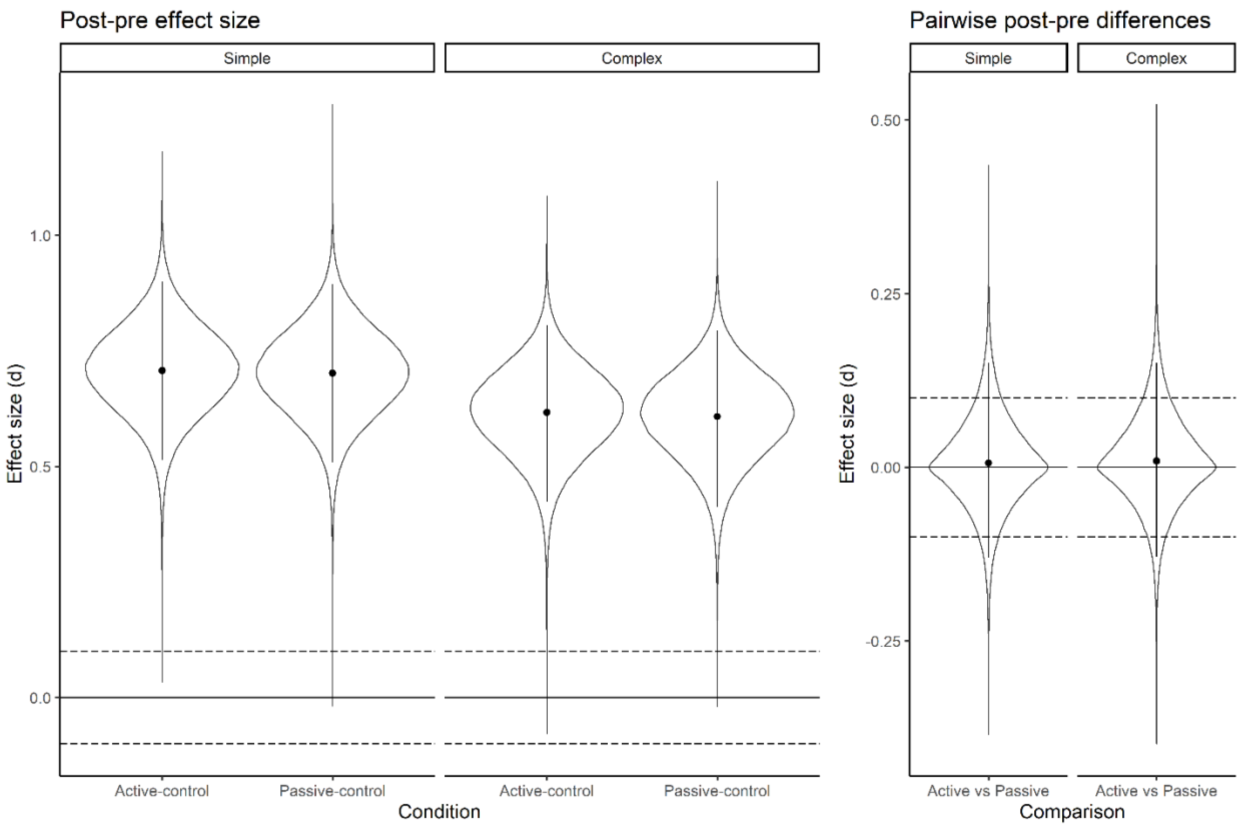
Note. This figure presents change in EF score for time (baseline – post-test) for the active and passive control conditions (left panel) and the pairwise differences between these conditions (right panel)

Post hoc analyses

To further examine possible changes in speed and task switching, we conducted post hoc analyses separately for the Connections Test complex and simple scores (refer to Table 5.4 for statistics relevant to this section). We found that for the passive control condition, simple scores meaningfully improved from baseline to post-test, d = 0.70, ($P_{(meaningful)}$ = 100%), and complex scores also improved meaningfully, d = 0.61 ($P_{(meaningful)}$ = 100%), both with a moderate effect. A similar pattern of results emerged for the active control condition, where simple scores, d = 0.71 ($P_{(meaningful)}$ = 100%), and complex scores, d = 0.62 ($P_{(meaningful)}$ = 100%) both improved meaningfully with a moderate effect (see Figure 5.4 for graphical representation).

Figure 5.4

Plots of Posterior Estimates of Effect Size (d) for Simple and Complex Pre- to Post-Test Changes, and Pairwise Differences in Change Across Conditions (Study 2)



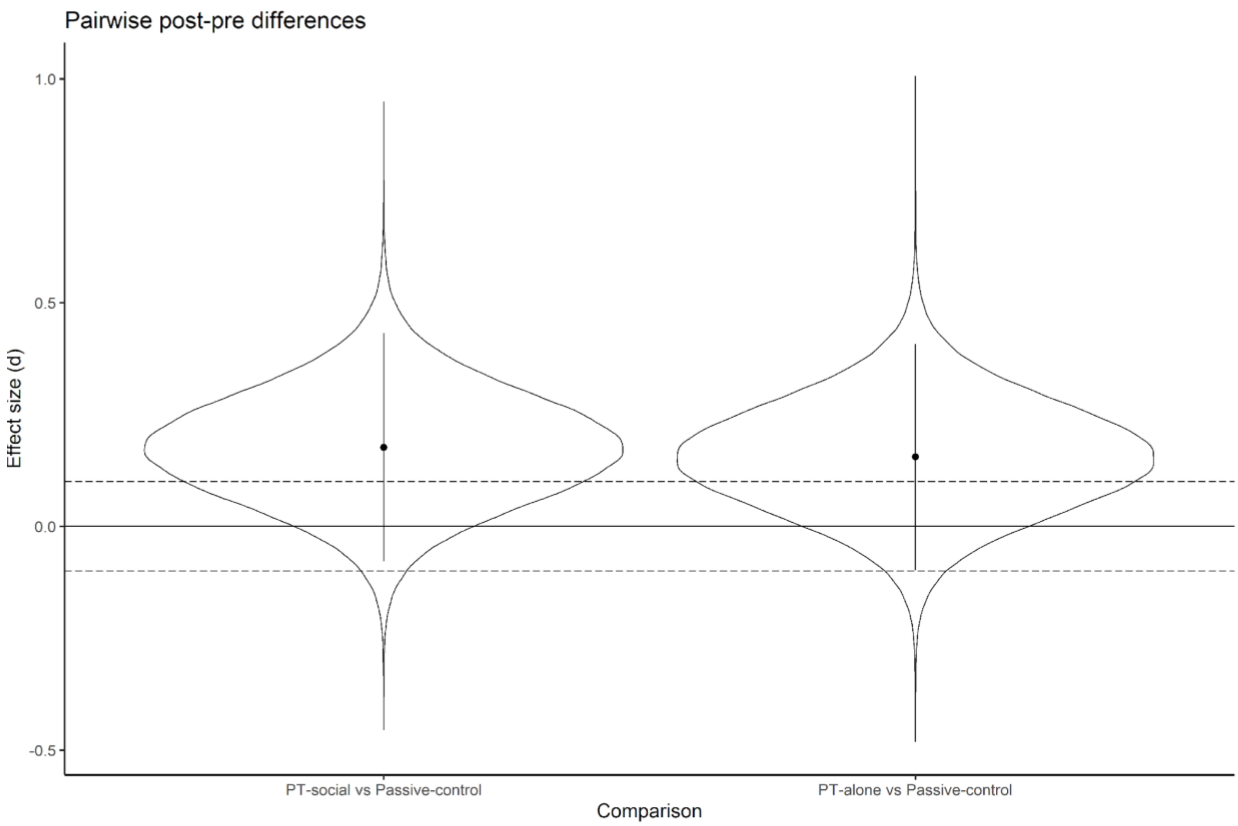
Note. This figure presents changes in time (baseline – post-test) for simple and complex Connections Test scores separately, for the active and passive control conditions (left panel) and the pairwise differences between these conditions (right panel).

Combined Post Hoc Analysis – Study 1 and Study 2

The effect sizes suggested a larger increase in simple scores (speed) from baseline to post-test for both Study 1 perspective-taking conditions (i.e., PT-social: $d = 0.86$; PT-alone: $d = 0.84$) relative to the Study 2 passive control condition (i.e., $d = 0.70$). Therefore, we conducted post-hoc analyses to explicitly determine whether meaningful differences existed (see Figure 5.5). The evidence for the difference in simple scores between both perspective-taking conditions (PT-alone and PT-social) and the passive control was ambiguous and did not support any confident conclusions. However, the balance of evidence suggested a small or negligibly sized difference trending towards a larger increase in simple scores for PT-alone than the passive control ($d = 0.16$, $HDI_{95\%} = [-0.10, 0.41]$, $P_{(meaningful)} = 68.0\%$), and similarly a small or negligibly sized difference trending towards a larger increase in simple scores for PT-social than the passive control condition ($d = 0.18$, $HDI_{95\%} = [-0.08, 0.43]$, $P_{(meaningful)} = 72.4\%$). These findings provide some evidence for a possible benefit of perspective-taking for processing speed; however, effect sizes were small to negligible.

