Age-Related Differences in Mnemonic Neural Representations: Perceptual and Semantic Contributions

by

Zachary Adam Monge

Department of Psychology and Neuroscience
Duke University

Date:_______________________
Approved:

____
Roberto Cabeza, Supervisor

____
David J. Madden

____
Gregory R. Samanez-Larkin

____
Kelly S. Giovanello

Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor
of Philosophy in the Department of
Psychology and Neuroscience in the Graduate School
of Duke University

2020

ABSTRACT

Age-Related Differences in Mnemonic Neural Representations: Perceptual and Semantic Contributions

by

Zachary Adam Monge

Department of Psychology and Neuroscience
Duke University

Date:_______________________
Approved:

____
Roberto Cabeza, Supervisor

____
David J. Madden

____
Gregory R. Samanez-Larkin

____
Kelly S. Giovanello

Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor
of Philosophy in the Department of
Psychology and Neuroscience in the Graduate School
of Duke University

2020

Abstract

Preliminary evidence demonstrates that age-related differences in episodic memory performance become greater in tasks that have greater perceptual demands (e.g., task stimuli are visually degraded), but are attenuated in tasks that have greater semantic demands (e.g., task requires utilizing previous knowledge). This work suggests that age-related differences in how perceptual and semantic information are represented in the brain have an impact on episodic memory. Broadly, the goal of this thesis was to investigate this idea. To investigate this goal, while undergoing functional magnetic resonance imaging scanning, samples of younger and older adults studied and later retrieved their memories of pictures of either scenes (Study 1 and 2) or objects (Study 3). The first two studies found that, compared to younger adults, in older adults, (1) in occipitotemporal cortex, the quality of perceptual-related representations was attenuated, but, intriguingly, (2) in anterior temporal lobes and prefrontal cortex, the quality of semantic-related representations was similar and even enhanced; these effects were found to be related to episodic memory. Study 1 demonstrated this pattern in individual brain regions and Study 2 demonstrated that this pattern was also present in how information was distributed across the whole-brain network. In Study 3 it was found that these age-related differences in functional neural representations are the result of age-related visual signal loss and compensatory semantic-enhancing mechanisms. Taken together, the three studies highlight that age-related differences in neural representations have an impact on cognition and especially episodic memory.

Dedication

To my wife, Alexsandra A. Monge, and son, Zachary T. Monge.

Contents

List of Tables

List of Figures

Acknowledgements

I thank my advisor, Roberto Cabeza, for his support and mentorship, providing me with resources and opportunities to advance my career, and for helping me become a better scientist. I also thank David Madden for his continuous support and providing me with many opportunities that have greatly helped my graduate school career. I would also like to thank my other committee members, Gregory Samanez-Larkin and Kelly Giovanello, for their thoughtful comments and guidance with my research. Lastly, I thank everybody else who has helped me throughout graduate school, especially members of the Cabeza Lab, members of the Madden Lab, Duke BIAC's MRI Technologists (Susan, Natalie, Luke, Lamont, and Jennifer), and all the study participants who graciously dedicated their time for furthering my research and served as reminder of why I became a cognitive aging researcher.

1. Introduction

Aging is associated with a robust decline in performance on many cognitive tasks, such as working memory, processing speed, and memory tasks (Denise C Park et al., 2002; Timothy A. Salthouse, 2000). This is especially the case for episodic memory, which refers to the memory for personally-experienced individual past events (Tulving, 1972, 1985a). This age-related memory decline in episodic memory is associated with a worse quality of life, where age-related memory deficits are associated with decreased activities of daily living (Schmitter-Edgecombe, Woo, & Greeley, 2009) and in a large survey of older adults, “deterioration of memory” was the most commonly endorsed source of stress (Aldwin, 1990). In addition, episodic memory deficiencies are typically the first symptom of Alzheimer’s disease, making the investigation of mechanisms underlying age-related episodic memory decline clinically significant (Bäckman, Small, & Fratiglioni, 2001; Dubois et al., 2007; Mayeux, 2010). There are many factors that may influence the degree of age-related differences in episodic memory but based upon the behavioral literature there are two factors that appear to be especially important – perceptual and semantic factors.

Regarding perceptual factors, aging is associated with a robust decline in performance on perceptual tasks (e.g., Jackson & Owsley, 2003b; Nameda, Kawara, & Ohzu, 1989a; Cynthia Owsley, 2011) and age-related differences in memory become even greater during tasks in which participants are required to rely more on perceptual processing (e.g., Anstey, Butterworth, Borzycki, & Andrews, 2006; Cronin-Golomb, Gilmore, Neargarder, Morrison, & Laudate, 2007; Dickinson & Rabbitt, 1991). These studies suggest that perceptual deficiencies are at least partially responsible for the decline in memory and many other cognitive processes (for a review, see Monge & Madden, 2016).

Regarding semantic factors, despite aging being associated with a decline in performance on many cognitive tasks, semantic cognition, which is the ability to use knowledge in support of behavior (for a review, see Lambon Ralph, Jefferies, Patterson, & Rogers, 2017), appears to be preserved and possibly even enhanced in aging (Denise C Park et al., 2002; Verhaeghen, 2003). Furthermore, behavioral evidence demonstrates that when older adults are able to rely on knowledge in service of completing memory tasks, this reliance ameliorates some age-related episodic memory performance differences (for a review, see Umanath & Marsh, 2014). This evidence suggests the intriguing possibility that older adults' additional reliance on knowledge in service of memory serves as a compensatory mechanism. Combined with the literature demonstrating that perceptual demands negatively impact older adults' memory performance, perhaps the memory semantic-enhancing effect is compensating for perceptual deficiencies. The goal of this thesis is to investigate this idea from a cognitive neuroscience perspective. The three studies presented here investigate neural mechanisms underlying age-related differences in episodic memory and specifically the influence of perceptual and semantic neural representations. Before presenting these studies, I review behavioral evidence of age-related differences in perceptual and semantic performance, the neural correlates of perceptual and semantic processing, and neural representations. Lastly, I discuss the key questions addressed in this thesis.

1.1. Behavioral Evidence of Age-Related Differences in Perceptual and Semantic Task Performance

As mentioned above, aging is associated with a decline in performance on perceptual-related tasks and preservation and possibly enhancement in performance on semantic-related tasks. Below, I review the literature demonstrating these effects and discuss how these effects impact age-related differences in episodic memory performance.

1.1.1. Perceptual Performance in Aging

Normal aging is associated with a decline in visual perceptual abilities, specifically a decline in (a) visual acuity (Jackson & Owsley, 2003a; C. Owsley, 2011; Owsley, Sekuler, & Siemsen, 1983), which refers to the ability to detect small, high contrast targets (e.g., the gap in Landolt Cs) and (b) visual contrast sensitivity (Greene & Madden, 1987b; Nameda, Kawara, & Ohzu, 1989b; Owsley et al., 1983; Owsley & Sloane, 1987), which refers to the lowest contrast at which the difference between a homogeneous field and a spatial grating (i.e., an alternating series of light and dark bands) can be detected. Visual acuity decline in aging may at least partially be attributed to increased refractive errors in aging and is further compounded by older adults using expired corrective prescription lens (Reid L. Skeel, Nagra, VanVoorst, & Olson, 2003; Tielsch, Sommer, Witt, Katz, & Royall, 1990). Visual contrast sensitivity deficiencies are of particular interest in the study of cognitive aging because (a) contrast sensitivity has been demonstrated to have a stronger association than visual acuity to neuropsychological performance and long-term quality of life (Lord, Clark, & Webster, 1991; Reid L Skeel, Schutte, van Voorst, & Nagra, 2006); (b) contrast sensitivity is associated with decreased performance in everyday activities, such as driving (Rubin, Roche, Prasada-Rao, & Fried, 1994; Wood & Owens, 2005), judging distances and mobility (Rubin et al., 1994) and discriminating highway signs (Evans & Ginsburg, 1985); and (c) recent meta-analyses have failed to find associations between visual acuity and cognitive task performance in aging (Houston, Bennett, Allen, & Madden, 2016; La Fleur & Salthouse, 2014), perhaps indicating that other measures of visual perception, such as contrast sensitivity, may be better indicators of cognition; it should be noted that these meta-analyses only included correlational studies, leading to the possibility that experimental manipulations of visual acuity may affect cognitive performance.

Intriguingly, performance on perceptual and higher-order cognitive tasks are strongly related to each other (Paul B Baltes & Ulman Lindenberger, 1997b; Ulman Lindenberger & Paul B Baltes, 1994b). For more than five decades, researchers have attempted to study and explain the relation between cognitive and perceptual decline in aging, which has resulted in four predominant hypotheses that attempt to explain this relation: (1) the common-cause hypothesis, which states that a third factor associated with aging, which detrimentally affects both cognition and perception, contributes to a decline in these two domains (Paul B Baltes & Ulman Lindenberger, 1997a; Ulman Lindenberger & Paul B Baltes, 1994a); (2) the sensory deprivation hypothesis, which states that over time a decline in perception causes a gradual degradation in neural substrates, which in turn affects cognition (Ulman Lindenberger & Paul B Baltes, 1994a); (3) the cognitive load on perception hypothesis, which states that older adults perform worse on perceptual tasks due to impoverished cognition (Li, Lindenberger, Freund, & Baltes, 2001; Ulman Lindenberger, Marsiske, & Baltes, 2000); and (4) the information degradation hypothesis, which states that degraded perceptual signal inputs, resulting from age-related neurobiological processes, lead to errors in perceptual processing, which in turn may affect non-perceptual, higher-order cognitive processes (Schneider & Pichora-Fuller, 2000).

Unfortunately, most studies examining the association between cognitive and perceptual decline in aging have been correlational (e.g., Paul B Baltes & Ulman Lindenberger, 1997a; Ulman Lindenberger & Paul B Baltes, 1994a), not allowing for these hypotheses to be tested sufficiently. Specifically, correlational analyses cannot determine whether modifying the perceptual signal strength of study participants has immediate effects on cognitive performance; an intervention or experimental manipulation is needed. A demonstration that manipulating perceptual signal strength directly affects cognitive performance would provide direct support for the information degradation hypothesis, but contradict assumptions of the common-cause, sensory deprivation, and cognitive load on perception hypotheses. The latter hypotheses all imply that modifying the perceptual signal strength of individuals should either not directly affect cognitive performance, but each for different reasons. According to the common-cause hypothesis, since a common source independently causes cognitive and perceptual decline, and perception is not hypothesized to be the source, an enhancement of perceptual signal strength should not affect cognition. For the sensory deprivation hypothesis, since this hypothesis states that long-term sensory deprivation leads to neural degeneration and ultimately cognitive decline, it is unlikely that enhancing perceptual signal strength will immediately reverse neural degeneration and enhance cognitive abilities. Lastly, for the cognitive load on perception hypothesis, since it states that a decline in cognition causes a decline in perceptual abilities, enhancing perception should not affect cognition.

Despite the prevalence of correlational analyses examining this relation, several studies have attempted to test the validity of the information degradation hypothesis by experimentally manipulating older and younger adults’ perceptual inputs. This hypothesis predicts that both older and younger adults’ cognitive performance should be immediately affected by perceptual signal manipulations, but experimental manipulations should have a greater effect on older adults due to (a) age-related slowing of perceptual processing (Faust, Balota, Spieler, & Ferraro, 1999; David J Madden, 2001; Timothy A Salthouse, 1996, 2000) and (b) in some cases insufficient cognitive/neural top-down mechanisms, as a result of age-related neural degeneration (Raz et al., 2005), being unable to compensate for decreased bottom-up, perceptual signals in older adults. In addition, the information degradation hypothesis predicts that different cognitive processes may be differentially affected by an identical bottom-up, perceptual signal manipulation, since individual cognitive states utilize unique top-down mechanisms and bottom-up, perceptual signals may differentially interact with these top-down processes.

Indeed, there are studies that support the information degradation hypothesis. For example, Toner et al. (2012) administered to older and younger adults a touch-screen, digit cancellation task, in which participants had 60 s to cancel the 4s and 9s presented in a matrix of numbers ranging from 1-9 by physically touching the numbers on the screen (this study also reported results for Alzheimer's and Parkinson's disease patients, not discussed here.). The digit cancellation task was presented under three visual contrast levels – low (22% Michelson contrast [(maximum – minimum luminance) / (maximum + minimum luminance)]), high (69% Michelson contrast), and a unique, proximal match condition. The proximal match condition was designed to be a "vision-fair" condition, in which before completing the digit cancellation tasks, participants completed a backward masking, number identification task with a verbal response. For each participant, a unique identification accuracy threshold (i.e., critical contrast) was obtained from the contrast at which participants identified the numbers at 80% accuracy. As expected, the critical contrast threshold was higher for older than younger adults, representing an age-related decline in visual contrast sensitivity, and the older adults exhibited worse task performance than the younger adults in both the low and high visual contrast conditions. Consistent with the information degradation hypothesis, compared to younger adults, older adults exhibited better task performance (in terms of the number of targets cancelled in the allotted time) in the high than low contrast condition. There was, however, no age group by contrast condition interaction, indicating that both the older and younger adults were equally affected by the contrast manipulation. The lack of an interaction may be due to several reasons; for example, the younger adults may have been at a ceiling level of performance, or the screen-touch outcome measure, involving a manual response, may have masked effects of visual sensory processing. Intriguingly, for the analyses restricted to the vision-fair, proximal match condition, both the older and younger adults demonstrated comparable task performance. This study provides one of the most compelling pieces of evidence supporting the information degradation hypothesis, because not only were both the older and younger adults' task performance better at higher than lower visual contrast conditions, but the older adults' performance could be raised to the level of the younger adults by simply equating the proximal signal strength of the two age groups. The latter result demonstrates that age-related differences in task performance in the high and low visual contrast conditions were due to perceptual signal strength differences, rather than higher-order cognitive or motor/speed processing differences, that when equated led to equal task performance in both age groups.

Although there is this behavioral evidence that perceptual signal strength affects downstream higher-order cognitive processes, it remains unclear how this occurs. Perhaps degradation of perceptual signal strength affects how the brain represents perceptual information leading to degraded perceptual representations. It may be the case that degraded perceptual representations have detrimental downstream effects leading to the behavioral findings observed within the literature. This idea has largely been unstudied and is explored later in this thesis.

1.1.2. Semantic Performance in Aging

Intriguingly, in contrast to perceptual performance, in aging, semantic performance appears to be preserved and possibly even enhanced. Historically, this observation has been found with vocabulary tests, where, compared to younger adults, typically older adults exhibit better performance on vocabulary tests (e.g., Denise C Park et al., 2002; Verhaeghen, 2003). It should be noted that this observed age-related difference in vocabulary test performance has been critiqued as reflecting a cohort effect, where the education system, at least within the United States, previously placed a greater emphasis on vocabulary perhaps leading to older individuals performing better on vocabulary tests (Duane F. Alwin & McCammon, 1999; D. F. Alwin & McCammon, 2001). However, the preservation and possible enhancement of knowledge can be seen in other domains, where older adults remember material from their formal education (Bahrick & Hall, 1991), continue to be able to use expertise to conduct their professions (e.g., Colonia-Willner, 1998; Hardy & Parasuraman, 1997; Shimamura, Berry, Mangels, Rusting, & Jurica, 1995), and even continue to accumulate knowledge through their lifetimes (Cornelius & Caspi, 1987; Staudinger, Cornelius, & Baltes, 1989). Furthermore, older adults contain a large semantic knowledge base (Hoffman, 2019; Verhaeghen, 2003) and perhaps can be viewed as "knowledge experts."

In sum, semantic-based processing is one of the few cognitive processes that remains relatively preserved in aging. As many individuals remain highly functional in advanced age, perhaps it is the case that older adults compensate for other cognitive deficiencies with additional reliance on semantic-based processing. Below, we review literature testing this idea.