Figure 5.5

Plots of Posterior Estimates of Effect Size (d) for simple Pre- to Post-Test Changes for the Pairwise Differences Between Perspective-Taking Conditions Versus Passive Control (Study 2)



Note. This figure presents change in simple Connection test score for time (baseline – post-test) for the pairwise differences between both the experimental conditions (PT-social and PT-alone) versus the passive control.

Table 5.4

Posterior Mean, Effect Size (Cohen's d), and ROPE probabilities for All Combinations of Condition (Active Control and Passive Control) and Time (Baseline, Post-test, Difference) on Complexity (EF score, Simple, Complex) Score

	Baseline (Time 1)	Post-test (Time 2)	Difference (Time 2 - Time 1)	*d* †	Probability [below, within, above] the ROPE (±0.1)
EF score (Complex – Simple + 48)					
Active	28.12 [25.96, 30.27]	27.61 [25.44, 29.76]	-0.51 [-1.46, 0.32]	-0.09 [-0.26, 0.06]	[0.42, 0.58, 0.00]
Passive	28.24 [26.12, 30.43]	27.72 [25.59, 29.89]	-0.53 [-1.48, 0.29]	-0.09 [-0.27, 0.05]	[0.43, 0.57, 0.00]
Simple					
Active	32.87 [29.22, 36.51]	36.85 [33.17, 40.46]	3.98 [2.91, 5.06]	0.71 [0.51, 0.90]	[0.00, 0.00, 1.00]**
Passive	36.38 [32.73, 40.04]	40.32 [36.78, 44.07]	3.95 [2.87, 5.00]	0.70 [0.51, 0.90]	[0.00, 0.00, 1.00]**
Complex					
Active	12.99 [9.35, 16.65]	16.46 [12.79, 20.10]	3.47 [2.40, 4.53]	0.62 [0.42, 0.81]	[0.00, 0.00, 1.00]**
Passive	16.62 [12.98, 20.30]	20.04 [16.38, 23.72]	3.42 [2.34, 4.48]	0.61 [0.41, 0.79]	[0.00, 0.00, 1.00]**

Note. $HDI_{95\%}$ are displayed in square brackets.

† *d* reflects the effect size of the Time 2 minus Time 1 difference for the estimated means. Probability above the ROPE indicates the probability that the true difference fell above the negligible range and indicates greater score at Time 2 compared to Time 1. * 80% certainty of HDI falling outside the ROPE. ** HDI fell completely outside the ROPE.

Ybarra Equivalent Analyses

As this study was an extension and replication of previous designs used by Ybarra et al. (2008, 2011) we also conducted additional pairwise comparisons to allow for more direct comparisons between our and Ybarra et al.'s findings. Specifically, Ybarra et al. (2011) looked solely at post-test comparisons that were relatively shorter than our post-test (Time 2) session. In case a boost in executive functioning performance truly exists but is only short-lasting, a possible effect may be lost within the four sets of trials in our post-test. Therefore, we compared the perspective-taking conditions (social interaction and alone) to the passive control condition on Set 5 only, as opposed to Sets 5 – 8 (Time 2), to be able to capture any possible short-lived boosts to performance. However, the estimates were highly uncertain (e.g., probability mass extended on both sides of the ROPE) and we were therefore unable to make any claims about whether or not a true difference between the experimental groups and the control group existed. All relevant descriptive and inferential statistics can be found in Table 5.5.

Table 5.5

Posterior Mean and $HDI_{95\%}$ for single estimates at Set 5 only, and Pairwise Comparison Effect Size (Cohen's d) and $HDI_{95\%}$,, and Probability Below, Within and Above ROPE for the Two Experimental Conditions and the Passive Control Condition

Condition	Set 5 single estimates	Pairwise comparisons	*d*	Probability [below, within above] the ROPE (±0.1)
PT-social	27.81 [25.36, 30.42]	PT-social v Passive control	-0.02	[0.37, 0.27, 0.36]
PT-alone	27.88 [25.37, 30.47]	PT-alone v Passive control	-0.00	[0.35, 0.26, 0.38]
Passive control	27.70 [25.32, 30.02]	PT-social v PT-alone	0.01	[0.26, 0.55, 0.19]

Taken together, findings from the passive and active control conditions demonstrate that processing speed and switching ability improved from baseline to post-test at comparable rates. Therefore, this increases our certainty of what pattern of improvement we can expect from a normal practice effect. Additionally, these findings provide some weak evidence suggesting that although perspective-taking may not improve EF scores, it may contribute to acute boosts in processing speed.

5.4. General Discussion

The present studies attempted to extend on the work of four previous studies (Ybarra et al., 2008, 2011) that explored perspective-taking as a possible mechanism underlying an acute social interaction benefit for executive functioning performance. Specifically, our extension contributed to the evidence of perspective-taking as a viable mechanism by examining whether acute boosts in executive functioning exist when perspective-taking occurs alone, as opposed to occurring as part of a social interaction. However, the current findings were not consistent with results of the previous studies. Specifically, although we expected to observe an improvement in executive functioning as a result of perspective-taking and/or social interaction, a spurious finding of executive functioning performance worsening was found as a result of processing speed improving (presumably as a result of practice) at a faster rate than switching processes. Further, where mixed findings were previously reported regarding social interaction benefits on processing speed (Ybarra et al., 2008, 2011), our findings provided some modest evidence for a perspective-taking benefit on processing speed above and beyond simple practice effects (based on the performance of a passive control group). We discuss implications and possible explanations for the failure to replicate previous findings below.

5.4.1. Possible Explanations for the Discrepancy in Executive Functioning Findings

Our observation of evidence contradicting past findings of boosts in cognitive performance attributable to social interaction could be a result of key differences in study design. One possibility for the discrepant findings is that where Ybarra et al. (2008, 2011) used a post-test only design across their multiple studies, our study incorporated a pre- post-test comparison. This provided the additional benefit of allowing for more definitive claims about changes or boosts from baseline as a result of perspective-taking. Without a pre-test condition to compare to, this raises the possibility that no true change in functioning occurred in the Ybarra et al. studies (2008, 2011) and that the differences observed were a result of pre-existing group differences. The use of randomisation in the Ybarra et al. (2008, 2011) studies, and the fact that the boosting effects were observed across multiple samples makes this unlikely. What is more likely is the tendency for scientific journals to only publish studies with favourable outcomes, often referred to as the *file drawer problem* (Rosenthal, 1979). Although there is a substantial amount of literature demonstrating a relationship between social resources and cognition over longer time scales (Kuiper et al., 2016), there seems to be little work published around the acute causal effects of social engagement on cognition. Although it is only possible to speculate, it may be that ours is not the only study to fail to demonstrate clear evidence for short-term benefits of executive functioning arising from social engagement.

Although our pre- post-test design can be seen as a strength compared with previous work in the area, repeated testing can induce ‘practice effects’ which have been known to complicate interpretation of cognitive test performance. Trail Making Test – Parts A and B have both been shown to be susceptible to such practice effects (Bartels et al., 2010). As participants in our studies returned to testing after a substantial break from the task, the improvements in complex and simple task performance were consistent with the literature around the *Spacing Effect* (Dempster, 1989). This is a phenomenon demonstrating that spaced practice (i.e., rest intervals within the session) yields superior outcomes to mass practice (i.e., practicing a task continuously without rest) (Donovan & Radosevich, 1999). One explanation relevant to the current study that could explain such practice-induced score gains is learned strategies to complete the task quicker over time (i.e., becoming faster at scanning the page and motor skills; Bartels et al., 2010). Bartels et al. (2010) also suggests other practice-induced effects such as participants experiencing reduced anxiety in or growing familiarity with the testing environment. Further, it is possible that practice may facilitate the physical and cognitive execution of the task. Past studies examining speed of processing research have included hundreds of practice or warm up trials before the true experimental data were collected, in order to ensure that participants had learned the task and data were not influenced by any practice effects (e.g., Brewer & Smith, 1989). This literature supports the likelihood that the declines observed in EF score from pre- to post-test in our data were an artefact of increasing speed as a result of practice. A second reason for the discrepancy between our results and those of Ybarra et al. (2008, 2011) may relate to differences in the measure of executive functioning used. An investigation observing which cognitive abilities are associated with the Connections Test found that this task primarily reflects cognitive abilities of speed and fluid intelligence but does not tap working memory skills outside of fluid intelligence (Salthouse, 2011). Some studies using large batteries of cognitive tests have found a relationship between social activity and certain components of executive functioning (i.e., working memory) but not others (i.e., verbal fluency or attention Kelly et al., 2017), that social engagement effects may not be robust across different components of EF. This possibly may be consistent with Ybarra et al. (2011) who found meaningful differences in executive functioning between social interaction and control conditions when using a working memory task. However, an explanation based on subtle differences between components of EF does not explain why Ybarra et al. (2011) also found differences using the Trail Making Test; a task measuring abilities comparable to those assessed in the current study using the connections test.

A third difference between study designs that may have diluted social interaction effects in the present study was that our participants engaged socially for less time than was the case in Ybarra et al.'s (2008, 2011) social interaction conditions. Where in the current study participants spent 5 minutes in their social interaction, Ybarra et al. (2008) had participant pairs debate on a social issue for 6 minutes, and Ybarra et al.'s (2011) study designs either involved 8-minute interactions of getting to know the other person or taking turns assessing the veracity of truth or false statements about themselves. It is possible that participants need to engage in an interaction for a minimum amount of time for acute benefits to be evident, and that the social interaction task used in our study did not meet this threshold. For instance, it is possible that shorter interactions do not give people the chance to sufficiently reduce feelings of anxiety associated with interacting with an unfamiliar social partner, which have been shown to negatively affect cognitive test performance (Bartels et al., 2010).

Another difference between methods concerned the type of social interactions that were elicited. Specifically, Ybarra et al. (2011) reported gains in executive functioning as a result of social interactions that induced perspective-taking, however their interaction tasks were competitive in nature (e.g., the interaction partner was referred to as an "opponent"). Ybarra et al. (2011) suggests that competitive interactions are beneficial to cognition when they involve perspective-taking and mind-reading processes, as opposed to when they elicit withdrawal and self-protection. Our social interaction on the other hand was a cooperative task as partners were encouraged to answer prompts about the film together. Ybarra et al. (2011) demonstrated that participants assigned to cooperative and basic “get-to-know you” interactions outperformed those in competitive social interactions, however perspective taking was not directly manipulated. Therefore, the previous studies did not provide a directly comparable cooperative, perspective-taking interaction condition to compare our results with.

Fifth, although Ybarra et al.’s (2011) assessment of mood and motivation associated with their manipulations demonstrated no differences between conditions, the measure used was not comprehensive or validated. Positive affect (defined as long-lasting, consciously accessible feelings subtly changed by the immediate physical environment) has been shown to improve performance on various cognitive tasks (Ashby et al., 1999; Fredrickson, 2004; Isen, 1999). Fredrickson’s (1998) *broaden-and-build theory* argues that positive emotions broaden an individual’s scope for attention and cognition, which in turn has the effect of building physical, intellectual, and social resources (Fredrickson, 2001, 2004). Research has demonstrated support for Fredrickson’s (1998) proposed relationship between positive emotions and intellectual resources, where positive emotions have been shown to facilitate learning and mastery (e.g., Bryan et al., 1996; Bryan & Bryan, 1991; Masters et al., 1979), memory performance (e.g., Isen, 1987; Isen et al., 1978), and to promote problem-solving (Isen, 1987). Additionally, social interactions may also increase motivation, even implicitly, to perform better in cognitive tasks, where a growing literature shows that motivational influences (e.g., delivery of performance-contingent rewards and punishments) can affect cognitive test performance (Chiew & Braver, 2011; Pessoa, 2009). Therefore, we speculate that whereas Ybarra et al.’s (2008, 2011) tasks (e.g., getting to know the other person and playing a true/false interaction game) may have induced some subtle shifts in positive affect and motivation among participants that were not captured by their brief assessments, our more ‘test’ like social interaction environment may have been less motivating and positive affect inducing. Indeed, our analysis indicated that higher arousal emotions and motivation decreased across the study interval in each of the Study 1 conditions (whereas sadness ratings increased).

Previous evidence has also suggested that certain types of social interactions can have detrimental effects on executive functions. By utilising a female sample, we avoided the possible confound of men performing worse on EF tasks after interacting with attractive females as a result of attempts at impression management (Karremans et al., 2009). However, self-presentational concerns may have affected executive functioning performance among participants in the present study. Specifically, it is possible that as participants were working together to complete a written task in a ‘test’ like format, that they were concerned about not appearing unintelligent to their counterparts. Research has shown detrimental effects on executive functioning as a consequence of self-presentation concerns that impose a working memory load and self-regulatory efforts which in turn are thought to deplete cognitive resources (Muraven & Baumeister, 2000). Considering these differences in our method in conjunction with the different types of interactions that can induce worsening of executive functioning performance, we speculate that quite specific experimental conditions may be required to demonstrate any acute cognitive benefits resulting from social engagement. Furthermore, if this is the case, it raises questions as to the ecological validity of the previous findings (Ybarra et al., 2008, 2011). Further attempts at replication may be required to establish whether our results represent an anomaly, or if the findings reported by Ybarra and colleagues can only be robustly demonstrated under quite specific experimental conditions.

5.4.2. Possible Perspective-Taking Boost on General Cognitive Functioning

Our findings were suggestive of a possible perspective-taking boost on processing speed. To recapitulate, in comparison to our passive control condition performance (i.e., what might be expected from a normal practice effect), the observed size of the improvement in processing speed (e.g., simple Connection test scores only) appeared slightly larger for both perspective-taking conditions (i.e., PT-social: $d = 0.86$; PT-alone: $d = 0.84$; passive-control: $d = 0.70$). The difference in the size of the improvement between conditions was too small to make any definitive claims about acute benefits of perspective-taking on processing speed. Further, whereas this modest finding is consistent with some previous findings suggesting that perspective-taking improved processing speed (Ybarra et al., 2008), not all previous studies have shown this pattern (e.g., Myhre et al., 2017; Ybarra et al., 2011). Given that engaging in social interaction did not appear to have any additional benefits on cognitive functioning above and beyond that of perspective-taking, this raises the possibility that perspective-taking- but not social interaction- plays a role in enhancing speed performance. This finding is relevant to broader cognitive ability. For instance, Salthouse (1996) suggests that processing speed is a *cognitive primitive*; a key contributing factor underlying other functions (e.g., higher order tasks) that are subject to age-related decline. As age is known to precipitate slowing which contributes to reduced capacity to perform other cognitive tasks (Karbach & Verhaeghen, 2014), it can be argued that improved processing speed has the potential to improve other age-related cognitive abilities. However, given the small to negligible effect size, our young sample, and the inconsistencies in the literature, further replication efforts in diverse samples are required to further examine possible benefits of perspective-taking for processing speed.

We note the consistent finding that process-based training protocols that target capacities such as processing speed and executive functioning are known to have greater gains for older adults than younger adults. This finding is due to younger adults having less room for improvement as they generally begin with higher cognitive capacity than older adults (Karbach & Verhaeghen, 2014). Similarly, we speculate that our young-adult sample may have been generally highly socially engaged and already reaping the maximum benefits social engagement can provide for cognition. Perhaps then, greater acute improvement in cognition as a function of short-term social interactions may be observed in older adults who are less socially engaged. Future research would benefit from investigating possible boosts for cognitive performance arising from social interactions and/or perspective taking in samples of older adults.

5.4.3. Limitations and Outlook

Given that we found no evidence of an acute boost in executive functioning as a result of social interaction, this raises the question of why the broader literature points to positive associations between social resources and executive functioning, and cognition more generally. Our sample were healthy, young, first-year university students who were likely not suffering from any kind of decline or impairment in their cognition at the time of participation in the study. It is possible that the effect may have been evident in a sample of people (e.g., older adults) who had more room for improvement.

We also speculate that associations observed outside of the lab in long-term longitudinal research (Kuiper et al., 2016) are a result of processes operating over much longer time scales that result in social resources conferring benefits for cognition. For example, in line with *resource priming theory* (Ybarra et al., 2008), it is possible that priming of resources over short time scales are facilitated by regular, stimulating, diverse forms of social engagement which underlie longer term changes. This is potentially due to their role in enhancing cognitive reserve (Hertzog et al., 2008; Windsor et al., 2020). Although, in line with resource priming theory, we expected that perspective-taking would exercise cognitive flexibility and subsequently improve performance on the Connections Test which also taps cognitive flexibility (Dillard & Shen, 2007), we did not find this. Perhaps other aspects of executive functioning are more directly relevant to social interaction such as attention, memory, and inhibition and therefore exercising such aspects of executive functioning within social interactions over long time periods might ultimately result in enhancement of cognitive abilities. It is plausible then that in line with perspectives on cognitive aging such as the enrichment hypothesis (e.g., Hertzog et al., 2008), mental stimulation through the accumulation of short-term practices (i.e., made into lifestyle changes) has the capacity to improve cognitive functioning in the long-term. Future research would benefit in testing this theory with measurement-burst studies (e.g., day-to-day or moment-to-moment assessments of social engagement compared to other intellectually engaging activity) over short time scales, which may help to capture broader cognitive changes in more ecologically valid settings.