1.2. Age-Related Differences in Perceptual and Semantic Contributions to Episodic Memory

The overall decline in perceptual performance and enhancement in semantic performance in aging appears to also affect memory performance. For example, during autobiographical memory retrieval, compared to younger adults, older adults' descriptions of their memory reflect more semantic details and less perceptual details (Levine, Svoboda, Hay, Winocur, & Moscovitch, 2002). Age-related differences in perceptual and semantic contributions to episodic memory may be further evaluated by experimentally manipulating the perceptual or semantic demands of episodic memory tasks.

1.2.1. Perceptual Contributions

Regarding the perceptual contributions to episodic memory, unfortunately, this area of research remains relatively unstudied but there is preliminary evidence that this age-related decline in perceptual performance has a detrimental effect on episodic memory performance. For example, Dickinson and Rabbitt (1991) attempted to mimic older adults’ perceptual deficiencies by experimentally manipulating younger adults’ perceptual signal strength with occlusion filter lenses and examined the impact of this manipulation on memory for short passages. In this study, participants read two short passages aloud while being recorded; one passage was read without any visual impairment and another was read in which the participants’ vision was distorted with occlusion filter lenses. After reading the passages, participants were asked to recall content from the stories. During encoding, an analysis of the recordings showed that none of the participants made errors while reading in either condition, indicating that participants were able to successfully read both the distorted and non-distorted passages. During retrieval, the authors found evidence of visual perceptual signal strength affecting non-perceptual, higher-order cognitive processes, where participants recalled less content for the passages read under the distorted than non-distorted condition. Even though this study was conducted only in a sample of younger adults, the study suggests that older adults’ perceptual deficiencies are likely to detrimentally impact down-stream episodic memory processes or representations.

In addition to Dickinson and Rabbitt (1991), in which participants’ perceptual signal strength was experimentally manipulated, the impact of perceptual deficiencies on episodic memory can be seen in false memory studies in which participants must discriminate between perceptually similar stimuli. Typically, in these studies participants study stimuli and during testing must discriminate between perceptually similar stimuli. In general, these studies find that, compared to younger adults, older adults exhibit a higher false alarm rate, demonstrating that older adults struggle to discriminate between perceptually similar stimuli (Koutstaal, Schacter, Galluccio, & Stofer, 1999; K. A. Norman & Schacter, 1997; Tun, Wingfield, Rosen, & Blanchard, 1998). Combined with the findings from Dickinson and Rabbitt (1991), perhaps in these false memory studies older adults do not encode perceptual details of the stimuli and, therefore, during retrieval struggle to discriminate between the stimuli. In sum, there is preliminary evidence that the age-related decline in perceptual-based processing has a damaging effect on episodic memory.

1.2.2. Semantic Contributions

Regarding semantic contributions, there also appear to be age-related differences in the influence of semantic demands on episodic memory performance (for an in-depth review, see Umanath & Marsh, 2014). In these studies, typically, the experimenter manipulates the amount of prior knowledge participants may use to complete the task. In older adults, it has been found that the use of prior knowledge may have both a beneficial and detrimental influence on episodic memory performance. Regarding beneficial effects, this effect has been demonstrated in several paired-association tasks, in which, compared to younger adults, older adults remember pairs better if the pairs are semantically related (Donald H. Kausler & Lair, 1966; Zaretsky & Halberstam, 1968a, 1968b), even to the point where older adults remember pairs at the same level as younger adults (M. Naveh-Benjamin, 2000). This effect has also been demonstrated in the investigation of the influence of domain-specific knowledge. For example, in Castel (2005), younger and older adults studied pictures of groceries with listed prices and later recalled the grocery item prices. Half of the pictures were presented with market-value prices and the other half with unusual prices. It was found that, compared to younger adults, older adults had worse memory for the unusual prices, but, intriguingly, the age-related differences in memory were not present for the market-value prices. In sum, these studies demonstrate that older adults' reliance on knowledge has a beneficial effect on episodic memory performance.

However, other studies suggest that older adults' additional reliance on knowledge may be detrimental to episodic memory performance. The majority of these studies demonstrate that older adults' additional reliance on knowledge may interfere with memory for information that contradicts their previous knowledge. For example, in MacKay, Abrams, and Pedroza (1999), younger and older adults studied and recalled correctly and incorrectly spelled words. Despite younger and older adults at encoding detecting a similar number of incorrectly spelled words, compared to younger adults, older adults exhibited worse memory for the incorrectly spelled words. Perhaps this finding is the result of proactive interference, which has been found to increase with age (for a review, see Jacoby, Hessels, & Bopp, 2001), where older adults' previous knowledge is interfering with the acquisition of new "knowledge." It should be noted that typically the studies finding that older adults' increased reliance on knowledge is detrimental to memory are testing memory for essentially useless information, such as the incorrect spelling of words (MacKay et al., 1999) or incorrect math equations (Ruch, 1934). It may be the case that older adults are not as motivated to study and learn useless information. Indeed, in older but not younger adults, memory performance has been shown to be related to their interest in the studied content (McGillivray, Murayama, & Castel, 2015).

1.2.3. Summary of Findings

In sum, at the behavioral level, it does appear that there are age-related differences in the contributions of perceptual and semantic factors to episodic memory. For perceptual factors, the age-related decline in perceptual performance appears to have a detrimental effect on episodic memory. For semantic factors, compared to younger adults, older adults appear to rely more on knowledge in service of episodic memory tasks, which may have both a detrimental or beneficial effect on episodic memory. On the one hand, compared to younger adults, in older adults increased reliance on knowledge may make them more susceptible to proactive interference, not allowing them to learn new information as well. However, there are cases where it appears that older adults' domain knowledge has an enhancing effect on episodic memory.

This overall age-related semantic enhancing effect on episodic memory may be compensatory. This is an active area of research and it is still largely unclear at this time, but there are some hypotheses proposing the semantic enhancing effect as compensatory. For example, the default-executive coupling hypothesis of aging (Spreng & Turner, 2019b; Turner & Spreng, 2015) suggests that the age-related semantic enhancement is compensating for cognitive control processes, which decline in aging (e.g., Duchek, Balota, & Thessing, 1998; Timothy A. Salthouse, 1990; Spieler, Balota, & Faust, 1996). This can be seen in Cohen-Shikora, Diede, and Bugg (2018), where younger and older adults completed a Stroop color-word test in which in an early-segment of the task participants were encouraged to attend either more (more color-word congruent trials) or less (more color-word incongruent trials) to the word. Later in the task where there was no bias toward attending more or less to the word (i.e., 50% congruent), both younger and older adults similarly demonstrated flexible acquisition and shifting of control settings. This study demonstrates that, compared to younger adults, when older adults are able to rely on prior experience (here, whether to attend more or less to the word), they exhibit similar cognitive control performance. Perhaps it is the case that prior experience in the form of knowledge may also compensate for cognitive control deficiencies. However, there are many possible reasons why cognitive control performance declines with age and this effect could be the direct result of perceptual deficiencies (Monge & Madden, 2016; Schneider & Pichora-Fuller, 2000). Based upon the behavioral literature reviewed above, it may be that the age-related semantic enhancement is compensating for perceptual deficiencies. This idea is explored in the studies presented within this thesis.

1.3. Neural Correlates of Perceptual and Semantic Processing

In addition to behavioral studies investigating age-related differences in perceptual and semantic processing, there have also been many neuroimaging studies examining these processes. This literature has predominately used functional MRI (fMRI) and univariate activation analyses to investigate age-related differences in the neural correlates of perceptual and semantic processing.

1.3.1. Perceptual Processing

Regarding perceptual processing, here, I focus on visual processing because the literature investigating is visual processing is larger than other modalities (e.g., auditory) and the studies presented later in this thesis focus of visual perception. Before discussing univariate activation within the brain, it is important to understand age-related differences in how visual information reaches the brain. Several neural changes occur to the visual system in aging that likely account for the previously mentioned visual acuity and contrast sensitivity decline (for a review, see David J Madden, Whiting, & Huettel, 2005). At the level of the sensory organ, there is a general degeneration of the eyes in aging, which in older adults decreases the amount of light that may reach the retina (Weale, 1961). These changes to the eyes include an increase in the density and hardness of the crystalline lens, a decrease in the resting diameter of the pupil, an increase in the opacification of the lens, and a decrease in the number of receptor cells (Scialfa, 2002). At the level of the cortex, during visual perceptual tasks, compared to younger adults, older adults often exhibit decreased magnitude and spatial extent activation of visual sensory cortex (e.g., Randy L Buckner, Snyder, Sanders, Raichle, & Morris, 2000; Huettel, Singerman, & McCarthy, 2001; Ross et al., 1997; Ward, Aitchison, Tawse, Simmers, & Shahani, 2015). These cortical activation changes in aging may have neural and cognitive consequences, for example, leading older adults to compensate for decreased visual cortex activation by recruiting additional anterior regions (e.g., prefrontal cortex) in service of successful cognition (Simon W Davis, Dennis, Daselaar, Fleck, & Cabeza, 2008). However, the mechanisms contributing to decreased visual cortical activation in older adults, and the associated consequences, remain an active area of investigation (Roberto Cabeza & Dennis, 2012; C. Grady, 2012a; Denise C Park & Reuter-Lorenz, 2009).

1.3.2. Semantic Processing

Regarding semantic processing, even though performance on semantic tasks is relatively preserved in aging, there do appear to be age-related differences in the neural correlates of semantic processing. Before discussing age-related differences in the neural correlates of semantic processing, I will discuss the literature investigating these neural correlates predominately within younger adults (Lambon Ralph et al., 2017). There is a network of regions that appear to be important for semantic processing: anterior temporal lobes, inferior frontal gyrus, posterior middle temporal gyrus, the "multiple demand" network, and the default mode network. In general, the semantic network is predominately left lateralized (Hodges, Patterson, Oxbury, & Funnell, 1992; Tyler et al., 2004; Warrington & McCarthy, 1983), but also recruits right lateralized regions (for a review, see Jung-Beeman, 2005). Regarding the anterior temporal lobes, it is believed that this region stores multi-model semantic representations (Lambon Ralph et al., 2017). Combined with the inferior frontal gyrus and posterior, which have been found to be important for semantic control (Badre & Wagner, 2002; Hoffman, Jefferies, & Lambon Ralph, 2010; Noonan, Jefferies, Visser, & Lambon Ralph, 2013; Whitney, Kirk, O'Sullivan, Lambon Ralph, & Jefferies, 2011), it is believed that the activation of semantic representations in the anterior temporal lobes is regulated by the inferior frontal gyrus and posterior middle temporal gyrus (Lambon Ralph et al., 2017). The “multiple demand” network (Duncan, 2010; Fedorenko, Duncan, & Kanwisher, 2013), which includes the left dorsal inferior parietal cortex, left inferior frontal sulcus and dorsal anterior cingulate cortex, is also often activated during semantic tasks (Noonan et al., 2013), perhaps reflecting general task demands. Lastly, the default mode network (R. L. Buckner, Andrews-Hanna, & Schacter, 2008; Raichle, 2015), which includes ventral parietal cortex, medial prefrontal cortex and posterior cingulate cortex, is sometimes activated during semantic tasks (Seghier & Price, 2012; Wirth et al., 2011), perhaps reflecting the retrieval of semantic representations.

Regarding age-related differences in the neural correlates of semantic processing, a recent meta-analysis has shown that overall it appears that both younger and older adults utilize similar left-lateralized regions typically associated with semantic processing (Hoffman & Morcom, 2018). However, compared to younger adults, older adults recruit additional right lateralized frontal and parietal regions, particularly regions associated with domain-general processing. This effect was strongest when older adults performed worse than younger adults, leading to the possibility that older adults’ additional recruitment of domain-general regions may reflect neural dedifferentiation. It should be noted that this meta-analysis did not observe any effects related to the anterior temporal lobes, perhaps because of technical difficulties imaging the anterior temporal lobes due to their proximity to their air-filled sinuses (Devlin et al., 2000). Fortunately, positron emission tomography (PET) may be used to overcome this limitation. For example, in Whiting et al. (2003), younger and older adults underwent PET scanning while completing a lexical decision task (word/nonword decision). Intriguingly, compared to the younger adults, older adults more strongly activated the inferior temporal cortex and this activation was associated with lexical factors. This finding suggests that, compared to younger adults, older adults rely more on anterior ventral visual regions in service of semantic-related processing.

1.3.3. Limitations

The studies reviewed above investigating age-related differences in the neural correlates of perceptual and semantic processing provide vital information but do not inform on age-related differences in how perceptual and semantic information are represented in the brain. As discussed below, this likely an important area of research in the cognitive neuroscience of aging and memory.

1.4. Neural Representations

There are many hypotheses attempting to explain cognitive and neural mechanisms underlying the age-related decline in episodic memory, such as the resource deficit (Craik, 1986) and associate deficit (M. Naveh-Benjamin, 2000) hypotheses, but the literature reviewed above demonstrating that older adults' episodic memory performance is at least partially dependent on the amount of perceptual and semantic information available suggests that another mechanism may be abnormal mnemonic representations. In this section, I review the literature on neural representations and age-related differences in neural representations.

1.4.1. Mnemonic Representations

Modern memory theories state that during episodic memory encoding, memory traces are stored in the neocortex and pointers to these cortical locations are stored in the hippocampus (Alvarez & Squire, 1994; Randy L Buckner & Wheeler, 2001; Kenneth A. Norman & O'Reilly, 2003). During retrieval, with the help of the hippocampus, similar cortical locations are reactivated, leading to consciously remembering the original event. It is believed that modality-specific memories are stored in modality-specific brain regions. For example, visual episodic memory studies have demonstrated that visual memories are represented within the occipitotemporal cortex (Maureen Ritchey, Wing, LaBar, & Cabeza, 2013; Wing, Ritchey, & Cabeza, 2014), which is an area of the brain important for perceptual processing (Leeds, Seibert, Pyles, & Tarr, 2013; Ungerleider & Haxby, 1994). This was demonstrated in Wing et al. (2014), where they examined the reactivation of specific items. In the study, participants studied pictures of scenes and later retrieved their memories of the scenes. The authors found that specific scenes were reactivated within the occipitotemporal cortex, and that occipitotemporal cortex reactivation was associated with hippocampal activity during encoding, suggesting that the hippocampus facilitates memory reactivation. In sum, this study provides evidence that mnemonic information is represented in the cortex and is reactivated with the assistance of the hippocampus.

1.4.2. Methods to Investigate Functional Neural Representations

Historically, functional neuroimagers investigated the neural correlates of various cognitive processes with the use of univariate activation analyses, which, within regions of interest, typically involves calculating the mean activation of sets of voxels. This method is sufficient for investigating neural correlates but is limited in the investigation of functional neural representations because it is commonly believed that information is not simply represented in mean activity but rather in the activation pattern of voxels (for reviews, see Nikolaus Kriegeskorte, Mur, & Bandettini, 2008; K. A. Norman, Polyn, Detre, & Haxby, 2006). Therefore, over the past two decades several methods have been developed to investigate functional neural representations. Three commonly used methods in the discipline of the cognitive neuroscience of memory are multi-voxel pattern analysis, representational similarity analysis, and ERS.

Multi-voxel pattern analysis makes use of machine learning algorithms, where typically a machine learning algorithm is trained to use brain activation patterns from a region of interest (ROI) to discriminate between stimuli type (e.g., faces vs. houses; for reviews, see Haxby, Connolly, & Guntupalli, 2014; K. A. Norman et al., 2006). The classifier is then tested on held out data and if the classifier can successfully discriminate between the stimuli type, the stimuli type is assumed to be represented in this brain region. In the study of memory, multi-voxel pattern analysis may be used to study the reactivation of memory traces by training the classifier on encoding data and testing it on retrieval data (e.g., Koen & Rugg, 2016; Kuhl, Rissman, Chun, & Wagner, 2011; Schlichting & Preston, 2014). Using the held-out retrieval data, if the classifier can successfully discriminate between the stimuli type, it is assumed that memory traces were reactivated. Although multi-voxel pattern analysis can be a robust method for investigating neural representations, especially in studies with clear stimuli categories (e.g., faces and houses), it does not tell much about the type of information represented in a brain region. Typically, reverse inference is used to interpret the results. A method that overcomes this limitation of multi-voxel pattern analysis is representational similarity analyses.