CHAPTER 6: General Discussion

6.1. Overview

This thesis outlined the findings of three research studies that examined associations of social resources with cognitive functioning in older adults (Chapters 3 and 4) and younger adults (Chapter 5) across different timescales. To recapitulate, the first study (Chapter 3) used data from longitudinal and cross-sectional datasets to examine whether social resources play a compensatory role in buffering the effects of aging on cognitive performance among those with limited educational opportunities. The second study (Chapter 4) used daily diary data to examine whether older adult's cognitive performance on a given day was related to the activities (including social activities) that were engaged in on that day. This study further examined whether the affective valence of a social exchange (i.e., whether the social exchange was appraised as positive or negative) was associated with cognition at the daily level, and whether the *novelty* of the positive/negative social exchange (based on participants' typical exposure to positive/negative exchanges) impacted the strength of the daily covariation. The third and final study (Chapter 5) used an experimental design to examine whether perspective-taking was a central mechanism explaining the social-cognition relationship by examining whether acute boosts in executive functioning existed when perspective-taking occurred alone, as opposed to within a social interaction. Overall, we found some weak evidence linking social resources with processing speed performance in older adults in our long-term longitudinal study (Chapter 3). However, we did not find any evidence in our micro-longitudinal study to support previous findings of fluctuations of social activity engagement and cognition (Chapter 4). We also did not find any evidence of social interaction causing acute boosts in younger adult's cognition above and beyond the effects of perspective-taking (Chapter 5). In the sections that follow, we (1) highlight each of the study findings along with their importance and novelty, (2) the clinical implications of these combined findings, and (3) discuss methodological limitations along with potential directions for future research.

6.2. Summary of Research Findings and Original Contributions

6.2.1. Social Resources as Compensatory Reserve for Low Educational Attainment

The results from our long-term longitudinal findings (Chapter 3) revealed that higher levels of social activity engagement were associated with better perceptual speed performance, but not initial letter fluency performance. Loneliness was also associated with worse performance on tests of perceptual speed and initial letter fluency. However, the lack of associations with rates of change, and the fact that these findings were not replicable using cross-sectional data reduced our confidence that these associations represented robust associations.

We also found some support that social resources are protective of cognition for those with low levels of educational attainment (in line with Windsor et al.'s (2020) proposed *Compensatory Reserve Hypothesis*). Specifically, a four-way interaction was found in the long-term longitudinal processing speed findings which indicated that the most vulnerable group of older adults (in terms of decline in processing speed over time) were those who had *low* education, *were* lonely, and had *low* levels of social activity participation. In contrast, there was a meaningfully slower rate of decline in processing speed for those who had *low* education, were *not* lonely, and had *high* levels of social activity participation. However, once participants who were identified as having possible dementia at any time-point in the study were excluded to minimise the potential for reverse causality effects, the four-way interaction was no longer meaningful. This indicated that those participants who developed incipient dementia over the study may not have been cognitively able to continue with their usual social engagements and may have also felt more lonely. This finding placed a strong caveat on the reliability of the initial four-way interaction as reverse causality represents a plausible alternative explanation for the findings to notions of compensatory reserve.

Finally, the cross-sectional analyses demonstrated a positive association between engagement with life and category fluency performance even with social resource variables included in the model. This finding suggested that meaningful activity in general (regardless of whether the activity is social in nature) relates to fluency performance. However, once again reverse causality cannot be ruled out given the cross-sectional nature of the ELMS data.

6.2.2. Activity Engagement, Affective Social Exchanges, and Cognitive Performance at the Daily Level

Results from our micro-longitudinal analyses (Chapter 4) revealed that older adults' speed performance on a given day was *not* related to the activities they engaged in earlier that day (i.e., no within-person associations of activity engagement and processing speed performance were found). Similarly, the affective valence of a social exchange (i.e., how enjoyable a positive social exchange or severe a negative social exchange was rated) was not associated with processing speed. In fact, by utilising Bayesian analyses we were able to demonstrate that the evidence favoured the null hypothesis (i.e., HDI fell completely within the ROPE) for all activity domains (save for physical, which trended in the same direction) and enjoyment ratings (severity ratings also trended in the same direction).

Further, there was no clear evidence in either direction to support average levels of severity or enjoyment ratings, or any activity engagement domain being associated with processing speed (i.e., no between-person associations of activity engagement or affective valence of social exchanges with processing speed performance were found), except for informational activity. Specifically, the pattern of results indicated that those who in general spent more time in the day coaching or mentoring others, or in conversations or meetings that focussed on solving a problem, had worse performance on the processing speed task. One plausible explanation for this finding was that short-term engagement in these types of scenarios may have produced some negative emotion (e.g., presenting to an audience might produce worry or fear). Although not observed at the daily level, accumulation of these negative emotions over time may have produced a long-term stress response known to negatively impact cognition. However, as our negative exchanges within- and between-person findings do not support this, and the relationship was weak (i.e., less than 80% of the HDI fell outside the ROPE), it was likely this was a chance finding.

Finally, we did not find the novelty of the positive/negative exchange to impact the strength of the daily covariation of the positive/negative exchange and cognition (i.e., no meaningful within-person x between-person interactions were found). For completeness, cross-level interactions were tested for each activity domain; however there was no evidence of average levels of activity affecting the daily relationship between the respective activity with cognition.

6.2.3. Perspective-Taking as a Mechanism Underlying an Acute Social Interaction Boost in Cognition

Finally, the findings from our experimental study (Chapter 5) conducted with a sample of younger adult women were suggestive of a possible perspective-taking boost in perceptual speed performance. Specifically, we randomly allocated participants into one of three conditions: perspective-taking social interaction, perspective-taking alone, or control alone. Executive functioning was measured using the Connections test which involved taking the difference of the complex (i.e., alternating alpha-numeric) and simple (alpha or numeric only) conditions and was administered both pre- and post-test. Although we expected to observe an improvement in executive functioning as a result of perspective-taking and/or social interaction, a spurious finding of executive functioning performance *worsening* was found. All conditions had greater overall simple and complex scores at post-test compared with baseline, however the amount of improvement was meaningfully greater for the simple (large effect) compared to the complex (moderate effect) connections, explaining the EF score reduction from pre- to post-test. As both complex and simple score improvements in the perspective-taking conditions were comparable to those observed in the control group, this suggested that the observed increase in all conditions were indicative of a practice effect.

Reflecting on our methodological design, we speculated that we may have unintentionally introduced demand effects in our control group akin to an 'intellectual activity' type of condition that has been shown in previous research to boost cognitive performance (e.g., Ybarra et al., 2008). Therefore, we conducted an additional study to address the control condition showing similar improvements on Connection test scores to both the perspective-taking (social interaction and alone) conditions. Here, we compared the performance of participants assigned to an active control condition (equivalent to the control condition in the first study) to performance of participants assigned to a passive control condition that was not intellectually stimulating.

We did not find meaningful differences in the magnitude of pre- to post-test change between the two control conditions in this second study. However, post-hoc analyses separating the simple and complex scores of the Study 2 control conditions demonstrated improvement from pre- to post-test with a moderate effect for both simple and complex scores (where previously the control condition in Study 1 demonstrated a *large* effect for simple scores). Further, post-hoc analyses demonstrated that both perspective-taking conditions (social interaction and alone) had a slightly larger increase in simple scores than the passive control condition. Therefore, these findings provided some modest evidence for a perspective-taking benefit on processing speed above and beyond simple practice effects. However, as effect sizes were small to negligible, caution must be applied when interpreting these findings. As there was no observable difference in improvement scores between the two perspective-taking conditions (social or alone), this indicated that social interaction did not appear to have any additional benefits on general cognitive functioning above and beyond that of perspective-taking.

These studies offered a contribution to knowledge by addressing gaps in the literature through replication and extension of previous studies. Together, the findings share commonality in that social activity was not found to be a strong predictor (or a predictor at all) of cognition across any of the observed timescales (from our long-term, cross-sectional, daily, or acute findings). However, processing speed appeared to be the most susceptible cognitive domain for improvement. The fact that we did not find any strong support for a social engagement-cognition relationship across any of the studies was surprising given the considerable amount of previous research evidence supporting such a relationship (e.g., Desai et al., 2020; Evans et al., 2018; Kuiper et al., 2016; Lara, Martín-María, et al., 2019).

6.3. Social Resources and Cognition: The Broader Context

The studies included in this thesis contributed to the social engagement-cognition literature by addressing several key questions related to potential mechanisms linking social resources with cognitive functioning across different time scales. The following section aims to situate the key findings from this thesis within the context of the broader literature.

Although the studies published in the literature to date tell a relatively consistent story of social resources playing a role in maintaining cognition in older age (e.g., Kuiper et al., 2016), our findings were largely inconsistent with those of the previous literature. We offer some explanations for these discrepancies. First, we suspect that different timescales of measurement may be critical for detecting associations between social engagement or social resources and cognitive test performance. Specifically, our longitudinal findings provided some (albeit weak) support for social engagement-cognition links reported previously, and most of the existing evidence is based on findings from similar large-scale cohort designs (e.g., systematic review and meta-analyses often use cross-sectional or longitudinal data). However, shorter-term studies have been far less frequent. This could be due to micro-longitudinal studies being a newer area of research in this field, and/or perhaps a result of publication bias (e.g., journals not publishing findings with null results) (Rosenthal, 1979). Nonetheless, our findings remain broadly consistent with the idea that acute boosts in some cognitive domains (by mechanism of perspective-taking) and long-term impacts of social engagement (via neurological pathways) could positively influence cognition in line with the broader literature (e.g., Fratiglioni et al., 2004; Ybarra et al., 2008). However, further research using micro-time scales is needed to adequately assess day-to-day (or moment-to-moment) covariation between social (or other activity engagement) and cognitive performance.

Another discrepant finding in our work compared to the broader literature was the finding that severity of negative exchanges was not related to cognitive performance at the daily level. This may have been a result of a lack of statistical power (see Chapter 4), however it is also the case that the literature investigating the impact of negative social exchanges on cognition has largely been conducted over longer timescales and findings have been mixed. Specifically, some studies have reported that people who experience more negative interactions have worse cognition (Wilson et al., 2015), while other studies have found that people who experience more negative interactions are likely to have *better* cognition (e.g., Hughes et al., 2008; Seeman et al., 2001; Windsor et al., 2014). This latter finding could be explained by different pathways. First, people with better cognition are more likely to be engaged in different/complex relationships, and so they may be more likely to be exposed to negative exchanges. Second, social partners may treat people who they see as more vulnerable more favourably, thereby avoiding conflict resulting in a positive association between cognitive ability and negative exchanges (i.e., those viewed as less cognitively able have fewer negative exchanges) (Fingerman & Charles, 2010). Another possibility is that as cognition declines, people avoid situations (like difficult social partners that may increase the likelihood of experiencing a negative social exchange) that could overly tax their cognitive resources (Hess, 2014). These explanations highlight the complex, context-specific influences on both the nature of social interactions and cognitive ability, as well as the importance of considering reverse causality.

Although previous studies have demonstrated that interventions to enhance social connections may support the maintenance of healthy cognitive functioning, there have been some studies showing that interventions promoting physical and cognitive activity were more beneficial to cognitive functioning than interventions enhancing social connections (Evans et al., 2019; Mortimer et al., 2012; Park et al., 2014). These findings, combined with our findings, may suggest that interventions targeting social isolation alone may be insufficient in reducing poor cognitive functioning in later life. However, even if social engagement is not necessarily the component of interventions that contribute to reducing cognitive decline in older adulthood, it is likely that engaging socially is a gateway to mental stimulation, positive mood, positive health behaviours, or other aspects of activity that relate to improvements in cognition. Therefore, there is likely no harm in suggesting social engagement to older adults as it might inadvertently create opportunities for older adults to boost their cognition via alternative pathways.

Finally, it is important to acknowledge that in a time of physical distancing to reduce spread during the current COVID-19 pandemic, older adults are at greater risk of becoming socially isolated or lonely. COVID-19 studies have begun to also demonstrate the importance of social engagement as a tool in maintaining cognition in older adults. Recent work in the UK examined the effect of COVID-19 induced social isolation on cognitive functioning by following participants over 13-weeks measured at five timepoints. The earliest time point reflected the strictest pandemic restrictions (e.g., leaving the house only for essential work that could not be completed at home, groceries, or individual outdoor exercise), and over the course of the study pandemic restrictions eased (e.g., at later time points people could meet up with others from up to two households indoors or outdoors, and hospitality, hairdressers, and social events reopened). The researchers reported that easing of restrictions (allowing for more mobility and social contact) coincided with improvement in a number of tests of cognitive function. This pattern was reinforced by evidence that individuals who were more isolated (e.g., those required to quarantine) demonstrated longer-lasting deficits in cognition. These findings suggest that continued pandemic restrictions to social contact may be highly detrimental to cognitive function. However, as there were no baseline measures of cognitive functioning, practice effects for task improvement could not be ruled out (Ingram et al., 2021). Other work has also cautioned that the social and physical reduction effects of the pandemic restrictions may increase the risk of developing dementia or faster dementia progression given that social and physical activity form components of cognitive reserve (Kwok et al., 2021). As such, if lockdown conditions continue to be used in the fight against COVID-19, strategies to alleviate subjective feelings of social isolation should be considered in vulnerable populations.

6.4. Limitations and Future Directions

As outlined in the limitation sections of each empirical chapter of this thesis (Parts 3.6.2, 4.5.3, and 5.10.3), in this section we draw attention to the limitations of the research studies described to inform future research endeavours. The correlational nature of the long-term longitudinal, micro-longitudinal, and cross-sectional analyses allowed for the possibility of reverse causality accounting for social engagement-cognition relationships. For example, it is plausible that those who are more cognitively able seek out stimulating activities that involve social interaction. First, in the long-term longitudinal findings, we controlled for possible reverse causality by excluding participants at baseline with possible dementia. Further, we included additional analyses that excluded participants at any wave with possible dementia status. Findings from the latter analyses supported a reverse causality explanation, as once these participants were removed from the analysis, the four-way interaction effect was substantially reduced in magnitude. Second, in our cross-sectional analyses, there was a strong possibility that our finding of participants with higher engagement with life performing better on a verbal fluency test was driven by better preserved cognition allowing for greater engagement with life.

Other aspects of the study designs posed some limitations. For example, a limitation of using a daily diary study is that the online environment is not as controlled as standard neurological assessments. This has the potential to create more noise in the data and make the measures less sensitive (i.e., a possible explanation for why we did not observe evidence for daily covariation of our variables with processing speed findings). In contrast, using an experimental design may not have generalisability to real world applications given the less ecologically valid nature of laboratory settings. Researchers are beginning to overcome some of these limitations as ecological momentary assessment approaches that include cognitive assessments continue to evolve (e.g., Zhaoyang et al., 2021). Ultimately a larger evidence base that draws on multiple different approaches that complement those of the existing longitudinal cohort designs may be needed to shed light on relevant mechanisms potentially linking social resources with cognition.

We also considered some of the measurement techniques used in the current thesis to be potential limitations. First, our long-term longitudinal analyses used a social activity engagement measure that asked participants to consider four specific social activities whereas a wide variety of social activities not assessed may contribute to cognition. In addition, participants were asked about activity in the past month which may have introduced appreciable recall-bias resulting in noisy estimates of actual activity level. Further, our loneliness measure although used in previous work (e.g., Courtin & Knapp, 2017; Menec et al., 2019; Wagner et al., 2013), was not as robust as other established loneliness measures that could be used (e.g., see Veazie et al., 2019 for common instruments used to measure social isolation). Using a dichotomous measure of loneliness also poses limitations, such as information that may be captured using a continuous variable may become lost (i.e., some people may be more severely lonely than others) and the statistical power to detect a relationship between loneliness and cognition may have therefore been reduced (see Altman & Royston, 2006). Additionally, although it is common practice to use education or occupational complexity as proxy measures of cognitive reserve (e.g., Opdebeeck et al., 2016), proxy variables may relate to clinical performance for reasons other than the "reserve" mechanism (Zahodne et al., 2013). For example, education correlates with childhood IQ, socioeconomic status, risk of disease, and health behaviours (Reed et al., 2010). Further, the same value of a proxy variable (e.g., 12 years of education) does not reflect the same experience in all people. To solve these issues with proxy variables, there have been promising investigations concerning quantifying cognitive reserve as residual variance in cognitive performance that remains after statistically controlling for demographic factors and brain pathology (e.g., see Zahodne et al., 2013). Researchers should consider using these measures of cognitive reserve in future research endeavours. Finally, in our experimental study, we may have inadvertently created an ‘intellectual activity’ condition instead of a control condition (explained in detail in Chapter 5). However, we aimed to rectify this design issue by creating a second study that created a true passive control condition.

A final consideration concerned the generalisability of findings for each of the studies. First, although using a longitudinal design has its benefits (e.g., it allows for capturing changes across long time periods), and Bayesian methods make use of all available data minimising bias in parameter estimates resulting from differential attribution, the participants providing the most longitudinal data points likely represented a positively biased minority of the sample. Second, the daily diary study required participants to be computer literate and as such the findings are not generalisable to more diverse populations of older adults. Further, the micro-longitudinal sample was relatively young and high functioning (*Mean age* = 62 years). Thus, caution is necessary when generalising the findings of these subgroups to the wider population. Similarly, in our experimental study, our sample were healthy, young, first-year university students. It is possible that the effects of interest would have been more evident in a sample of older adults with greater variability in their cognitive abilities who had more room for improvement on the cognitive tasks from pre- to post-test. Future research might benefit from recruiting older samples with greater diversity of cognitive abilities in an effort to replicate the social interaction benefits for cognition demonstrated in university samples by Ybarra et al. (2008, 2011). Unfortunately, plans to conduct such a study as part of the current thesis needed to be shelved as a result of COVID-19.

Finally, there is no one study design that we can recommend to test whether social resources play a role in protecting against neurodegenerative illnesses such as dementia. It would be unethical to manipulate how much social activity people engage in or what their social resource structures look like as part of a long-term investigation. Because of this, the operation of third factor variables remains a possibility in the designs available to test the social engagement-cognition relationship. However, future research might consider targeting non-demented older adult samples who have a wide range of cognitive abilities to participate in measurement burst type studies that capture both the short-term and long-term changes to better understand how different mechanisms might fit together (Sliwinski, 2008). For example, measurement burst studies could be used to examine whether a leaky balloon (see Section 1.5.1 for complete analogy), which represents normal cognitive decline over the lifespan, stays more inflated over a longer-time course if consistently blown into on a short-term basis. Further, examining associations between daily experiences and long-term outcomes with the combined use of interview and micro-longitudinal data would allow researchers to examine whether intellectual stimulation achieved through social connections that happen on a shorter-term scale (day-to-day or moment-to-moment) over long time-periods are contributing to long-term healthy cognitive aging.