With representational similarity analysis, the type of information represented in a ROI is estimated with stimuli models (for reviews, see Nikolaus Kriegeskorte & Kievit, 2013; Nikolaus Kriegeskorte et al., 2008). This is achieved by examining the similarity between stimuli based upon a model. For example, with a sensory model, stimuli similarity may be based on sensory visual features, such as shape (e.g., gun ≈ hair dryer), whereas with a semantic model, stimuli similarity may be based on semantic features (e.g., gun ≈ sword). The similarity between stimuli is represented in a matrix, which is termed a representational dissimilarity matrix. Next, within a ROI, the similarity of brain activation patterns is calculated typically by correlating the brain activation patterns obtained during stimuli presentations. The brain activation pattern similarity between stimuli presentations is also represented in a representational dissimilarity matrix. To infer what type of information is represented in a specific ROI, the stimuli-representation dissimilarity matrix and brain-representational similarity matrix are correlated with each other, which results in model-brain fit (second order correlation). If the magnitude of model-brain fit is high, it can be inferred that the feature represented in the specific type of model used to construct the stimuli representational dissimilarity matrix (e.g., a sensory model) is represented in that ROI. The ability to understand what type of information is represented in a ROI is often useful in the study of the cognitive neuroscience of aging and memory.

Lastly, encoding-retrieval similarity (ERS) is specifically used to investigate the reactivation of memory traces. This is achieved by, with a simple correlation, examining the similarity of brain activation patterns during the encoding and retrieval of a specific stimulus (Maureen Ritchey et al., 2013; Wing et al., 2014). If the correlation is relatively high, it can be inferred that the memory trace of that specific stimulus was reactivated. Typically, when investigating ERS, it is important to not only calculate the similarity of brain activation patterns during encoding and retrieval for the specific stimulus (item-level ERS), but also the similarity between (1) brain activation patterns for the specific stimulus during encoding and (2) brain activation patterns for every other stimulus during retrieval (set-level encoding-retrieval similarity; Wing et al., 2014). Set-level ERS allows for the examination of general reactivation of picture information and, therefore, is typically compared to item-level ERS in order to examine if ERS reflects the reactivation of an individual item or not. For example, in Wing et al. (2014), where participants studied and later retrieved pictures of complex scenes, in left occipitotemporal cortex, they found item-level ERS differed from set-level ERS, presumably reflecting the reactivation of scene memories, but in ventrolateral prefrontal cortex, even though both item- and set-level ERS increased with self-reported memory vividness, item- and set-level ERS were not statistically different; this finding likely reflects the recapitulation of memory processes. This ability to investigate the memory reactivation of specific stimuli provides a clear advantage over multi-voxel pattern analysis, which as mentioned above, may also be used to investigate memory reactivation but provides only a coarse measure of reactivation since multi-voxel pattern analysis is typically used to discriminate between broad stimuli categories (e.g., faces vs. houses).

1.4.3. Age-Related Differences in Perceptual Neural Representations

Regarding aging, preliminary evidence suggests that increased age is associated with representational deficiencies. Specifically, it appears that with increasing age, representations become less distinct, which has been termed age-related neural dedifferentiation. The term age-related dedifferentiation was first used to describe age-related differences in performance on cognitive tasks, where, compared to younger adults, older adults' performance on various tasks assessing different cognitive domains are more intercorrelated (Babcock, Laguna, & Roesch, 1997; Chen, Myerson, & Hale, 2002; U. Lindenberger & Baltes, 1997). Afterwards, the idea of age-related dedifferentiation wax extended to neural representations. In one of the first studies to systematically investigate this idea (Denise C. Park et al., 2004), while receiving fMRI scanning, a sample of younger and older adults viewed stimuli from different categories – faces, houses, chairs, and pseudowords. In younger adults, it is well known that stimuli from these categories are processed in distinct regions of the occipitotemporal cortex (Aguirre, Zarahn, & D'Esposito, 1998; Epstein & Kanwisher, 1998; Kanwisher, McDermott, & Chun, 1997; Polk et al., 2002). Replicating previous work, Park et al. found in the younger adults that specific voxels of the occipitotemporal cortex were selectively activated for specific stimuli categories. However, intriguingly, in the older adults, the activation of occipitotemporal cortex voxels was less selective to stimuli categories; the authors termed this observation as age-related neural dedifferentiation. These findings suggest that, as previously mentioned, compared to younger adults, older adults in the occipitotemporal cortex do not represent information as distinctly. This study inspired a plethora of other studies that further investigated age-related neural dedifferentiation and has been replicated several times (e.g., Chee et al., 2006; Payer et al., 2006).

These studies provide a valuable framework for understanding representations in aging but are limited in that they only examined univariate activation and not brain activation patterns. As mentioned above, it is believed that representations are not simply encoded in the mean activation of voxels within a brain region, but rather in brain activations patterns (for reviews, see Nikolaus Kriegeskorte et al., 2008; K. A. Norman et al., 2006). Therefore, it is likely essential in the investigation of age-related differences in neural representations to examine brain activation patterns. Indeed, more recent work investigating age-related neural dedifferentiation has examined brain activation patterns. For example, Carp, Park, Polk, and Park (2011) conducted a secondary analysis of Denise C. Park et al. (2004), in which younger and older adults viewed pictures from various stimuli categories. In the study the authors correlated brain activation patterns for trials within- and between- stimuli categories; it is assumed that a stronger stimuli neural representation is associated with higher brain activation pattern correlations for within- than between-categories. They found that within the occipitotemporal cortex that, compared to younger adults, older adults exhibited decreased correlation strength within-categories and increased correlation strength between-categories. This result demonstrates that, compared to younger adults, older adults' occipitotemporal cortex activation patterns did not differentiate these categories as well. This is an important finding because it provides clear evidence that aging is indeed associated with dedifferentiated representations in the occipitotemporal cortex.

As may be apparent from this brief literature review of studies investigating age-related neural dedifferentiation, dedifferentiation is predominately described as the selectivity of voxels or brain activation patterns for broad stimuli categories (e.g., faces vs. house). This is an interesting observation, but it does not inform on what type of feature older adults are not able to differentiate as well; there are many types of features that can be used to differentiate these categories, such as perhaps visual features or semantic features. Furthermore, most of these studies predominately focused on posterior-perceptual related regions. These regions are of interest in the discipline of the cognitive neuroscience of aging because of the previously mentioned robust age-related decline in perceptual processing (Jackson & Owsley, 2003b; Nameda et al., 1989a;

Cynthia Owsley, 2011), but it is likely also of interest to examine representations in more anterior-semantic related regions. As reviewed above, semantic cognition is relatively preserved and possibly even enhanced in aging (Denise C Park et al., 2002; Verhaeghen, 2003); perhaps it is the case that aging is associated with an enhancement in semantic-related representations. Investigating these limitations of previous studies is vital for further understanding age-related differences in neural representations.

There is, however, one recent study that attempted to examine these limitations. In Bruffaerts, Tyler, Shafto, Tsvetanov, and Clarke (2019), a sample of adults ranging from 24 to 87 years old viewed pictures of objects while receiving magnetoencephalography (MEG). The study used representational similarity analyses with stimuli models to examine age-related difference in visual and semantic representations and found that aging was associated with a decline in both visual and semantic representations. This is an important study because it attempted to examine age-related differences in how specific types of features are represented in the brain. There are, however, several major limitations of this study that undermine the conclusions. First, the model correlations were conducted on MEG signals averaging from all of the sensors. Averaging across all of the sensors does not allow for the examination of localized brain effects and, therefore, yields a broad measure. Previous studies conducting representational similarity analyses often find effects to be specific to certain brain regions (e.g., Clarke, Devereux, & Tyler, 2018; Clarke & Tyler, 2014; Groen et al., 2018b) and, therefore, it likely essential to examine localized effects. Although MEG does not allow for the same degree of localization as fMRI, perhaps if the study examined specific brain regions, such as the anterior temporal lobes, it would find that aging would not be associated with a decline in semantic model-brain fit. Second, the visual model was constructed concatenating activation values from nearly every layer in a deep convolutional neural network (DNN; layers 2-7 of the AlexNet (Krizhevsky, Sutskever, & Hinton, 2012b)). From previous studies using DNNs as image models, it is known that different layers model different types of information, where early layers model more low-level features and later layers model more high-level, categorical features (Güçlü & van Gerven, 2015; Khaligh-Razavi & Kriegeskorte, 2014; Nikolaus Kriegeskorte, 2015; Leeds et al., 2013; Wen et al., 2017). Therefore, constructing an image model concatenating all of the layers provides a broad visual model. It would be informative if the study also constructed models based upon individual DNN layers. Lastly, the semantic model was based upon semantic features collected from a sample of younger adults (K. McRae, G. S. Cree, M. S. Seidenberg, & C. McNorgan, 2005; Taylor, Devereux, Acres, Randall, & Tyler, 2012). As semantic cognition appears to improve in aging (Denise C Park et al., 2002; Verhaeghen, 2003), it is likely the case that if the semantic features were collected in a sample of older adults, they would list different features. Therefore, it is not surprising that age was associated with a decline in semantic model-brain fit, since the model was biased toward modeling semantic representation in younger adults. In sum, there has been great progress over the past few years in the investigation of age-related differences in neural representations, but there is still much work to be done.

1.4.4. Age-Related Differences in Mnemonic Neural Representations

The majority of studies investigating age-related differences in neural representations, as reviewed above, have investigated age-related differences during perception. It is also likely the case that representations during perception would affect downstream cognitive processes, such as episodic memory. Indeed, there have been several recent studies investigating age-related differences in mnemonic representations.

1.4.4.1. Memory Reactivation

Most studies investigating this topic have examined age-related differences in memory reactivation. In St-Laurent, Abdi, Bondad, and Buchsbaum (2014), a sample of younger and older adults studied short video clips, later recalled the videos, and rated the vividness of their memories. Overall, they found with the use ERS analyses that, compared to younger adults, older adults under reactivated several regions including the occipitotemporal cortex. This study, to our knowledge, provided the first piece of evidence showing that older adults exhibit neural mnemonic representation deficiencies.

However, the study failed to find an association within both younger and older adults between the strength of reactivation and the recall of visual and auditory details. This limitation indicates that the study failed to capture essential elements of episodic memory as episodic memories vary in the level of detail. To address this limitation, Johnson, Kuhl, Mitchell, Ankudowich, and Durbin (2015) also examined in younger and older adults memory reactivation. Participants studied pictures of scenes and objects, and later retrieved their memories of the pictures and rated the vividness of their memories. Using multi-voxel pattern analysis to discriminate between scene and object stimuli, they found within every ROI examined (prefrontal cortex, temporal cortex, parietal cortex, and occipital cortex) that, compared to younger adults, older adults exhibited reduced memory reactivation. In the analysis relating reactivation to memory vividness, compared to younger adults, in the older adults, memory vividness was trending toward being more strongly related to prefrontal cortex reactivation. As this study only used multi-voxel pattern analysis this finding is somewhat difficult to interpret, but perhaps the relation between memory vividness and prefrontal cortex reactivation in the older adults reflects greater reactivation of semantic features. The authors then conducted informational connectivity analyses (Coutanche & Thompson-Schill, 2013), in which they examined fluctuations in the representational timeseries between regions of interests. Intriguingly, they found that, compared to younger adults, older adults exhibited stronger informational connectivity between posterior to posterior regions of interest (e.g., temporal cortex-occipital cortex), but there were no age-related differences in informational connectivity between anterior to posterior regions of interest (e.g., prefrontal cortex-occipital cortex). Perhaps this finding reflects preserved prefrontal modulation of occipital regions in aging. In sum, similar to St-Laurent et al. (2014), Johnson et al. (2015) provides support for age-related deficits in memory reactivation of posterior brain regions, but contains many limitations, such as only examining reactivation of broad categories (scenes vs. objects) rather than the reactivation of specific events.

Even though St-Laurent et al. (2014) and Johnson et al. (2015) provided preliminary evidence that there are age-related differences in memory reactivation, there is also work not finding age-related differences (Thakral, Wang, & Rugg, 2019; T. H. Wang, Johnson, de Chastelaine, Donley, & Rugg, 2016). In T. H. Wang et al. (2016), younger and older adults studied pictures of objects and words describing concepts. Later, during retrieval, participants were presented a word and indicated if the word was originally presented as a picture describing the concept or was presented as just the concept. To examine memory reactivation, the authors trained a classifier on the encoding data to distinguish if the participant was studying a picture or a word and then tested the classifier on the retrieval data. Surprisingly, there were no age differences in memory reactivation. Thakral et al. (2019) conducted a re-analysis of the T. H. Wang et al. (2016) dataset using multivoxel pattern analysis to investigate age-related differences in the variability of memory reactivation. Based upon the neural differentiation literature, they believed that representations become less complex with increasing age, and therefore, aging would be associated with less variability in memory reactivation. Similar to T. H. Wang et al. (2016), they did not find age-related differences in memory reactivation variability. There are a number of possible explanations for the null aging result, but perhaps examining the reactivation for broad categories (words, pictures), rather than for individual events, was not sensitive enough to detect age-related differences. Therefore, utilizing techniques that examine the reactivation of individual events, such as ERS, is likely important in investigating age-related differences in memory reactivation. In the studies presented later in this thesis, we used ERS analyses to overcome this limitation.

1.4.4.2. Memory Effects During Encoding and Retrieval

The previously described studies examining age-related differences in memory representations predominately focused on memory reactivation but did not examine memory effects that may be present during either encoding or retrieval. It may be the case that in addition to age-related deficiencies in memory reactivation there are are-related deficiencies in representational quality associated with memory effects. In one of the first studies to investigate this issue, Zheng et al. (2017), a sample of younger and older adults studied pictures from three categories (scenes, faces, and objects); each item was presented three times. Following, outside of the scanner, participants completed an old/new recognition task. To examine representations, for each item, they examined the similarity between brain activation patterns between each of the three item repetitions (within-item pattern similarity). For the subsequent memory effects (remembered vs. forgotten) between the age groups, the only significant difference was that, compared to the younger adults, the older adults exhibited higher within-item pattern similarity in the left inferior parietal lobule and frontal pole. When examining only the remembered trials, the authors found that, compared to the younger adults, older adults exhibited reduced within-item pattern similarity in the occipitotemporal cortex. Intriguingly, across subjects, it was found that within-item pattern similarity in the occipitotemporal cortex correlated with univariate activation in the prefrontal cortex (collapsed across all trials) only within the older adults, suggesting greater frontal modulation of sensory-related representations in the older adults.

Bowman, Chamberlain, and Dennis (2019) investigated the idea that aging is associated with deficits in discriminating perceptual features and that this deficit affects episodic memory. In the study, younger and older adults studied pictures of objects. During retrieval, while receiving fMRI scanning, participants completed a remember-know-new paradigm (Tulving, 1985b), in which they were presented targets (e.g., picture of a crow presented during encoding), item lures (e.g., another picture of a crow not presented during encoding), thematic lures (e.g., a picture of a pigeon not presented during encoding), and novel lures (e.g., a picture of a grocery cart not presented during encoding). Since the ability to discriminate between the targets and many of the lures requires discriminating perceptual features, this paradigm allows for testing age-related differences in perceptual representations. The study found that, compared to younger adults, when comparing item and target lures, older adults exhibited lower discriminability of neural patterns in the midline occipital cortex; these effects were also related to memory performance. These results suggest that aging is associated with a decline in neural differentiation of perceptual-related features and that this neural dedifferentiation detrimentally affects older adults' memory.

More recently, Dennis et al. (2019) examined neural representations supporting associative memory. Associative memory is of interest in the study of cognitive aging because it exhibits a greater age-related decline than item memory (for a review, see Spencer & Raz, 1995). In the study, younger and older adults studied pictures presented in different types of associations (item-item and item-context). Using multi-voxel pattern analysis to test for neural discriminability of the association types, the only region found to exhibit age-related differences was the perirhinal cortex. This finding suggests that, compared to younger adults, older adults may exhibit a greater reliance on perirhinal cortex, rather than the hippocampus (for a review, see Diana, Yonelinas, & Ranganath, 2007), to bind associative items. The perirhinal cortex is particularly interesting because it is part of the anterior temporal system, which is important for semantic processing (for a review, see M. Ritchey, Libby, & Ranganath, 2015). Perhaps it is the case that when encoding associative memories, compared to younger adults, older adults rely more on binding, rather than perceptual features, semantic features. This idea was not explicitly investigated in this study but could be with the use of representational similarity analyses.