6.5. Conclusion

Overall, this thesis contributes knowledge on the utility of social resources for cognition in older and younger adulthood and demonstrates value in considering the role social resources play in the prevention of cognitive decline. In summary, the timescales of measurement should be considered in the complex nature of the social engagement-cognition relationship. Where we were able to demonstrate relationships using long-term longitudinal data (e.g., some evidence for the compensatory reserve hypothesis), these associations may have been a result of reverse causality, and levels of social activity and daily social exchanges were not related to cognition using a daily time scale. Finally, our experimental results suggested that perspective-taking (independent of social interaction) might produce acute boosts in processing speed performance among younger women.

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APPENDIX A

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APPENDIX B

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APPENDIX C

Table A.1

ALSA Model Including Social Activity, Loneliness, and Education as Predictors of Initial Letter Fluency Trajectories Among Those Without Probable Dementia at All Timepoints (n = 398)

	Intercept			Linear slope			Quadratic slope		
Parameter	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE	Est.	$HDI_{95\%}$	Prob. [below, within, above] ROPE (±0.05)
Fixed effects									
Intercept/slope	-0.12	[-0.33, 0.09]		-0.01	[-0.12, 0.09]	[0.26, 0.63, 0.12]	-0.05	[-0.09, -0.01]	[0.49, 0.52, 0.00]
Covariates									
Age at baseline	-0.03	[-0.12, 0.05]		0.01	[-0.03, 0.06]				
Female	-0.01	[-0.11 0.08]		-0.02	[-0.06, 0.02]				
Count of comorbidities	0.05	[-0.05, 0.14]		0.01	[-0.03, 0.04][b]				
Depressive affect	-0.02	[-0.12, 0.08]		-0.04	[-0.08, 0.01]				
Main predictors									
Education	0.10	[-0.04, 0.25]	[0.02, 0.21, 0.77]	0.02	[-0.10, 0.14]	[0.13, 0.57, 0.31]			
Social activity engagement	0.09	[-0.08, 0.25]	[0.05, 0.28, 0.66]	0.02	[-0.07, 0.10]	[0.06, 0.71, 0.23]			
Lonely	-0.06	[-0.27, 0.16]	[0.52, 0.31, 0.17]	0.03	[-0.07, 0.14]	[0.06, 0.56, 0.38]			
Education x social activity engagement	-0.04	[-0.18, 0.09]	[0.45, 0.45, 0.09]	-0.02	[-0.13, 0.10]	[0.29, 0.57, 0.13]			
Education x lonely	-0.08	[-0.22, 0.06]	[0.67, 0.30, 0.04]	0.04	[-0.08, 0.17]	[0.07, 0.30, 0.46]			
Social activity engagement x lonely	-0.04	[-0.20, 0.13]	[0.43, 0.42, 0.15]	0.02	[-0.07, 0.11]	[0.06, 0.69, 0.25]			
Education x social activity engagement x lonely	0.02	[-0.12, 0.15]	[0.18, 0.51, 0.32]	-0.02	[-0.13, 0.10]	[0.28, 0.59, 0.13]			
Random effects									

Level 3 (couple)		
Intercept (SD)	0.75	[0.60, 0.88]
Slope (SD)	0.03	[0.00, 0.09]
Intercept-slope correlation	0.14	[-0.87, 0.94]
Level 2 (individual)		
Intercept (SD)	0.75	[0.60, 0.88]
Slope (SD)	0.03	[0.00, 0.09]
Intercept-slope correlation	0.14	[-0.87, 0.94]
Residual	0.47	[0.44, 0.50]

Note. [a] 80% certainty of HDI falling within the ROPE. [b] HDI fell completely within the ROPE. [*] 80% certainty of HDI falling outside the ROPE. [**] HDI fell completely outside the ROPE.

APPENDIX D

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APPENDIX E

Connections Test Practice Task

Number

1	11	12	13
2	3	10	14
4	7	9	15
5	6	8	16

Letter

A	B	E*	D*
E	C	F*	C*
F	D	B*	G*
G	H	A*	H*

Number-Letter

1	A	2	C
E	B	3	4
6	5	D	8
F	7	G	H

Letter-Number

A	F	6	G
2	1	5	7
C	B	E	H
3	D	4	8

Note. This is an illustration of the practice task given to each participant for each condition of the Connections test. The actual task consisted of 49 target circles in an array of 7 x 7.

APPENDIX F

Pre-validation of Film

To avoid inadvertently eliciting emotions (positive or negative) likely to affect performance on the post-test executive functioning task, we aimed to produce a film stimulus that was affectively neutral in its nature. Before we used the film in the main studies, we conducted a short pre-validation study asking participants about their emotional responses to the film to ensure its neutral affect. If our film was of neutral affect, we expected to see no difference in ratings of discrete emotions (positive or negative), affect (positive or negative), or arousal when comparing current ratings to those of Schaefer et al.'s (2010) neutral films.

Method

Participants

An email was circulated to staff and postgraduate students in the College of Education, Psychology and Social Work at Flinders University, inviting them to participate in a pre-study validation of emotional response to a short film. The final sample (n = 23, *males* = 6, *age range* = 23 – 50 years, M = 27.41 years) excluded two participants who did not respond on any of the measures.

Procedure

Participation in the study was completed online using the web-based survey software *Qualtrics*. We first recorded basic demographic information, namely participant's gender and age. Then participants watched the 6-min film. Following this, participants were asked to rate the film on the following three scales, consistent with those used by Schaefer et al. when validating their database of emotion-eliciting films.

Differential Emotions Scale (DES).

We used a version of the DES (Izard et al., 1974; McHugo et al., 1982) to assess discrete emotions in response to watching a film. This version of the DES has been used in previous validations of emotional films (e.g., McHugo et al., 1982; Philippot, 1993; Schaefer et al., 2010; Schaefer & Philippot, 2005). Each of the 16 items on the DES consists of groups of emotional adjectives. Participants were asked to rate the extent they felt each state as they were watching the film clip on a 7-point Likert type scale, from 1 (not at all) to 7 (very intense). In line with the method used by Schaefer et al. (2010), positive composite scores were created by taking the average of the following DES items: 1) joyful, happy, amused; 2) warm hearted, gleeful, elated; 3) loving, affectionate, friendly; 4) moved; and 5) satisfied, pleased. The negative composite scores were created the same way using the following DES items: 1) sad, downhearted, blue; 2) angry, irritated, mad; 3) fearful, scared, afraid; 4) anxious, tense, nervous; 5) disgusted, turned off, repulsed; 6) disdainful, scornful, contemptuous; 7) guilty, remorseful; and 8) ashamed, embarrassed.

Positive Affect Negative Affect Scale (PANAS).

Participants were asked to indicate to what extent they experienced emotions reflecting positive affect (active, alert, attentive, determined, enthusiastic, excited, inspired, interested, proud, and strong) and negative affect (afraid, ashamed, distressed, guilty, hostile, irritable, jittery, nervous, scared and upset) at that present moment using a 5-point rating scale (very slightly or not at all, a little, moderately, quite a bit, extremely). In line with the method used by Schaefer et al. (2010), positive affect (PA) and negative affect (NA) scales were created by averaging scores from the PANAS (Crawford & Henry, 2004) positive and negative affect subscale items respectively.

Arousal.

Participants rated their level of arousal while watching the film on a 7-point Likert type scale from 1 (I felt no emotions at all) to 7 (I felt very intense emotions).

Results

To recapitulate; to determine whether the film participants evaluated was classifiable as a neutrally affective film, we directly compared the ratings observed in the current pilot study to those of Shaefer et al.'s (2010) neutral films on the same scales. We expected to see no difference in ratings of positive or negative composite score, positive or negative affect, or arousal to the published means. We used a region of practical equivalence (ROPE) of ± 1 SD of the published means to constitute a negligible difference. Relevant descriptive statistics for Schaefer et al.'s (2010) published findings and our pilot findings along with the probabilities that our pilot mean is within the ROPE are presented in Table A.2.

A Bayesian equivalent t-test revealed decisive evidence that the positive composite pilot score was equivalent to the published score ($P_{(within\ ROPE)}$ = 100%). Similarly for the negative composite score, although we cannot exclude with 95% confidence that the pilot negative affect ratings were meaningfully higher than the published ratings ($P_{(meaningful)}$ = 22.3%), the balance of evidence was in favour of no difference between the pilot and published scores ($P_{(within\ ROPE)}$ = 77.7%). For positive affect, although we cannot exclude with 95% confidence that the pilot positive affect ratings were meaningfully higher than the published ratings ($P_{(meaningful)}$ = 8.9%), the balance of evidence was in favour of no difference between the pilot and published scores ($P_{(within\ ROPE)}$ = 91.1%). However, there was evidence that the negative affect pilot score was equivalent to the published score ($M_{(within\ ROPE)}$ = 100%). Finally, although we cannot completely rule out a negligible effect with 95% confidence ($P_{(within\ ROPE)}$ = 22.8%), the balance of evidence was in favour of the arousal pilot score being greater than the published score ($P_{(meaningful)}$ = 77.2%).