1.4.4.3. Limitations of Past Studies

These previous studies investigating age-related differences in mnemonic neural representations provide vital information but are limited in ways similar to the perceptual neural representation studies. First, for the most part, it is unclear what type of features, compared to younger adults, older adults are not able to differentiate as well leading to memory deficits. Bowman et al. (2019) somewhat addressed this limitation by comparing neural pattern discriminability between targets and item lures, where to discriminate between these stimuli type likely required differentiating perceptual features, but perceptual features still includes a broad category of features (for a review, see Nikolaus Kriegeskorte et al., 2008). The use of representational similarity analyses may inform on the representation of what types of features lead to these age-related mnemonic deficiencies. Second, past studies investigating age-related differences in mnemonic representations have largely focused on perceptual-related brain regions and not semantic-related brain regions. As mentioned above, perhaps it is the case that semantic representations are enhanced in aging. Dennis et al. (2019) found that, compared to younger adults, older adults may exhibit a greater reliance on perirhinal cortex, which is part of the anterior temporal system (for a review, see M. Ritchey et al., 2015), in representing mnemonic information, perhaps reflected older adults greater reliance on semantic representations. However, the study used multi-voxel pattern analysis to discriminate neural patterns from stimuli associations, which does not inform what type of features are being represented in that brain region. These limitations of previous studies leave much work to be done in the investigation of age-related differences in mnemonic neural representations.

1.5. Key Questions

As can be seen from the literature review, there is preliminary evidence that there are age-related differences in neural representational quality and that the quality of these representations is related to memory. It is, however, unclear what types of representations younger and older adults differentially represent (i.e., perceptual vs. semantic representations) and mechanisms underlying age-related differences in neural representational quality. Broadly, the goal of this thesis is to address these issues, which are addressed with three key questions. First, are there age-related differences in perceptual and semantic-related neural representations and does the quality of these representations also impact mnemonic representations? This question is tested in Chapter 2, which investigates in visual cortex and anterior temporal lobes age-related differences perceptual and semantic representations (Monge, Wing, et al., under review). Second, are there age-related differences in how perceptual and semantic information are shared across the whole brain network? This question is tested in Chapter 3, which utilizes informational connectivity and network analyses to investigate age-related differences in the whole-brain network contributions of perceptual and semantic representations (Monge, Ritchey, & Cabeza, under review). Lastly, does visual signal loss and compensatory semantic-enhancing mechanisms explain age-related differences in mnemonic neural representations? This question is tested in Chapter 4, which investigates the impact of visual signal loss on age-related differences in perceptual and semantic representations and how this relates to memory (Monge, Davis, Hovhannisyan, & Cabeza, in preparation).

2. Age-Related Dedifferentiation and Hyperdifferentiation of Perceptual and Mnemonic Representations

2.1. Introduction

As we age, the anatomy and physiology of our brain declines, impairing cognitive abilities such as perception and memory (C. Grady, 2012b; C. L. Grady, 2008). Most prior fMRI studies investigating the neural bases of these impairments have focused primarily on processes (operations performed on information) and only rarely examined age effects on representations (the quality of information processed). However, there is fMRI evidence that activation patterns elicited by different types of visual stimuli (faces, places, etc.) are less distinct in older adults than in younger adults (Chee et al., 2006; Goh, Suzuki, & Park, 2010; Denise C. Park et al., 2004; Payer et al., 2006; Voss et al., 2008). This phenomenon, known as age-related neural dedifferentiation, suggests that aging impairs the quality of visual representations. Yet, two fundamental questions remain unanswered: (1) what aspects of visual representations are impaired by aging? and (2) do age-related deficits in visual representations impair downstream representations such as visual memory traces? The current study investigates these two critical questions.

1. What aspects of the visual representations are impaired by aging? This is a critical issue because visual representations consist of multiple features, which are processed in different brain regions and are affected differentially by aging. In

particular, it is well established that sensory features are processed primarily in early visual cortex and that these sensory features form conjunctions of categorical features in more anterior ventral pathway regions, such as the anterior temporal lobe (Bussey, Saksida, & Murray, 2005; Clarke & Tyler, 2014). The sensory-to-categorical feature distinction is relevant to aging because older adults tend to be impaired in processes utilizing sensory features (e.g., sensory processing) but not in processes more reliant on categorical features (e.g., conceptual and semantic processing; Cherry et al., 2012; Mohanty, Naveh-Benjamin, & Ratneshwar, 2016; Monge & Madden, 2016; Cynthia Owsley, 2011). Thus, we hypothesized that age-related visual dedifferentiation impairs sensory features in early visual cortex but not categorical features in the anterior temporal lobe (Hypothesis 1). Given than some aspects of categorical-related processing are actually better in older adults than younger adults (Long & Shaw, 2000; Denise C Park et al., 2002), an intriguing possibility is that categorical features in the anterior temporal lobe could be enhanced by aging.

We investigated Hypothesis 1 using representational similarity analyses (Nikolaus Kriegeskorte & Kievit, 2013; Nikolaus Kriegeskorte et al., 2008), in which similarity across stimuli are coded by different stimuli models. In the sensory model, stimuli similarity is based on sensory visual features, such as shape (e.g., gun ≈ hair dryer), whereas in the categorical model, it is based on categorical features (e.g., gun ≈

sword). The stimuli model is then correlated with similarity in fMRI activation patterns for the same set of stimuli. The resulting model-brain fit (2^{nd} order correlation) identifies brain regions that process and/or store representations emphasizing sensory and/or categorical visual features (Fig. 1a). As stimuli models code the differences between images based upon a feature of interest (e.g., sensory, categorical), model-brain fit may be interpreted as a measure of differentiation, where higher values in a brain region indicate greater neural differentiation.

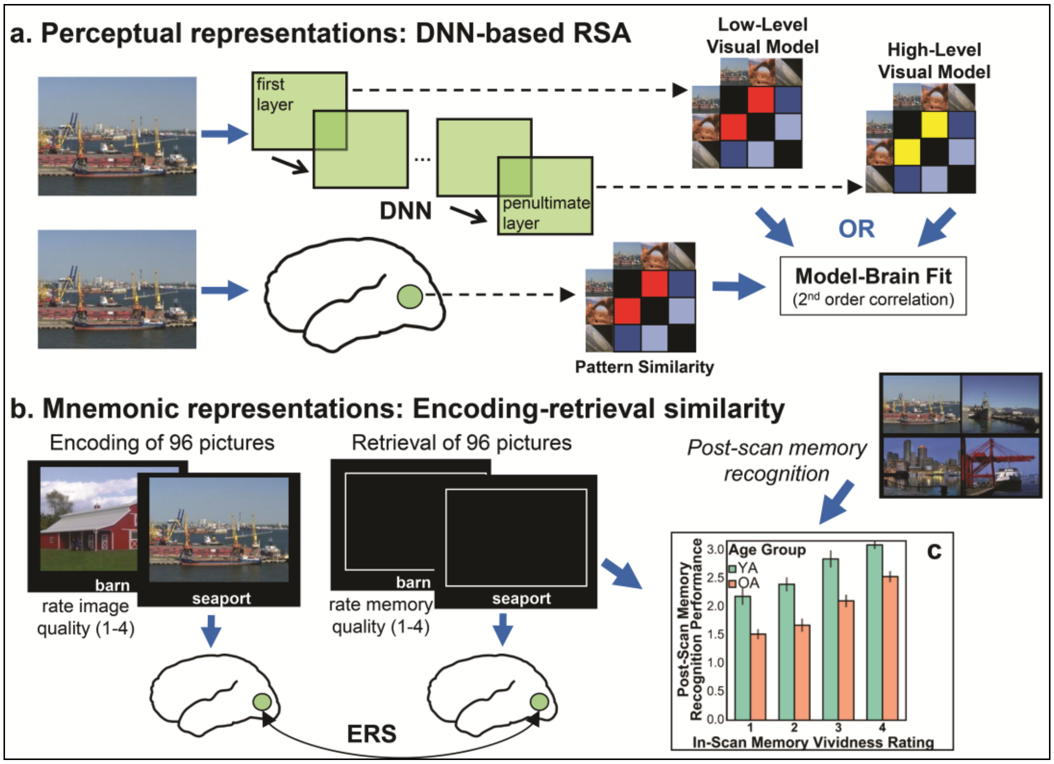


Figure 1: Perceptual and Mnemonic Representations Analysis Approach. Panel a shows a model of the analysis combining representational similarity analysis and DNN layers. To create models from DNN layers, the image stimuli are submitted to the pre-trained DNN and at each layer of interest, the "activation" values are

extracted. Here, our layers of interest were the first and penultimate layers. For each image and layer of interest, the vectors of activation values are correlated with each other resulting in a stimuli model for each layer of interest. The stimuli models may then be used to predict brain activation patterns (model-brain fit). Panel b shows our paradigm in which participants, while undergoing fMRI scanning, studied images (while rating the quality of the images) and later retrieved their memories of the scenes (while rating the vividness of their memories). We quantified the similarity of encoding to retrieval representations by calculating ERS. Panel c shows for each in-scan vividness rating value, the corresponding post-scan memory recognition performance; the corresponding post-scan memory recognition performance reflects the average score (0=Miss, 1=Hit [confidence 1], 2=Hit [confidence 2], 3=Hit [confidence 3], 4=Hit [confidence 4]). The in-scan vividness ratings were related to post-scan memory recognition performance; error bars represent the standard error of the mean. ERS = encoding-retrieval similarity; DNN = deep convolutional neural network; fMRI = functional MRI; OA = older adult; RSA = representational similarity analysis; YA = younger adult.

Here, our stimuli models were derived from DNNs (Krizhevsky, Sutskever, & Hinton, 2012a; LeCun, Bengio, & Hinton, 2015). DNNs consist of layers of convolutional filters and can be trained to classify images into categories with a high level of accuracy. During training, DNNs “learn” convolutional filters in service of classification, where filters from early layers predominately detect sensory features and from late layers, categorical features (Zeiler & Fergus, 2014). Previous work has demonstrated that DNNs model representations along the ventral visual pathway, where early layers map brain activation patterns predominately in early visual cortex and late layers map brain activation patterns in more anterior ventral visual pathway regions (Güçlü & van Gerven, 2015; Khaligh-Razavi & Kriegeskorte, 2014; Nikolaus Kriegeskorte, 2015; Leeds et al., 2013; Wen et al., 2017). With models traditionally used to map brain activation patterns it is difficult to model this hierarchy of sensory to categorical features, especially with scenes where their categories are less clear. Deep convolutional neural networks allow for this hierarchy to be investigated within a single framework. Furthermore, DNNs outperform traditional theoretical models of the ventral visual pathway (e.g., HMAX, object-based models; Cadieu et al., 2014; Groen et al., 2018a). Therefore, a DNN is an ideal model to investigate this sensory-to-categorical feature distinction. Here, we used a pre-trained 16-layer DNN, the VGG16 (Simonyan & Zisserman, 2014), which was successfully trained to classify 1.8 million scenes into 365 categories (Zhou, Lapedriza, Khosla, Oliva, & Torralba, 2017). The first layer generated a sensory model, since this model is derived from a layer that detects sensory features, and the penultimate layer, a categorical model, since this model is derived from the layer before the images are explicitly categorized into the trained categories (Bankson, Hebart, Groen, & Baker, 2018; Barry J. Devereux, Clarke, & Tyler, 2018; Groen et al., 2018a). Given the posterior-anterior organization of the ventral visual pathway, we expected that the sensory model would correlate with activation patterns in early visual cortex, and the categorical model, with activation patterns in anterior temporal lobe. On the basis of Hypothesis 1, we predicted that, compared to younger adults, (1) the correlation between brain activation patterns and the sensory model (i.e., model-brain fit) would be reduced in older adults, whereas (2) the correlation between brain activation patterns and the categorical model would be spared (or even enhanced) in older adults. 2. Do age-related deficits in visual representations impair downstream representations such as visual memory traces? Age-related sensory and cognitive deficits are strongly related to each other (P. B. Baltes & U. Lindenberger, 1997; U. Lindenberger & P. B. Baltes, 1994), possibly because sensory deficits cascade through the cognitive system impairing downstream cognitive processes (Monge & Madden, 2016). Consistent with this idea, degrading stimuli (i.e., mimicking sensory impairment) by adding noise yields cognitive deficits in younger adults that resemble cognitive deficits in older adults (G. C. Gilmore, R. A. Spinks, & C. W. Thomas, 2006; Monge & Madden, 2016; Murphy, Craik, Li, & Schneider, 2000; Pichora-Fuller, Schneider, & Daneman, 1995). In contrast, spared categorical processing in o may explain why age-related memory deficits are attenuated for semantically-rich stimuli (D. H. Kausler, 1994; Moshe Naveh-Benjamin, 2000). Thus, the sensory to categorical dissociation we postulated for perceptual representations (Hypothesis 1) is likely to apply also to mnemonic representations. In the case of mnemonic representations, however, the age-related deficit is likely to affect not only visual cortex but also downstream memory-binding regions, such as the hippocampus. Thus, we hypothesized that aging impairs mnemonic representations for sensory features in the early visual cortex and hippocampus but preserved, or possibly even enhanced, categorical features in the anterior temporal lobe

(Hypothesis 2). We investigated Hypothesis 2 using a reactivation fMRI paradigm (Danker & Anderson, 2010; M. D. Rugg & Vilberg, 2013). As illustrated by Fig. 1b, during encoding scans, samples of younger and older adults viewed 96 pictures of scenes paired with labels, and during retrieval scans, they recalled the scenes in response to the labels and rated the quality of their memories. These in-scan ratings were validated with a post-scan forced-choice memory recognition test, which showed that greater in-scan ratings were associated with better post-scan accuracy (Fig. 1c; see the Materials and Methods for more details on participants and the experimental design). Previous reactivation fMRI studies with older adults compared broad categories of stimuli (Abdulrahman, Fletcher, Bullmore, & Morcom, 2017; Johnson et al., 2015; Thakral et al., 2019; T. H. Wang et al., 2016) or presented stimuli multiple times during encoding (St-Laurent et al., 2014), precluding reactivation measures for individual events. In contrast, we measured the reactivation of individual events (each scene) by directly measuring ERS in activation patterns (Maureen Ritchey et al., 2013; Wing et al., 2014). On the bases of Hypothesis 2, we predicted that, compared to younger adults, older adults would show reduced ERS in the early visual cortex but spared (or even enhanced) ERS in anterior temporal lobe.

2.2. Materials and Methods

2.2.1. Study Participants

Our study sample included 22 younger adults and 22 older adults. One younger adult and one older adult were excluded from analysis because of functional data missing from the first fMRI run due to a technical error. Another older adult was excluded from analysis due to a poor quality T1 image, not allowing the participant's functional images to be properly normalized into MNI space. This left a study sample of 21 younger adults (12 women, age range = 18-30 years, M = 23.5 years, SD = 3.0 years) and 20 older adults (9 women, age range = 61-82 years, M = 70.5 years, SD = 5.4 years). Participants self-reported to be free of significant health problems (including atherosclerosis, neurological and psychiatric disorders), and not taking medications known to affect cognitive function or cerebral blood flow (except antihypertensive agents). Also, all participants were right-handed and completed at least 12 years of education. The older adults were additionally screened for dementia via the Mini-Mental State Examination (MMSE; inclusion criterion ≥ 27; M = 29.2, SD = 0.7; Folstein, Folstein, & McHugh, 1975); no exclusions were necessary based upon this criterion. After study completion, participants were monetarily compensated for their time. Study results from the sample of younger adults were previously reported in other manuscripts (Geib, Stanley, Wing, Laurienti, & Cabeza, 2017; Wing et al., 2014). The

Duke University Institutional Review Board approved all experimental procedures, and participants provided informed consent prior to testing.

2.2.2. Experimental Design

Participants completed three encoding runs followed by three retrieval runs. During the encoding runs, participants explicitly studied a total of 96 pictures of complex scenes (32 images per run, order randomized within run). During each encoding trial (4 sec), participants were presented a single picture with a short descriptive label below the image (e.g., “tunnel” or “barn”). Within the trials, participants were asked to rate, on a four-point scale (1 = low quality, 4 = high quality), the quality of the image. This was to ensure participants would pay attention to the details of each image. Each encoding trial was followed by an active baseline interval of 8 sec, in which participants were presented digits from 1 to 4 and pushed the button corresponding to the presented numbers.

The retrieval runs were identical in format to the encoding runs, except the pictures of the scenes were not presented. During each retrieval trial, participants were presented the descriptive scene label previously presented with the picture of the scene, and participants were instructed to recall the corresponding image from encoding with as much detail as possible. Participants then rated, on a four-point scale, the amount of detail with which they could remember for the specific picture (1 = least amount of detail, 4 = highly detailed memory).

2.2.3. MRI Data Acquisition

MRI data were collected on a General Electric 3T MR750 whole-body 60 cm bore MRI scanner and an 8-channel head coil. The MRI session started with a localizer scan, in which 3-plane (straight axial/coronal/sagittal) localizer faster spin echo (FSE) images were collected. Following, using a SENSE spiral-in sequence (repetition time [TR] = 2000 msec, echo time = 30 msec, field of view [FOV] = 24 cm, 34 oblique slices with voxel dimensions of 3.75 x 3.75 x 3.8 mm^3), the functional images were acquired. The functional images were collected over six runs – three encoding runs and three retrieval runs; there was also a functional resting-state run after the third encoding run, which is not reported here. Stimuli were projected onto a mirror at the back of the scanner bore, and responses were recorded using a four-button fiber-optic response box (Current Designs, Philadelphia, PA, USA). Following, a high-resolution anatomical image (96 axial slices parallel to the AC-PC plane with voxel dimensions of 0.9 x 0.9 x 1.9 mm) was collected. Finally, diffusion-weighted images were collected, which are not reported here. Participants wore earplugs to reduce scanner noise, and foam pads were used to reduce head motion, and, when necessary, participants wore MRI-compatible lenses to correct vision.

2.2.4. FMRI Data Preprocessing

For each run, the first six functional images were discarded to allow for scanner equilibrium. All functional images were preprocessed in a SPM12 (London, United Kingdom) pipeline. Briefly, the functional images were slice timing corrected (reference slice = first slice), realigned to the first scan in the first session, and subsequently unwarped. Following, the functional images were coregistered to the skull-stripped high-resolution anatomical image (skull-stripped by segmenting the high-resolution anatomical image and only including the gray matter, white matter, and cerebrospinal fluid segments). The functional images were normalized into MNI space using DARTEL (Ashburner, 2007); the study specific high-resolution anatomical image was created using all of the study participants. The voxel size was maintained at 3.75 x 3.75 x 3.8 mm^3 and the normalized-functional images were not spatially smoothed. Lastly, the DRIFTER toolbox (Sarkka et al., 2012) was used to denoise the functional images.

2.2.5. FMRI Analysis

2.2.5.1. Functional Representational Similarity

To obtain the beta estimates for each event, we conducted a single-trial model analysis within a general linear model. These beta estimates were calculated using a least squares-separate approach (Mumford, Turner, Ashby, & Poldrack, 2012). This approach estimates a first-level model in which one regressor models a specific event of interest and another regressor models all the other events (each run included a regressor modeling these other trials). Each event was modeled with a stick function placed at stimulus onset convolved with a standard hemodynamic response function with the temporal and dispersion derivative. Each model also included the six raw motion regressions, a composite motion parameter (derived from the Artifact Detection Tools [ART]), outlier TRs (scan-to-scan motion > 2.0 mm or degrees, scan-to-scan global signal change > 9.0 z score; derived from ART), the white matter timeseries, and cerebrospinal fluid timeseries. In each model we also modeled the temporal and dispersion derivatives and implemented a 128 sec cutoff high-pass temporal filter. These beta-images were used for (1) the representational similarity analysis combined with DNNs and (2) ERS. These analyses were conducted using in-house MATLAB (Natick, MA, USA) scripts. For the ERS analyses, we excluded trials in which participants responded (during retrieval) either not at all or in less than 250 msec.

2.2.5.2. Representational Similarity Analysis Combined with Deep Convolutional Neural Networks

To examine our first goal, we combined representational similarity analysis (Nikolaus Kriegeskorte & Kievit, 2013; Nikolaus Kriegeskorte et al., 2008) and stimuli models derived from DNNs (Khaligh-Razavi & Kriegeskorte, 2014; Nikolaus Kriegeskorte, 2015; Leeds et al., 2013; Wen et al., 2017). The stimuli models (96 x 96 matrix) from each layer of interest were correlated (Spearman correlation) with the brain activation patterns similarity matrix (96 x 96 matrix) derived from searchlight spheres. For the searchlight analysis (Nikolaus Kriegeskorte, Goebel, & Bandettini, 2006), a 5 x 5 x 5 voxel cube (Wing et al., 2014) was placed around a voxel location and the activation values from this cube were extracted and vectorized. At the voxel location, this procedure was conducted for each stimulus and the activation values from each stimulus were correlated (Fisher-transformed Pearson's r) with each other, representing the brain activation patterns. The brain activation patterns were then correlated (Spearman's correlation) with the DNN-stimuli models (model-brain fit), which was the value placed in the voxel location. This procedure was repeated for every voxel in the brain and the output of this analysis was searchlight volumes representing brain activation pattern-DNN layer stimuli model similarity.

For the DNN, we used the popular VGG16 (Simonyan & Zisserman, 2014) pre-trained on approximately 1.8 million images of scenes in service of categorizing the images into 365 scene categories (Zhou et al., 2017). The VGG16 consists of 13 convolutional layers and 3 fully-connected layers. We created stimuli models from the first DNN layer (reflecting sensory features) and penultimate DNN layer (reflecting categorical features). It should be noted that we chose these two layers because they reflect the extremes of the DNN, but that stimuli models constructed from surrounding layers are correlated with each other (Appendix A). These stimuli models were constructed by feeding the study stimuli through the pretrained DNN and for each stimulus at each layer of interest (i.e., the first and penultimate layers), extracting the activation values. For each layer of interest, the activation values between stimuli were correlated (Pearson correlation) with each other. This yielded two 96x96 matrices (one for each layer of interest), which represent the similarity of the DNN activation values and are the image models (sensory and categorical image models).

After conducting the searchlight analysis examining model-brain fit, the searchlight volumes were spatially smoothed with a 5 mm Gaussian kernel (Clarke, Pell, Ranganath, & Tyler, 2016; Clarke & Tyler, 2014). Then, for each model, we extracted model-brain fit from a priori regions of interest derived from the AAL atlas (Tzourio-Mazoyer et al., 2002), which consisted of early visual cortex (bilateral calcarine, cuneus, and lingual regions of interest) and anterior temporal lobe (left dorsal temporal pole and ventral temporal pole). We chose to examine only the left anterior temporal lobe because of our interest in categorical representations and an extensive literature demonstrating greater processing of categorical-related features (e.g., conceptual processing) in the left hemisphere (Hodges et al., 1992; Tyler et al., 2004; Warrington & McCarthy, 1983). See the Introduction for an explanation of a priori ROI choice.

2.2.5.3. Encoding-Retrieval Similarity

To examine our second goal, we calculated ERS for each item using a searchlight procedure (Nikolaus Kriegeskorte et al., 2006). For each item, encoding and retrieval activation values were extracted from searchlight spheres and the encoding and retrieval vectors were correlated with each other. A 5 x 5 x 5 voxel cube was placed around each voxel and the activation values were extracted and vectorized. For each item, the encoding and retrieval vectors were correlated and the resulting correlation value (Fisher-transformed Pearson's r, which is ERS) was placed in the original voxel location. Within each voxel location, the ERS value for each stimulus (a total of 96 values for each image) was averaged across all stimuli. This procedure was repeated for every voxel within the brain. Afterwards, the searchlight volumes were spatially smoothed with a 5 mm Gaussian kernel (Clarke et al., 2016; Clarke & Tyler, 2014). We then extracted ERS from a priori regions of interest derived from the AAL atlas (Tzourio-Mazoyer et al., 2002), which consisted of early visual cortex (bilateral calcarine, cuneus, and lingual regions of interest), anterior temporal lobe (left dorsal temporal pole and ventral temporal pole), and the hippocampus (bilateral hippocampi). See the Introduction for an explanation of a priori ROI choice. In addition to item-level ERS, as a control analysis, we also calculated set-level ERS, which is ERS between an item and every other item within the set (Maureen Ritchey et al., 2013; Wing et al., 2014); this analysis was constrained to the items that were subsequently remembered on the post-scan memory task.

2.2.6. VGG16 Fine-Tuning

In our preliminary analysis validating the VGG16 as a model of low- to categorical representations in our study (see Results), we fine-tuned the VGG16 to classify our images into indoor vs. outdoor pictures. This was achieved by removing the last layer of the VGG16 and adding a layer with two outputs (with a softmax activation function), corresponding to indoor and outdoor scenes. The revised VGG16 was then trained using three pictures from each image category (images from the post-scan recognition task besides the target images) and tested on the pictures presented within the scanner. After 30 epochs, the revised VGG16 was able to classify the images (indoor vs. outdoor) with 94.8% accuracy. The revised VGG16 was only used for this preliminary analysis.

2.2.7. Statistical Analysis

All statistical analyses (unless otherwise stated) were conducted within StatsModels (Seabold & Perktold, 2010) ran in Python 3 (Python Software Foundation) using two-sided linear mixed effects models. Before entering the data into the linear mixed effects models, all values were z-transformed. For the analyses statistically controlling for signal-to-noise ratio (SNR), SNR was entered into the model as a nuisance variable. All effect sizes reported in the manuscript were Cohen's d.

2.3. Results

2.3.1. Preliminary Analyses

Before testing our two hypotheses, we conducted two preliminary analyses to validate the VGG16 (Simonyan & Zisserman, 2014) as a model of sensory to categorical representations in our study. First, the VGG16 was already successfully trained to classify 1.8 million scenes into 365 categories (Zhou et al., 2017), but we wanted to confirm it could also classify the 96 images employed in our study. Given that some of the scene labels we used (e.g., seaport, Fig. 1b) are different than the categories used to train the VGG16, we used instead a binary indoor-outdoor scene classification (see the Materials and Methods for more details). The VGG16 achieved this classification with 94.8% accuracy. It should be noted that the model with this binary indoor-outdoor scene classification was only used to validate the use of the VGG16 within our study; the pretrained VGG16 was used for stimuli model construction. Second, we correlated the sensory and categorical stimuli models and found that they were only moderately correlated with each other ($r = 0.32$), indicating that each model represents unique features. Having confirmed the validity of VGG16, we turned to our two hypotheses.

2.3.2. Perceptual Representations: Deep Convolutional Neural Network-Based Representational Similarity Analysis

Our first hypothesis was that age-related visual dedifferentiation impairs the differentiation of sensory features in early visual cortex but not categorical features in the anterior temporal lobe, which may even be enhanced in aging. Using DNN-based representational similarity analysis, we tested this hypothesis by comparing age-related differences in model-brain fit for the sensory model based on the first VGG16 layer and for the categorical model based on the penultimate VGG16 layer. We tested this hypothesis in two a priori ROIs – early visual cortex and anterior temporal lobe. As illustrated in Fig. 2a, which shows z-scored 2nd order correlations, the evidence was consistent with our first hypothesis: compared to the younger adults, in early visual cortex, the sensory model-brain fit was reduced in the older adults ($\beta = -0.39$, $z = 19.86$, $p < .0001$, $d = 0.83$), whereas in the anterior temporal lobe ($\beta = 0.26$, $z = 12.82$, $p < .0001$, $d = 0.53$), the categorical model-brain fit was enhanced in the older adults (see Appendix B, panel a for raw model-brain fit values). In other words, whereas early visual cortex showed age-related dedifferentiation, the anterior temporal lobe showed age-related hyperdifferentiation. As the anterior temporal lobe is particularly vulnerable to low SNR, we repeated the analysis statistically controlling for SNR and still found that in the anterior temporal lobe that categorical model-brain fit was enhanced in the older adults compared to younger adults ($\beta = 0.26$, $z = 15.61$, $p < .0001$). We did not find statistically significant age-group differences of the sensory model-brain fit in the anterior temporal lobe (β = 0.17, z = 1.39, p = .17, d = 0.33), but we did find that, compared to younger adults, the categorical model-brain fit in the early visual cortex was reduced in the older adults (β = -0.27, z = 3.25, p < .01, d = 0.54). In sum, this is, to our knowledge, the first evidence of age-related hyperdifferentiation of activation patterns in the ventral pathway or any brain region.

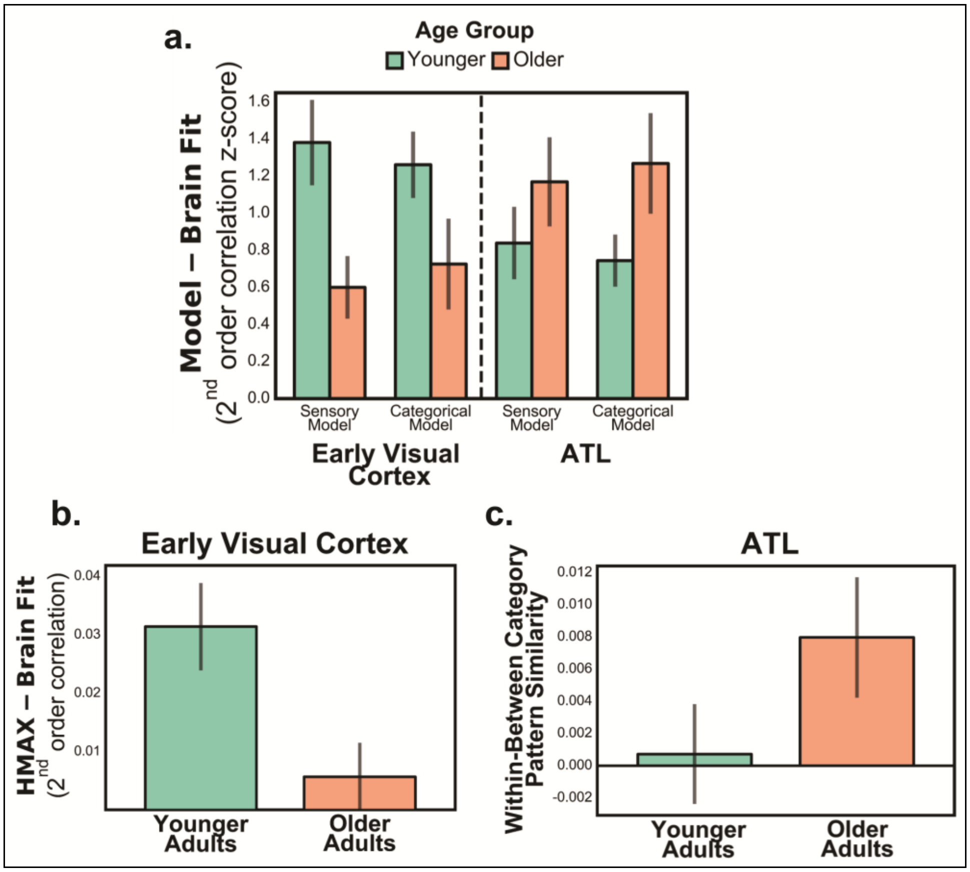


Figure 2: Age-Related Neural Dedifferentiation and Hyperdifferentiation. Panel a shows within the early visual cortex and ATL the stimuli model (sensory and categorical)-brain fit; the figure shows z-scored (mean set to one) 2nd order

correlations. Compared to the YAs, in the early visual cortex, we found that the sensory model-brain fit was reduced in the OAs (age-related dedifferentiation), whereas in the ATL, the categorical model-brain fit was enhanced in the OAs (age-related hyperdifferentiation). Panel b shows the HMAX C1 response model-brain fit in early visual cortex. We found that, compared to YAs, OAs exhibited reduced HMAX-brain fit in early visual cortex. Panel c shows the brain activation patter similarity for within-categories – between-categories (categories = indoor vs. outdoor scenes) in the ATL. We found that, compared to the YAs, OAs exhibited enhanced activation pattern similarity for within- than between-categories in the ATL. Error bars represent the standard error of the mean. Error bars represent the standard error of the mean. ATL = anterior temporal lobe, OAs = older adults, YAs = younger adults.