Table A.2

Summary of Estimated Parameters for Schaefer et al.'s (2010) Neutral Films and the Pilot Film (Mean and Standard Deviation) for Positive Composite Score, Negative Composite Score, Positive Affect, Negative Affect, and Arousal

	Published	Pilot		
	Mean (SD)	Posterior Mean	Posterior SD	Probability [below, within, above] the SD
Positive composite score	1.66 (1.00)	1.98 [1.63 – 2.33]	0.85 [0.60 – 1.13]	[0.00, 1.00, 0.00] [b]
Negative composite score	1.17 (0.25)	1.35 [1.18 – 1.53]	0.42 [0.30 – 0.56]	[0.00, 0.78, 0.22]
Positive affect	1.37 (0.40)	1.64 [1.45 – 1.84]	0.45 [0.32 – 0.60]	[0.00, 0.91, 0.09] [a]
Negative affect	1.20 (0.30)	1.16 [1.07 – 1.26]	0.23 [0.16 – 0.30]	[0.00, 1.00, 0.00] [b]
Arousal	1.79 (1.00)	2.96 [2.52 – 3.41]	1.08 [0.77 – 1.42]	[0.00, 0.23, 0.77]

Note. $HDI_{95\%}$ are displayed in square brackets. Probability fell inside the negligible range indicates no difference in mean between the pilot and the published mean. [a] 80% certainty of published mean falling within the pilot mean HDI. [b] Published mean fell completely within the pilot mean HDI.

Discussion

Findings indicated that the pilot film was rated no differently to the published neutral films for positive composite scores, negative scores, positive affect, and negative affect. However, arousal levels were rated higher for the pilot video than Schaefer et al.'s (2010) neutral films. Although our mean was meaningfully higher than the published mean, we still consider the arousal pilot mean score ($M_{95\%}$ = 2.96 [2.51 – 4.40]) to be low, given the scale (0 = I felt no emotions at all to 7 = I felt very intense emotions). Therefore, we take these findings as successfully inducing a neutral affect of equivalent standard to that Schaefer et al. (2010) when watching this film.

APPENDIX G

Table A.3

Study 1 Posterior Mean, Effect Size, and ROPE Probabilities for All Combinations of Condition (PT-social, PT-alone, Control-alone), Time (Baseline, Post-Test, Difference), and Measure of Affect (Global, Anger, Contentment, Fear, Guilt, Happiness, Sadness, Surprise)

	Baseline (Time 1)	Post-test (Time 2)	Difference (T2 – T1)	*d*	Probability [below, within, above] the ROPE (±0.1)
Global Affect					
PT-social	0.15 [0.01, 0.28]	-0.20 [-0.34, -0.07]	-0.35 [-0.53, -0.17]	-0.37 [-0.56, -0.18]	[1.00, 0.00, 0.00]**
PT-alone	0.21 [0.07, 0.35]	-0.20 [-0.33, -0.06]	-0.41 [-0.60, 0.23]	-0.43 [-0.63, -0.23]	[1.00, 0.00, 0.00]**
Control-alone	0.20 [0.07, 0.33]	-0.16 [-0.29, -0.04]	-0.36 [-0.54, -0.19]	-0.38 [-0.57, -0.20]	[1.00, 0.00, 0.00]**
Anger					
PT-social	1.58 [1.38, 1.78]	1.13 [0.93, 1.33]	-0.44 [-0.70, -0.19]	-0.79 [-1.26, -0.34]	[1.00, 0.00, 0.00]**
PT-alone	1.59 [1.39, 1.79]	1.21 [1.00, 1.40]	-0.38 [-0.64, -0.10]	-0.68 [-1.15, -0.19]	[0.99, 0.01, 0.00]**
Control-alone	1.71 [1.51, 1.92]	1.20 [0.99, 1.39]	-0.52 [-0.80, -0.25]	-0.92 [-1.44, -0.45]	[1.00, 0.00, 0.00]**
Contentment					
PT-social	2.57 [2.24, 2.93]	2.69 [2.35, 3.05]	0.12 [-0.33, -0.59]	0.12 [-0.35, 0.60]	[0.17, 0.31, 0.53]
PT-alone	2.49 [2.13, 2.85]	2.30 [1.91, 2.68]	-0.19 [-0.72, 0.31]	-0.20 [-0.75, 0.32]	[0.61, 0.25, 0.13]
Control-alone	2.48 [2.14, 2.82]	2.79 [2.43, 3.14]	0.31 [-0.16, 0.81]	0.32 [-0.16, 0.79]	[0.04, 0.17, 0.79]
Fear					
PT-social	1.09 [0.99, 1.19]	1.04 [0.93, 1.13]	-0.06 [-0.19, 0.07]	-0.20 [-0.63, 0.23]	[0.67, 0.24, 0.08]
PT-alone	1.17 [1.06, 1.27]	1.09 [0.99, 1.19]	-0.08 [-0.21, 0.05]	-0.27 [-0.71, 0.17]	[0.77, 0.19, 0.04]

Control-alone	1.12 [1.02, 1.21]	1.06 [0.96, 1.15]	-0.06 [-0.18, 0.06]	-0.19 [-0.61, 0.22]	[0.67, 0.25, 0.08]
Guilt					
PT-social	1.23 [1.09, 1.36]	1.10 [0.95, 1.23]	-0.13 [-0.31, 0.04]	-0.33 [-0.78, 0.11]	[0.86, 0.12, 0.03]*
PT-alone	1.36 [1.21, 1.50]	1.21 [1.07, 1.35]	-0.15 [-0.33, 0.02]	-0.38 [-0.84, 0.06]	[0.90, 0.09, 0.01]*
Control-alone	1.19 [1.05, 1.32]	1.08 [0.94, 1.21]	-0.11 [-0.28, 0.06]	-0.28 [-0.71, 0.17]	[0.80, 0.16, 0.05]*
Happiness					
PT-social	2.45 [2.14, 2.76]	2.10 [1.79, 2.43]	-0.35 [-0.73, 0.09]	-0.40 [-0.87, 0.08]	[0.89, 0.08, 0.02]*
PT-alone	2.27 [1.96, 2.59]	1.72 [1.38, 2.04]	-0.56 [-1.00, 0.14]	-0.65 [-1.18, -0.17]	[0.99, 0.01, 0.00]**
Control-alone	2.32 [2.03, 2.62]	1.94 [1.66, 2.24]	-0.38 [-0.76, 0.01]	-0.44 [-0.89, 0.01]	[0.93, 0.06, 0.01]*
Sadness					
PT-social	1.37 [1.18, 1.55]	1.43 [1.24, 1.61]	0.06 [-0.19, 0.29]	0.11 [-0.34, 0.54]	[0.16, 0.32, 0.52]
PT-alone	1.33 [1.14, 1.51]	1.47 [1.28, 1.65]	0.14 [-0.09, 0.39]	0.26 [-0.17, 0.71]	[0.04, 0.21, 0.75]
Control-alone	1.39 [1.22, 1.57]	1.50 [1.32, 1.67]	0.11 [-0.12, 0.33]	0.19 [-0.21, 0.61]	[0.07, 0.26, 0.67]
Surprise					
PT-social	2.32 [2.01, 2.63]	1.30 p1.00, 1.61]	-1.02 [-1.43, -0.62]	-1.23 [-1.73, -0.72]	[1.00, 0.00, 0.00]**
PT-alone	2.45 [2.14, 2.76]	1.54 [1.23, 1.86]	-0.92 [-1.33, -0.46]	-1.10 [-1.61, -0.55]	[1.00, 0.00, 0.00]**
Control-alone	2.60 [2.30, 2.92]	1.32 [1.01, 1.61]	-1.29 [-1.73, -0.87]	-1.54 [-2.11, -1.01]	[1.00, 0.00, 0.00]**

Note. HDI*95%* are displayed in square brackets.

d reflects the effect size of the Time 2 minus Time 1 difference for the estimated means.

Probability below ROPE indicates a decrease in relative affect scores at Time 1 to Time 2. * 80% certainty of HDI falling outside the ROPE. ** HDI fell completely outside the ROPE.