Although the a priori ROI analysis was used to test our hypothesis, as an exploratory analysis, we conducted the whole-brain searchlight analysis. Consistent with previous research that early DNN layers identified posterior brain regions mediating sensory representations, and later layers, anterior brain regions mediating categorical representations (Güçlü & van Gerven, 2015; Khaligh-Razavi & Kriegeskorte, 2014; Nikolaus Kriegeskorte, 2015; Leeds et al., 2013; Wen et al., 2017), within both the younger and older adults, the first layer of the VGG16 was primarily associated with visual cortices and the penultimate layer was additionally linked to anterior temporal, parietal, and frontal regions (shown in unthresholded, color-coded maps in Fig. 3; see Appendix C for cluster coordinates). Qualitatively, in these maps, it can be seen that the sensory model is more strongly associated with earlier visual cortex region activation patterns in younger than older adults, whereas the categorical model is more strongly associated with more anterior ventral visual pathway region, such as the anterior temporal lobe, activation patterns in older than younger adults (see white arrows). In sum, the whole-brain searchlight analysis largely mirrors the a priori ROI analysis.

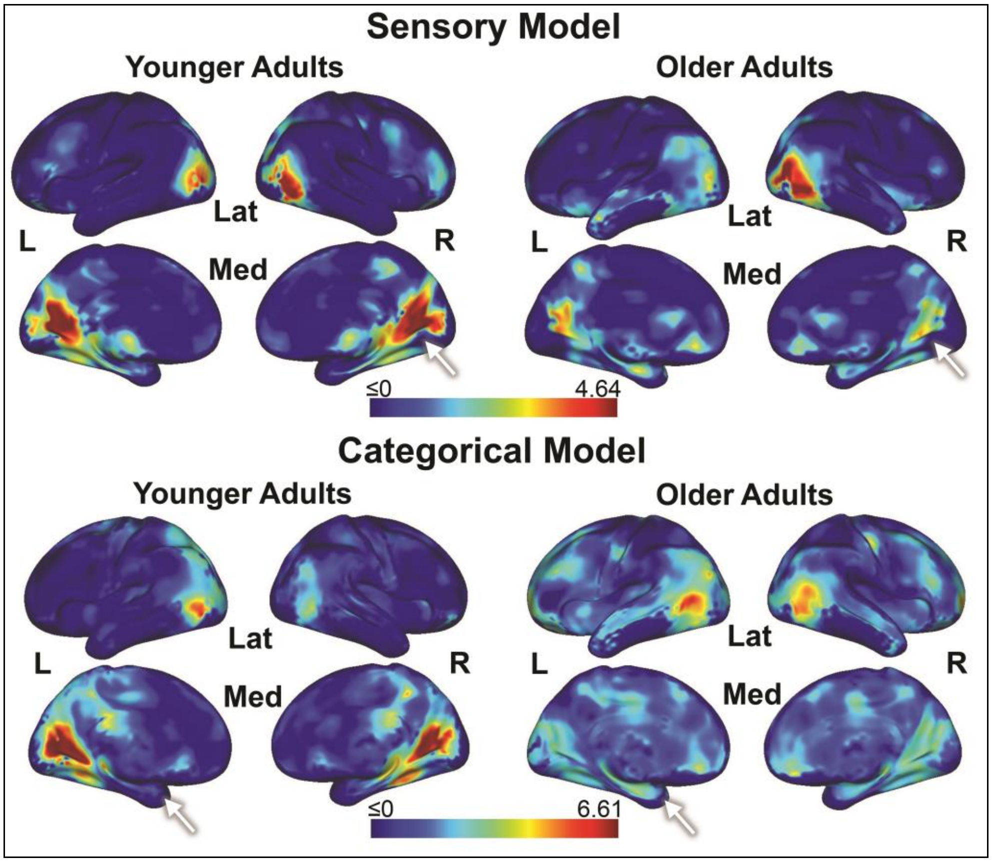


Figure 3: Sensory and Categorical Model-Brain Fit. The figure shows the whole-brain searchlight analysis of the stimuli model (sensory and categorical)-brain fit. Within both the YAs and OAs, we found that the sensory model (based upon the first DNN layer) correlated predominately with brain activation patterns in the visual cortices and the categorical model (based upon the penultimate DNN layer) additionally correlated with brain activation patterns in anterior temporal, parietal, and frontal regions. Qualitatively, in these maps it can be seen that that the sensory model is more strongly associated with earlier visual cortex region activation patterns in YAs than OAs, whereas the categorical model is more strongly associated with more anterior ventral visual pathway region, such as the ATL, activation patterns in OAs than YAs (see white arrows). DNN = deep convolutional neural network; L = left; Lat = lateral; Med = medial; OAs = older adults; R = right; YAs = younger adults.

Although DNNs provide stronger models of visual representations in the ventral visual pathway than traditional theoretical models (e.g., HMAX, object-based models; Cadieu et al., 2014; Groen et al., 2018a) and we believe are an ideal model to investigate this sensory to categorical feature distinction, DNNs are sometimes critiqued for being too complex and, therefore, less interpretable. We believe that this level of complexity is necessary to map representations within the brain and that DNNs are one of the few models available that are complex enough to map fMRI representations (Nikolaus Kriegeskorte & Douglas, 2018), but the critique of interpretability is well received. Therefore, we examined age-related differences in the a priori ROIs using more traditional models. For sensory representations, we used the C1 responses of the HMAX model (Clarke & Tyler, 2014; Serre, Wolf, Bileschi, Riesenhuber, & Poggio, 2007), which are proposed to reflect properties of early visual cortex (Riesenhuber & Poggio, 1999; Serre et al., 2007), and for categorical representations, we examined brain activation pattern similarity for within- compared to between-categories (indoor vs. outdoor scene trials). For the categories, we chose indoor and outdoor scenes because these categories likely share large amounts of objects and visual features, as demonstrated in our preliminary analysis using the VGG16 to classify indoor and outdoor scenes (see Preliminary analyses in the Results). Consistent with the DNN analysis, compared to the younger adults, the older adults exhibited reduced model-brain fit with the HMAX model in early visual cortex (Fig. 2b; β = -0.39, z = 13.73, p < .0001, d = 0.82), but enhanced activation pattern similarity for within- than between-categories in the anterior temporal lobe (Fig. 2c; β = 0.23, z = 3.36, p < .001, d = 0.46; see Appendix B, panel B for pattern similarity values of each category). These findings provide further evidence for age-related dedifferentiation of sensory features in early visual cortex and hyperdifferentiation of categorical features in anterior temporal lobe.

2.3.3. Mnemonic Representations: Encoding-Retrieval Similarity

Our second hypothesis was that aging impairs mnemonic representations for sensory features in early visual cortex and hippocampus but not for categorical features in the anterior temporal lobe. To test this hypothesis, we calculated ERS (Maureen Ritchey et al., 2013; Wing et al., 2014). We tested this hypothesis using the same a priori ROIs used to test our first hypothesis with the addition of the hippocampus because of the second hypothesis's relation to memory (see the Methods for more details). Consistent with Hypothesis 2, as shown within Fig. 4a, we found that, compared to younger adults, older adults exhibited reduced ERS in the early visual cortex (β = -0.35, z = 14.34, p < .0001, d = 0.74) and hippocampus (β = -0.45, z = 3.37, p < .001, d = 0.97), but increased ERS in the anterior temporal lobe (β = 0.20, z = 3.62, p < .001, d = 0.39; see Appendix B, panel c for raw ERS values). As the anterior temporal lobe is particularly vulnerable to low SNR, we repeated the analysis statistically controlling for SNR and still found the same effect within the anterior temporal lobe (β = 0.24, z = 2.98, p < .01). In sum, it appears that aging impairs mnemonic representations within regions associated with sensory features but enhances mnemonic representations within regions associated with categorical features.

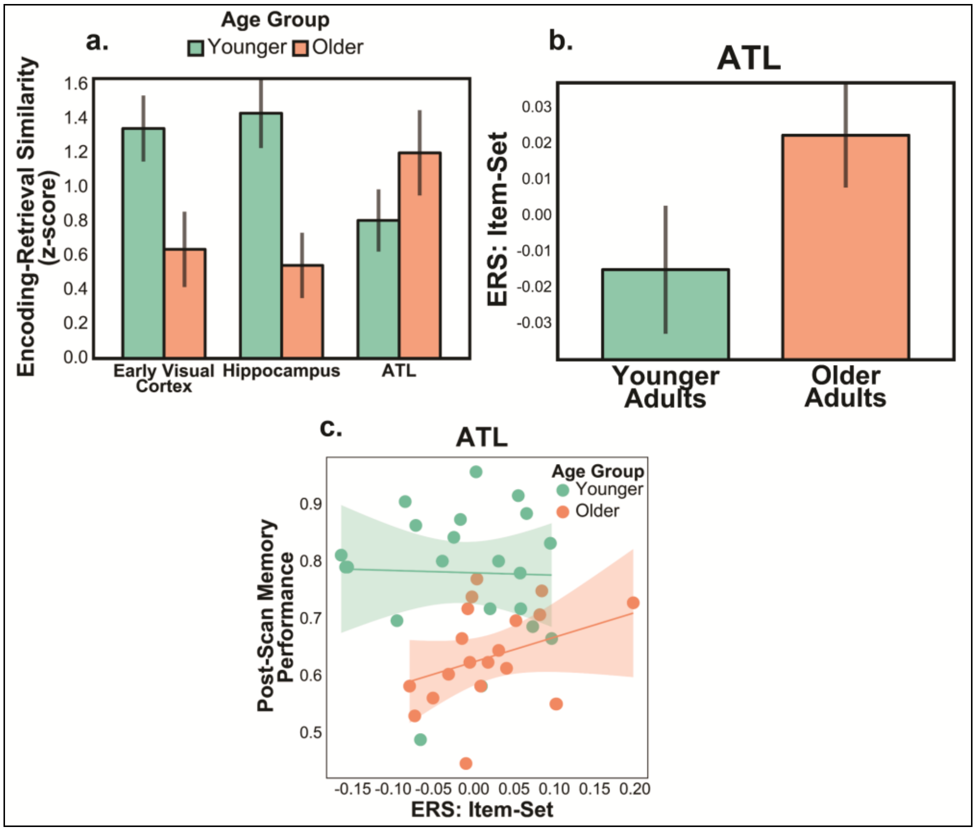


Figure 4: Age-Related Differences in Mnemonic Representations. Panel a shows age-related differences in ERS. We found, compared to the YAs, in the early visual cortex and hippocampus that the OAs exhibited reduced ERS, whereas in the ATL, the OAs exhibited increased ERS. The figure shows *z*-scored (mean set to one) ERS; error bars represent the standard error of the mean. Panel b shows item-specific ERS (item-set level ERS) in the ATL for trials that were subsequently remembered on the post-scan memory recognition task. We found that, compared to the YAs, OAs exhibited enhanced item-specific ERS in the ATL. Error bars represent the standard

error of the mean. Panel c shows the relation between item-specific ERS in the ATL (limited to the trials that were subsequently remembered) and performance on the post-scan memory recognition task. We found in the OAs that increased item-specific ERS in the ATL was associated with better performance on the post-scan memory recognition task; translucent bars around the regression lines represent the 95% confidence intervals. ATL = anterior temporal lobe; ERS = encoding-retrieval similarity; OAs = older adults; YAs = younger adults.

Within the previous analysis we examined ERS for individual items (i.e., item-level ERS). However, in order to make the claim that ERS is item-specific, it is necessary to also compare item-level ERS with set-level ERS (i.e., encoding-retrieval similarity between an item and the rest of the set; Koen & Rugg, 2016; Maureen Ritchey et al., 2013; Wing et al., 2014). Furthermore, in order to strengthen our claim that ERS here reflects memory, it is necessary to repeat the analysis only on items that were subsequently remembered on the post-scan memory recognition task. Therefore, we repeated the analysis subtracting set-level ERS from item-level ERS and only including trials that were subsequently remembered on the post-scan memory task. The only region that still exhibited the same age group difference pattern was the anterior temporal lobe, in which, compared to younger adults, older adults exhibited enhanced ERS in the anterior temporal lobe (Fig. 4b; $\beta = 0.25$, $z = 2.99$, $p < .01$, $d = 0.49$; see Appendix B, panel d for raw ERS values). The age-related increase in item-specific ERS in the anterior temporal lobe suggests that this region contributes to memory to a greater extent in older than younger adults. To investigate this idea, we examined the relation between item-specific ERS (item-set ERS) in the anterior temporal lobe and performance on the post-scan memory recognition task. As illustrated in Fig. 4c, greater anterior temporal lobe item-specific ERS was associated with better performance on the post-scan memory recognition task in the older adults ($\beta = 0.34$, $z = 4.07$, $p < .0001$) but not younger adults ($\beta = -0.03$, $z = 0.48$, $p = .64$); it should be noted, however, that the age group by ERS interaction was not statistically significant ($\beta = 0.15$, $z = 1.07$, $p = .28$).

In sum, consistent with our second hypothesis, we found that older adults exhibited reduced ERS in the visual cortex and hippocampus but increased ERS in the anterior temporal lobe. The latter effect was found to be item specific and related to better memory performance in the older adults, suggesting that anterior temporal lobe hyperdifferentiation enhances the contributions of anterior temporal lobe to memory in older adults.

2.4. Discussion

The overarching goal of the study was to examine age-related differences in the quality of perceptual and mnemonic representations. We had two main findings. First, in early visual cortex, activation patterns associated with sensory features showed dedifferentiation in older adults, replicating previous age-related dedifferentiation findings, whereas in the anterior temporal lobes, activation patterns associated with categorical features showed hyperdifferentiation in older adults. This is, to our knowledge, the first report of age-related hyperdifferentiation. Second, for mnemonic representations, we found that increased age was associated with attenuated ERS (i.e., memory reactivation) in the early visual cortex and hippocampus but enhanced ERS in the anterior temporal lobe. The enhanced ERS in the anterior temporal lobd was associated with better memory in older adults, suggesting a compensatory mechanism. These findings are discussed in greater detail below.

2.4.1. Age-Related Neural Dedifferentiation and Hyperdifferentiation

Several studies have previously found evidence for age-related neural dedifferentiation (Carp et al., 2011; Chee et al., 2006; Goh et al., 2010; Payer et al., 2006; Voss et al., 2008) but these studies did not examine the specific aspects of visual representations that are impaired by aging. Here, we compared age-related differences in the cortical differentiation of sensory vs. categorical features using a novel DNN-based representational similarity analysis approach (Güçlü & van Gerven, 2015; Khaligh-Razavi & Kriegeskorte, 2014; Nikolaus Kriegeskorte, 2015; Leeds et al., 2013; Wen et al., 2017). Consistent with our hypothesis, within early visual cortex, we found evidence for age-related neural dedifferentiation of sensory features, where, compared to the younger adults, brain activation patterns in early visual cortex exhibited a worse fit with the sensory model in the older adults (Fig. 2a); this finding was also replicated by using the more traditional HMAX model (Fig. 2b). It is well known that increased age is associated with a robust decline in visual performance (Monge & Madden, 2016; Cynthia Owsley, 2011). Our finding suggests that this decline may not only be the result of a decline in perceptual operations (processes) performed on visual information but also a deficit in the quality of visual information itself (representations).

In contrast to sensory features in early visual cortex, we found that categorical features in the anterior temporal lobe were not just spared but actually enhanced within older adults. Within the anterior temporal lobe, compared to younger adults, activation patterns had a better fit with the categorical model in the older adults (Fig. 2a); this finding was also replicated comparing within and between-category pattern similarity (Fig. 2c). Thus, in contrast to age-related dedifferentiation in early visual cortex, in the anterior temporal lobe, we found age-related hyperdifferentiation. As noted above, this is the first time this finding is reported. Regarding the regions that exhibited age-related hyperdifferentiation, the anterior temporal lobe is hypothesized to store prior knowledge (Lambon Ralph et al., 2017; Zhao et al., 2017) and, compared to younger adults, older adults have a greater knowledge network (Long & Shaw, 2000; Denise C Park et al., 2002), likely from more years of knowledge accruement. It is likely that certain processes, such as conceptual and semantic processing, are more reliant on categorical features. Perhaps the enhanced categorical model-brain fit in the anterior temporal lobe within the older adults reflects older adults utilizing enhanced semantic knowledge in service of perception.

As mentioned in the Introduction of this thesis, only one other study, to our knowledge, has used representational similarity analysis to investigate age-related differences in sensory- and semantic-related representations (Bruffaerts et al., 2019). Similar to our study, they also found that age was associated with a decline in the quality of sensory-related representations. However, unlike our study, they found that age was associated with a decline in the quality of semantic-related representations. It should be noted, however, that Bruffaerts et al. (2019) averaged MEG signals from across the whole brain, making the two studies somewhat difficult to compare. Previous studies conducting representational similarity analysis often find effects to be specific to certain brain regions (e.g., Clarke et al., 2018; Clarke & Tyler, 2014; Groen et al., 2018b) and, therefore, it likely essential to examine localized effects. Although MEG does not allow for the same degree of localization as fMRI, perhaps if the study examined specific brain regions, such as the anterior temporal lobes, it would find that age would not be associated with a decline in semantic model-brain fit. Also, the semantic model was based upon semantic features collected from a sample of younger adults (K. McRae et al., 2005; Taylor et al., 2012). As semantic cognition appears to improve in aging (Denise C Park et al., 2002; Verhaeghen, 2003), it is likely the case that if the semantic features were collected in a sample of older adults, they would list different features. Therefore, it is not surprising that age was associated with a decline in semantic model-brain fit, since the model was biased toward modeling semantic representation in younger adults. In sum, we believe that Bruffaerts et al. (2019) and our study provide important advancements in the investigation of age-related differences in neural representations and demonstrate that it will likely be useful for future studies to utilize multiple methodologies (e.g., fMRI, MEG) to investigate age-related dedifferentiation and hyperdifferentiation.

Lastly, from the current study it cannot be determined exactly why this pattern of age-related dedifferentiation for sensory features and hyperdifferentiation for categorical features occurs, but we believe this may reflect age-related differences in strategies to complete this task. It may be the case that in order for younger adults to successfully complete this task, it is more beneficial for them to encode the sensory features of the task stimuli, whereas in older adults, it is more beneficial for them to encode categorical features. Indeed, representations are not necessarily 'hard-wired' into the brain and the representational space can be warped in response to task demands (Martin, Douglas, Newsome, Man, & Barense, 2018; W. C. Wang, Brashier, Wing, Marsh, & Cabeza, 2018). In order to confirm our interpretation of the results, a study manipulating participants' use of sensory and categorical representations is necessary.

2.4.2. Age-Related Differences in Mnemonic Representations

Our second question examined age-related differences in mnemonic representations. To examine this question, we examined the reactivation of mnemonic representations, which was assessed as the similarity between activation patterns during encoding and retrieval (ERS). Consistent with previous studies (Johnson et al., 2015; St-Laurent et al., 2014), compared to the younger adults, in the older adults ERS was weaker in the early visual cortex (Fig. 4a). Given that we also found age-related dedifferentiation of sensory representations in this region, the age-related attenuation of ERS in early visual cortex likely reflects a negative impact of degraded sensory features on visual memories. It should be noted that even though there are studies that have also demonstrated attenuated reactivation within the visual cortex (Johnson et al., 2015; St-Laurent et al., 2014), three previous studies did not find this pattern (Abdulrahman et al., 2017; Thakral et al., 2019; T. H. Wang et al., 2016). These studies used multi-voxel pattern analysis to identify the reactivation of classes of stimuli (e.g, words vs. objects), whereas we used ERS to detect the reactivation of individual items. Thus, it is possible that multi-voxel pattern analysis is less sensitive than ERS in detecting age-related reactivation deficits. We also found an age-related ERS reduction in the hippocampus (Fig. 4a). This finding is consistent with evidence of impaired hippocampal activity in older adults (Kennedy, Boylan, Rieck, Foster, & Rodrigue, 2017; Nyberg, 2017), and it extends this evidence to multivariate activation patterns. The use of ERS to investigate hippocampal memory representations could be useful not only for investigating normal aging but also hippocampal dysfunction in Alzheimer's disease.

Finally, we found that, compared to younger adults, older adults exhibited enhanced ERS in the anterior temporal lobe (Fig. 4a). As the anterior temporal lobe has been associated with abstract semantic representations (Lambon Ralph et al., 2017; Zhao et al., 2017), enhanced anterior temporal lobe ERS in older adults may reflect a greater reliance on semantic knowledge in service of memory. This idea is consistent with our finding of age-related hyperdifferentiation for categorical features in this region (Fig. 2a). Supporting the importance of anterior temporal lobe representational quality for memory in aging, we found that in older adults, increased item-specific ERS in the anterior temporal lobe was associated with better performance on the post-scan memory recognition task (Fig. 4c). This across-subject correlation suggests that individual differences in memory performance may be at least partially mediated by neural representational quality.

The link of enhanced ERS in the anterior temporal lobe to better memory performance in older adults suggests that these representational changes are compensatory. In functional neuroimaging of aging, the term compensation has been typically applied to age-related increases in univariate activity, which are normally assumed to reflect differences in processes. However, there is no reason why compensatory mechanisms must be mediated only by processes and could not involve an enhancement in representations. In fact, the accumulation of knowledge during the lifespan is likely to lead to more distinct and detailed semantic representations, which could partially counteract the degraded quality of sensory representations. This is any intriguing possibility and further research is required to link enhanced ERS in older adults to functional compensation.

2.4.3. Conclusions

The traditional idea that aging is associated with a generalized decline in cognitive abilities and their underlying neural mechanisms has been challenged by evidence that although some cognitive and brain mechanisms are impaired by aging, others are not only spared but even enhanced by aging (Long & Shaw, 2000; Denise C Park et al., 2002). One aspect of cognition that is spared by aging are processes that rely on categorical features, such as conceptual and semantic processing, but the neural mechanisms of these spared functions are largely unknown. The results of the present study suggest that one factor contributing to the preservation of these processes in old age is the enhanced quality of categorical representations in the anterior temporal lobe. These spared categorical representations may contribute not only to perceptual but also to mnemonic aspects of cognition. Lastly, these findings have implications not only for understanding normal aging but also the effects of pathological aging (e.g., Alzheimer's disease), which, to our knowledge, has yet to be examined.

3. Age-Related Differences in Memory Representational Networks

3.1. Introduction

The discipline of the cognitive neuroscience of aging has predominately focused on age-related differences in the neural underpinnings of cognitive processes (e.g., the act of recalling a memory; for reviews, see C. L. Grady, 2008; C. L. Grady, 2012), with very few studies investigating age-related differences in the neural mechanisms supporting representations (e.g., the information contained within a memory trace). The latter include studies demonstrating that increased age is associated with less specificity in the utilization of occipitotemporal cortex (occipitotemporal cortex) regions, such as the fusiform face area and parahippocampal place area, which process stimuli-specific (e.g., faces, scenes) information. This reduction in neural specificity is known as age-related neural dedifferentiation (Chee et al., 2006; Goh et al., 2010; Denise C. Park et al., 2004; Payer et al., 2006; Voss et al., 2008). More recently, this line of work has been extended with the use of multivariate techniques (e.g., multi-voxel pattern analysis, representational similarity analysis) to demonstrate that aging is also associated with a decline in the quality of representations in regions typically associated with perceptual processing (e.g., OTC; Carp et al., 2011; Johnson et al., 2015; St-Laurent et al., 2014; Zheng et al., 2017). A general limitation of the foregoing studies is that the effects of aging on representations were examined only at the level of individual brain regions (cf.

Johnson et al., 2015). Yet, representations are shared across multiple regions, and it may be the case that this exchange is affected by aging. The current study investigated this issue.

How information is shared among regions can be examined using a relatively novel analysis technique called informational connectivity (Anzellotti & Coutanche, 2018; Coutanche & Thompson-Schill, 2013). Whereas functional connectivity assesses synchronized changes in mean univariate activity, informational connectivity measures synchronized changes in multivariate activity patterns. Thus, informational connectivity differs from functional connectivity, and it is assumed to reflect the exchange of representations across brain regions (Coutanche & Thompson-Schill, 2013). To our knowledge, previous informational connectivity studies have been limited to bivariate connectivity (e.g., connectivity between pairs of regions evaluated independently). However, as brain regions operate within large-scale networks, it is likely the case that bivariate informational connectivity tells only part of the story, and hence, it is important to also examine multivariate informational connectivity. The current study goes beyond previous studies by examining age-related differences in informational connectivity using multivariate graph theory analyses. We call the whole-brain informational connectivity interactions representational networks.

Networks may be analyzed with the use of graph theory (Rubinov & Sporns, 2010; van den Heuvel & Sporns, 2013), which in neuroscience views the brain as consisting of nodes (brain regions) and edges (connections between regions). Graph theory has previously been used to describe functional connectivity patterns in both younger adults (e.g., Cohen & D'Esposito, 2016; Cole et al., 2013; Matthew L Stanley, Dagenbach, Lyday, Burdette, & Laurienti, 2014) and in aging (e.g., Chan, Park, Savalia, Petersen, & Wig, 2014; Gallen, Turner, Adnan, & D'Esposito, 2016; Geerligs, Renken, Saliasi, Maurits, & Lorist, 2015; C. L. Grady, Sarraf, Saverino, & Campbell, 2016; Monge et al., 2017), and has been shown to be sensitive to the neural underpinnings of memory (Geib, Stanley, Dennis, Woldorff, & Cabeza, 2017; Geib, Stanley, Wing, et al., 2017; Monge, Stanley, Geib, Davis, & Cabeza, 2018; Monge, Wing, Stokes, & Cabeza, 2018). Here, we utilized graph theory to investigate age-related differences in representational networks.

In the current fMRI study, younger adults and older adults encoded pictures divided between three categories. Since the images were divided between three different categories, we were able train machine learning classifiers to take brain activation patterns and discriminate between the three categories (i.e., multi-voxel pattern analysis [MVPA]), which ultimately allowed us to construct representation networks. The representational network analysis had three main steps. First, we trained a MVPA classifier to distinguish between the three image categories (Fig. 5A). This allowed us to identify brain regions sensitive to picture information. Second, for each brain region, we generated a representational timeseries, which consisted of the classifier calculated probability that the stimulus category was presented during a trial (Fig. 5B); the classifier calculated probability can be interpreted as how strongly stimuli information is represented during each trial. Third, we used the representational timeseries from each brain region to create the whole-brain correlation matrix used in graph theory analyses, which we call a representational network (Fig. 5C). During fMRI scanning, in addition to studying the pictures, participants completed two encoding task conditions (alternating between runs), one focusing attention to perceptual features (colors, lines) and the other to semantic features (meaning). Although when encoding any picture, both perceptual and semantic features are encoded (Clarke et al., 2018; Clarke & Tyler, 2014; Barry J. Devereux et al., 2018), tasks in which participants shift their attention to either perceptual or semantic features allow for the examination of how these tasks warp the representational space. Therefore, for the perceptual and semantic task trials, separate networks may be constructed and compared. Lastly, after scanning, memory for the pictures was tested with an old/new recognition test.

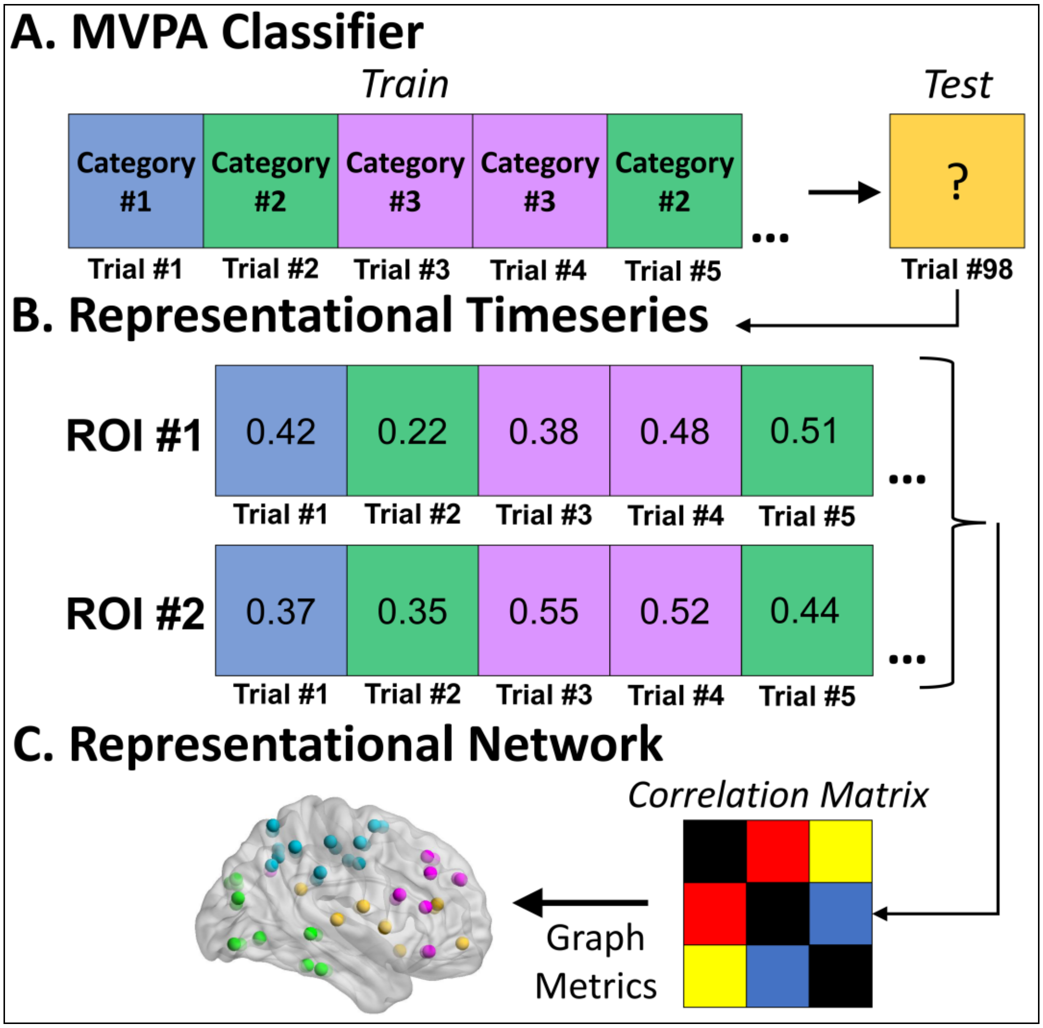


Figure 5: Representational Network Construction Pipeline. The figure shows a diagram of the representational network construction pipeline. First, within each ROI, we used an MVPA classifier with a leave-one-out cross validation procedure to determine the classifier calculated probability of the stimulus category of each event (Panel A). Second, the classifier probability for each event was placed into a vector, which is the representational timeseries (Panel B). The representational timeseries was constructed for every ROI chosen to be included in the network. Third, the representational timeseries from each ROI were correlated with each other to construct, for each participant, a representational network (Panel C). Graph metrics were calculated to describe the representational network topology. The brain overlay of the regions of interest (center of mass of the AAL atlas) was visualized with

BrainNet Viewer (Xia, Wang, & He, 2013). MVPA = multi-voxel pattern analysis; ROI = region of interest.