Table A.4

Study 1 Posterior Mean, Effect Size, and ROPE Probabilities for All Combinations of Condition (PT-social, PT-alone, Control-alone), Time (Baseline, Post-Test, Difference), and Measure of Motivation (Global, Engaging, Stimulating, Motivating)

	Baseline (Time 1)	Post-test (Time 2)	Difference (Time 2 – Time 1)	*d*	Probability [below, within, above] ROPE (±0.1)
Global Motivation					
PT SI	0.44 [0.25, 0.64]	-0.38 [-0.58, -0.19]	-0.82 [-1.09, -0.55]	-0.93 [-1.23, -0.62]	[1.00, 0.00, 0.00]**
PT alone	0.56 [0.37, 0.75]	-0.41 [-0.60, -0.22]	-0.97 [-1.23, -0.72]	-1.10 [-1.40, 0.81]	[1.00, 0.00, 0.00]**
Control alone	0.42 [0.24, 0.60]	-0.61 [-0.80, -0.44]	-1.03 [-1.28, -0.78]	-1.17 [-1.46, -0.87]	[1.00, 0.00, 0.00]**
Engaging					
PT SI	4.35 [4.04, 4.66]	3.77 [3.46, 4.09]	-0.58 [-1.00, -0.15]	-0.66 [-1.14, -0.17]	[0.98, 0.02, 0.00]**
PT alone	4.48 [4.17, 4.79]	3.73 [3.43, 4.04]	-0.74 [-1.17, -0.35]	-0.84 [-1.32, -0.38]	[1.00, 0.00, 0.00]**
Control alone	4.35 [4.07, 4.65]	3.61 [3.32, 3.91]	-0.74 [-1.14, -0.35]	-0.84 [-1.29, -0.39]	[1.00, 0.00, 0.00]**
Stimulating					
PT SI	4.44 [4.12, 4.77]	3.33 [3.01, 3.66]	-1.11 [-1.55, -0.70]	-1.20 [-1.68, -0.72]	[1.00, 0.00, 0.00]**
PT alone	4.51 [4.49, 4.19]	3.35 [3.03, 3.67]	-1.17 [-1.58, -0.74]	-1.26 [-1.68, -0.72]	[1.00, 0.00, 0.00]**
Control alone	4.32 [4.00, 4.63]	3.08 [2.75, 3.39]	-1.24 [-1.66, -0.84]	-1.34 [-1.82, -0.88]	[1.00, 0.00, 0.00]**
Motivating					
PT SI	4.04 [3.67, 4.42]	2.85 [2.48, 3.24]	-1.19 [-1.67, -0.68]	-1.08 [-1.54, -0.60]	[1.00, 0.00, 0.00]**
PT alone	4.09 [3.72, 4.47]	2.83 [2.46, 3.20]	-1.27 [-1.76, -0.79]	-1.15 [-1.61, -0.69]	[1.00, 0.00, 0.00]**
Control alone	4.01 [3.65, 4.37]	2.68 [2.31, 3.04]	-1.33 [-1.82, -0.88]	-1.21 [-1.67, -0.77]	[1.00, 0.00, 0.00]**

Note. $HDI_{95\%}$ are displayed in square brackets.

d reflects the effect size of the Time 2 minus Time 1 difference for the estimated means.

Probability below ROPE indicates a decrease in relative motivation scores at Time 1 to Time 2. * 80% certainty of HDI falling outside the ROPE. ** HDI fell completely outside the ROPE.

Table A.5

Study 2 Posterior Mean, Effect Size, and ROPE Probabilities for All Combinations of Condition (PT-social, PT-alone, Control-alone), Time (Baseline, Post-Test, Difference), and Measure of Affect (Global, Anger, Contentment, Fear, Guilt, Happiness, Sadness, Surprise)

	Baseline (Time 1)	Post-test (Time 2)	Difference (Time 2 – Time 1)	*d*	Probability [below, within, above] ROPE (±0.1)
Global Affect					
Active	0.27 [0.13, 0.41]	-0.23 [-0.36, -0.08]	-0.50 [-0.69, -0.30]	-0.51 [-0.72, -0.31]	[1.00, 0.00, 0.00]**
Passive	0.13 [-0.01, 0.26]	-0.17 [-0.31, -0.03]	-0.30 [-0.49, -0.10]	-0.31 [-0.51, -0.11]	[0.98, 0.02, 0.00]**
Anger					
Active	1.71 [1.47, 1.96]	1.21 [0.97, 1.46]	-0.49 [-0.83, -0.16]	-0.74 [-1.25, -0.24]	[0.99, 0.01, 0.00]**
Passive	1.65 [1.40, 1.90]	1.19 [0.95, 1.44]	-0.45 [-0.78, -0.11]	-0.68 [-1.17, -0.16]	[0.99, 0.01, 0.00]**
Contentment					
Active	2.44 [2.15, 2.74]	2.28 [2.00, 2.59]	-0.15 [-0.55, 0.24]	-0.19 [-0.68, 0.28]	[0.64, 0.25, 0.11]
Passive	2.56 [2.28, 2.87]	2.37 [2.07, 2.67]	-0.20 [-0.61, 0.18]	-0.24 [-0.73, 0.23]	[0.71, 0.21, 0.07]
Fear					
Active	1.21 [1.08, 1.34]	1.09 [0.97, 1.22]	-0.12 [-0.30, 0.05]	-0.37 [-0.93, 0.15]	[0.83, 0.13, 0.04]*
Passive	1.05 [0.93, 1.18]	1.10 [0.98, 1.23]	0.05 [-0.13, 0.22]	0.15 [-0.37, 0.68]	[0.18, 0.26, 0.56]
Guilt					
Active	1.43 [1.24, 1.63]	1.12 [0.92, 1.31]	-0.31 [-0.58, -0.04]	-0.58 [-1.10, -0.09]	[0.97, 0.02, 0.00]
Passive	1.33 [1.13, 1.52]	1.05 [0.85, 1.24]	-0.28 [-0.55, -0.02]	-0.53 [-1.03, -0.03]	[0.96, 0.04, 0.00]
Happiness					

Active	2.14 [1.87, 2.40]	1.84 [1.57, 2.10]	-0.30 [-0.67, 0.09]	-0.42 [-0.94, 0.12]	[0.88, 0.09, 0.03]*
Passive	2.30 [2.03, 2.57]	1.71 [1.43, 1.98]	-0.60 [-0.99, -0.22]	-0.84 [-1.41, -0.31]	[1.00, 0.00, 0.00]**
Sadness					
Active	1.44 [1.22, 1.67]	1.33 [1.10, 1.55]	-0.11 [-0.44, 0.20]	-0.20 [-0.76, 0.34]	[0.63, 0.22, 0.15]
Passive	1.28 [1.06, 1.51]	1.65 [1.42, 1.88]	0.37 [0.04, 0.70]	0.64 [0.07, 1.21]	[0.00, 0.03, 0.97]*
Surprise					
Active	2.11 [1.82, 2.41]	1.37 [1.08, 1.67]	-0.74 [-1.15, -0.34]	-0.94 [-1.48, -0.42]	[1.00, 0.00, 0.00]**
Passive	1.89 [1.59, 2.18]	1.33 [1.03, 1.62]	-0.56 [-0.95, -0.14]	-0.72 [-1.23, -0.19]	[0.99, 0.01, 0.00]**

Note. $HDI_{95\%}$ are displayed in square brackets.

d reflects the effect size of the Time 2 minus Time 1 difference for the estimated means.

Probability below ROPE indicates a decrease in relative affect scores at Time 1 to Time 2. * 80% certainty of HDI falling outside the ROPE. ** HDI fell completely outside the ROPE.

Table A.6

Study 2 Posterior Mean, Effect Size, and ROPE Probabilities for All Combinations of Condition (PT-social, PT-alone, Control-alone), Time (Baseline, Post-Test, Difference), and Measure of Motivation (Global, Engaging, Stimulating, Motivating)

	Baseline (Time 1)	Post-test (Time 2)	Difference (Time 2 – Time 1)	*d*	Probability [below, within, above] ROPE (±0.1)
Global Motivation					
Active	0.51 [0.32, 0.69]	-0.39 [-0.58, -0.21]	-0.90 [-1.16, -0.64]	-1.08 [-1.40, -0.76]	[1.00, 0.00, 0.00]**
Passive	0.58 [0.40, 0.76]	-0.69 [-0.87, -0.50]	-1.27 [-1.53, -1.01]	-1.52 [-1.86, -1.18]	[1.00, 0.00, 0.00]**
Engaging					
Active	4.09 [3.73, 4.45]	3.44 [3.07, 3.80]	-0.65 [-1.16, -0.15]	-0.67 [-1.18, -0.13]	[0.98, 0.02, 0.00]**
Passive	4.48 [3.76, 4.48]	3.23 [2.86, 3.60]	-0.89 [-1.40, -0.39]	-0.91 [-1.45, -0.39]	[1.00, 0.00, 0.00]**
Stimulating					
Active	4.25 [3.90, 4.58]	2.90 [2.55, 3.25]	-1.35 [-1.85, -0.87]	-1.48 [-2.04, -0.91]	[1.00, 0.00, 0.00]**
Passive	4.32 [3.98, 4.68]	2.61 [2.27, 2.97]	-1.70 [-2.20, -1.22]	-1.86 [-2.45, -1.26]	[1.00, 0.00, 0.00]**
Motivating					
Active	3.79 [3.37, 4.23]	2.35 [1.92, 2.79]	-1.45 [-2.03, -0.82]	-1.27 [-1.82, -0.71]	[1.00, 0.00, 0.00]**
Passive	3.84 [3.41, 4.28]	1.90 [1.46, 2.34]	-1.95 [-2.59, -1.36]	-1.72 [-2.32, -1.14]	[1.00, 0.00, 0.00]**

Note. $\text{HDI}_{95\%}$ are displayed in square brackets.

d reflects the effect size of the Time 2 minus Time 1 difference for the estimated means.

Probability below ROPE indicates a decrease in relative motivation scores at Time 1 to Time 2. * 80% certainty of HDI falling outside the ROPE. ** HDI fell completely outside the ROPE.