Our first goal was to examine age-related differences in the strength of informational connections in what we call representational modules. Modules are subsets of tightly interconnected regions, as identified by data-driven algorithms (Mišić & Sporns, 2016; Sporns & Betzel, 2016). Previous work on functional networks (Simon W Davis, Luber, Murphy, Lisanby, & Cabeza, 2017) have distinguished between modules associated with perceptual processing, including posterior regions such as the occipitotemporal cortex, and modules associated with semantic processing, including anterior regions, such as the anterior temporal lobes and medial/lateral prefrontal cortex. Therefore, we predicted that applying this data-driven modularity analysis to representational networks would also yield separate modules including the occipitotemporal cortex and anterior temporal lobe/prefrontal cortex. For each of these modules, the strength of informational connections maintained may be calculated, which indicates how important that module is in terms of distributing information across the whole-brain network. Behavioral studies have shown that perceptual processing declines in aging (Monge & Madden, 2016; Cynthia Owsley, 2011; Sekuler & Sekuler, 2000a) whereas semantic processing is relatively spared by aging (Cherry et al., 2012; Mohanty et al., 2016; Denise C Park et al., 2002; Spaniol, Madden, & Voss, 2006). Thus, we hypothesized that, compared to younger adults, in older adults the strength of informational connections in the posterior perception-related module would be lower, whereas the connections in the anterior, semantic-related module would be similar (Hypothesis 1).

Our second goal was to investigate age-related differences in whole-brain informational connectivity changes between perceptual and semantic tasks, and to link this task-related reconfiguration to memory performance. As mentioned above, in the fMRI paradigm investigated, we included two encoding task conditions, one focusing attention to perceptual features and the other to semantic features. The inclusion of these two tasks allowed us to examine how informational connections reconfigure in service of these tasks. Previous work indicates that younger adults utilize both perceptual and semantic representations when viewing visual stimuli (Clarke et al., 2018; Clarke & Tyler, 2014; Barry J. Devereux et al., 2018). We have recently demonstrated that when viewing visual stimuli, compared to younger adults, older adults rely more on semantic-related representations and that the utilization of semantic-related representations was compensatory (Monge, Wing, et al., under review). This work suggests that older adults may require greater shifts in the utilization of different types of representations in response to environmental demands. Therefore, we hypothesized that, compared to younger adults, older adults would display greater informational connection reconfiguration in response to perceptual vs. semantic demands, and that task-related reconfiguration would be associated with better memory (Hypothesis 2).

3.2. Methods

3.2.1. Study Participants

Twenty-one younger adults and 19 older adults participated in this study. Participants were recruited through either flyer or newspaper advertisements. Participants self-reported to be free of significant health problems (including atherosclerosis, neurological and psychiatric disorders), to not be taking medications known to affect cognitive function or cerebral blood flow (except antihypertensive agents), to be right-handed, to be native English speakers, and to have completed at least 12 years of education (younger adults: M = 16.2, SD = 2.0 years of education; older adults: M = 17.0, SD = 1.9 years of education). The older adults were additionally screened for dementia via the Mini-Mental State Examination (MMSE; inclusion criterion ≥ 27; Folstein et al., 1975); no exclusions were necessary based upon this criterion. One younger adults was excluded due to excessive head movement (several volume-to-volume movements > 3 mm), two younger adults were excluded due to the beta images not having whole-brain coverage, and three older adults were excluded from analysis due to technical problems during testing not allowing the participants to complete the scan session. This left a total of 18 younger adults (8 females, age range =

18-29 years, M = 23.4 years, SD = 3.2 years) and 16 older adults (7 females, age range = 61-83 years, M = 66.8 years, SD = 5.7 years). The Duke University Institutional Review Board approved all experimental procedures, and participants provided informed consent prior to testing. The study sample was previously reported in other manuscripts (Dew, Ritchey, LaBar, & Cabeza, 2014; M. Ritchey, LaBar, & Cabeza, 2011; Maureen Ritchey et al., 2013), including a comparison of univariate activity of the encoding task in younger and older adults (M. Ritchey, Bessette-Symons, Hayes, & Cabeza, 2011).

3.2.2. Stimuli

As mentioned in the Introduction, stimuli were divided between three categories, which were valence categories (negative, positive, and neutral). Stimuli consisted of 630 pictures from the International Affective Picture System (Lang, Bradley, & Cuthbert, 2008) and an in-house, standardized database that allowed us to equate the pictures better for visual complexity and content (e.g., human presence). Pictures were chosen to be evenly represented among three valence categories based upon a 9-point normative valence scale – negative (valence: 1-4), neutral (valence: 4-6), and positive (valence: 6-9).

3.2.3. Experimental Design

While receiving fMRI scanning, participants incidentally encoded pictures divided across the three valence categories (negative, positive, and neutral pictures). It should be noted that, here, our study goals were not to study emotion, but rather to use the three types of picture categories to identify brain regions sensitive to picture information, ultimately allowing us to construct representational networks (described below). The scan session was divided over 10 runs, in which the picture presentations were evenly divided across the three valence categories (140 negative, 140 positive, and 140 neutral pictures). Therefore, each run consisted of 14 pictures from each valence category. Within each run, the pictures were pseudo-randomized so that no more than three pictures of the same valence were consecutively presented, in order to avoid the induction of long-lasting mood states. Runs alternated between two distinct tasks – semantic and perceptual. In the semantic task, participants were instructed to carefully analyze each picture for its meaning and interpretation. In the perceptual task, participants were instructed to carefully analyze each picture for its perceptual features, particularly colors and lines. Before the start of each run, participants were informed which task was next and were instructed to tailor their processing of each picture to the current task. The order of the semantic and perceptual tasks was counterbalanced across participants and the assignment of stimulus lists to the semantic versus perceptual task was counterbalanced across participants.

The trial structure between the two tasks was similar. For each trial a picture was presented for 2 sec, followed by a jittered fixation interval (M = 2 sec). After the picture presentation, participants were instructed to rate the picture for its emotional arousal or intensity on a 4-point scale (1 = calm, 4 = excited); younger adults were given 1 sec to make this rating whereas older adults were given 2 sec. The older adults were given a longer response window to aid in equating age-related differences in task difficulty, which may facilitate results interpretation. Lastly, a question screen appeared that was designed to test participants' semantic or perceptual analysis of the picture. In the semantic task, the question screen stated, "Which word better describes the scene?" Two possible options were presented on-screen, both of which were written for each picture such that both could be related to the picture but only one described the true meaning of the picture. For example, an image depicting people climbing down the stairs from an airplane might be followed by the options "arrival" and "departure." In the perceptual task, the question screen said, "Which feature is there more of?" Two possible options were presented on-screen: either two color names or the words horizontal and vertical. In both tasks, these options were displayed for 1 sec in the younger adults and 2 sec in older adults; older adults were given more time to respond to aid in equating age-related differences in task difficulty, which may facilitate results interpretation. Trials were separated by an additional jittered fixation interval (M = 2 sec).

Following the encoding task, participants completed a memory recognition task. The younger adults completed the memory recognition task two days later, whereas the older adults completed the memory recognition task the following day. In the older adults, there was less time between the encoding and retrieval sessions to aid in equating age-related differences in task difficulty, which may facilitate results interpretation. During the memory recognition task, in addition to the pictures presented during encoding, participants were presented an additional 70 negative, 70 positive, and 70 neutral lures. For each trial, participants were presented a picture for 2 sec, followed by a jittered fixation interval (M = 2 sec). Participants indicated whether the item was old or new using a 5-point scale, with 1 = definitely new, 2 = maybe new, 3 = maybe old, 4 = definitely old, and 5 = remember. Participants were instructed that a remember response indicated the recollection of a specific detail from when they saw the picture during the encoding period, whereas a definitely old response did not include any specific details. The younger adults completed the retrieval session while receiving fMRI scanning, whereas the older adults completed the retrieval session outside of the scanner. Therefore, fMRI results are only reported for the encoding session.

3.2.4. MRI Data Acquisition

MRI data were collected on a 4T General Electric (GE Healthcare, Waukesha, WI, USA) scanner. The MRI session started with a T2-weighted sagittal localizer, in which the anterior (AC) and posterior (PC) commissures were identified in the midsagittal slice, and 34 contiguous oblique slices were prescribed parallel to the AC-PC plane. A high-resolution T1-weighted structural image was collected with a 12.2 msec repetition time (TR), 5.3 msec echo time (TE), 60° flip angle, 300 msec inversion recovery time, 24 cm field of view (FOV), a 256^2 matrix, 68 slices, slice thickness of 1.9 mm, and voxel size of 0.9 x 0.9 x 1.9 mm^3. Functional images were acquired using an inverse spiral sequence with a 2 sec TR, 31 msec TE, 24 cm FOV, 64^2 matrix, and a 60° flip angle. Thirty-four contiguous slices were acquired in an interleaved order with the same slice prescription as the anatomical images. Slice thickness was 3.8 mm, resulting in 3.75x3.75 x3.8 mm^3 voxels.

3.2.5. FMRI Analysis

3.2.5.1. Preprocessing

The first six functional images were discarded to allow for scanner equilibrium. All functional images were preprocessed in an SPM12 (London, United Kingdom) pipeline. Briefly, the functional images were slice timing corrected (reference slice = first slice), realigned to the first scan in the first session, and subsequently unwarped. Following, the functional images were coregistered to the skull-stripped T1 image (skull-stripped by segmenting the T1 image and only including the gray matter, white matter, and cerebrospinal fluid segments) and subsequently normalized to MNI space using DARTEL (Ashburner, 2007); the study specific anatomical image was created using all of the study participants. The voxel size was maintained at 3.75x3.75x3.8 mm^3 and the normalized-functional images were not spatially smoothed.

3.2.5.2. Functional Data Modeling

To obtain beta estimates for each event, we conducted a single-trial model analysis within a general linear model. To reduce the possible influence of collinearity, these beta estimates were calculated using a least squares-separate approach (Mumford et al., 2012). This approach estimates a first-level model in which one regressor models a specific event of interest and another regressor models all the other events (each run included a regressor modeling these other trials). Each event was modeled with a stick function at stimulus onset convolved with the canonical hemodynamic response function with the temporal derivative. As the time between picture viewing and the arousal rating/task question was jittered, we modeled both parts of the trial; however, only the beta images from the picture viewing were included in analysis. We chose to only examine the picture viewing beta images because we believe that the quality of representations would be the highest during this part of the trial and we did not expect large differences, in terms of the use of representations, during the picture viewing vs. arousal rating/task question trial components. Each model also included the six raw motion regressors, a composite motion parameter (scan-to-scan difference of maximal movement of any voxel within the brain bounding box derived from the Artifact

Detection Tools [ART]), outlier TRs (scan-to-scan motion > 2.0 mm or degrees, scan-to-scan global signal change > 9.0 z score; derived from ART), the white matter timeseries, and cerebrospinal fluid timeseries. The white matter and cerebrospinal fluid timeseries were included as nuisance regressors because these signals predominately reflect non-neural fluctuations, such as scanner instabilities, participant motion, and physiological artifacts (Dagli, Ingeholm, & Haxby, 1999; Windischberger et al., 2002); these timeseries were calculated by averaging across all the voxels within the white matter and cerebrospinal fluid masks (derived from the tissue probability maps > 90% probability). The proportion of outlier TRs were low (younger adults: M = 0.00095, SD = 0.00171; older adults: M = 0.00106, SD = 0.00121) and there was not an age-related difference in the proportion of outlier TRs (t(32) = 0.22, p = .83). In each model we also modeled the temporal derivative and implemented a 128 sec cutoff high-pass temporal filter. These beta-images were used for all subsequent fMRI analyses.

3.2.5.3. Multi-Voxel Pattern Analysis

In order to determine the nodes that would be included in the representational network construction (Fig. 5), using PyMVPA (Hanke et al., 2009) and scikit-learn (Pedregosa et al., 2011), we first conducted a standard MVPA. The goal of this analysis was to identify brain regions that represent information related to the stimuli. We chose to only include regions that represent stimuli information because it would be difficult to interpret informational connectivity between regions that are not found to represent information related to the stimuli. For each participant, the MVPA was conducted for every ROI (with the exception of the cerebellum) within the AAL atlas (total of 90 ROIs; Tzourio-Mazoyer et al., 2002). We chose to use the AAL atlas to be consistent with our previous work investigating memory-related functional networks (Geib, Stanley, Dennis, et al., 2017; Geib, Stanley, Wing, et al., 2017) and other studies investigating functional networks (for a review, see M. L. Stanley et al., 2013). For each ROI, all the beta-values from every event were z-transformed across the trial-series. The z-transformed images were trained and tested using a support vector machine (SVM) with a radial basis function kernel (similar to Haller et al., 2013; Ksander, Paige, Johndro, & Gutchess, 2018; Mumford et al., 2012; Rasmussen, Madsen, Lund, & Hansen, 2011). We chose to use a nonlinear classifier because of our interest in how different types of information were being shared between brain regions; a nonlinear classifier is capable of detecting information that still requires further processing (for a review, see Kragel, Carter, & Huettel, 2012) and, therefore, we believed that a nonlinear classifier would be more sensitive to brain regions representing different types of features (e.g., sensory features). For the MVPA, we used a leave-one-out cross validation procedure in which the classifier was trained on every event except for one event to distinguish between the three stimuli types (positive, negative, neutral). The trained classifier was then tested on the left-out event and it was recorded whether the classifier was correct or incorrect. This was repeated until every event was tested. In order to determine ROIs that would be included in representational network construction, a one sample t-test (collapsing across all participants) was used to determine within each ROI if classifier accuracy (collapsing across all trial types) was significantly above chance (i.e., 1/3). To determine statistical significance, we did not correct for multiple comparisons as this analysis was only used to determine the ROIs that would be included in representational network construction.

3.2.5.4. Representational Network Construction

After choosing the ROIs that would be included, for each participant we constructed the representational networks. The MVPA procedure used during network construction was identical to the standard MVPA procedure described above, except instead of outputting the predicted stimulus type, the classifier outputted the probability that it belonged to the actual stimulus type (as implemented within scikit-learn). Therefore, after using the leave-one-out cross validation procedure, each ROI for each event had an assigned classifier probability, which we term the representational timeseries. The representational timeseries from each ROI were then correlated with each other (Pearson correlation) to construct the representational network, which represents the similarity in the representational timeseries between every ROI. Within each representational network, the correlation coefficients were Fisher z-transformed (Cohen & D'Esposito, 2016). For each participant, three representational networks were constructed – all trials, semantic trials, and perceptual trials networks. We did not construct networks based upon subsequent memory effects (e.g., a network based upon memory hits) because this would yield unbalanced trial numbers being included in each network, which could bias the results.

3.2.5.5. Graph Metric Analysis

After constructing the networks, we used the Brain Connectivity Toolbox (Rubinov & Sporns, 2010) and custom MATLAB scripts to calculate several graph metrics. First, we conducted a modularity analysis to determine the modular architecture of the representational networks. For the modularity analysis, we used the Louvain algorithm (gamma set to the default value of 1.0) with an asymmetric treatment of the negative weights (Blondel, Guillaume, Hendrickx, de Kerchove, & Lambiotte, 2008). To conduct the modularity analysis, first, we created a participant-averaged representational network (based upon all study trials). We chose to collapse across all participants and trials so the nodes contained within the modules would be consistent when comparing between age groups and trial types. The Louvain algorithm was then applied to the participant-averaged representational network 150 times. The outputs of the Louvain algorithm are the community partition (the module assignment for each node) and the Q-value. The Q-value indicates how well the algorithm is able to segregate a network into modules, where higher values indicate that the network has a more distinctive, segregated modular architecture. The best community partition was identified as the run that produced the highest Q-value, and this partition was used for all subsequent analyses. For the control analysis comparing each participant's individual community partition to the group-averaged partition (see the Results), the participant-specific partitions were calculated using the same procedure as the group modularity analysis except rather than conducing the modularity analysis on the participant-averaged representational network, the analysis was conducted using each participant's representational network.

For each module (see Results) we calculated two graph metrics. To address our first goal, we calculated strength, which is the sum of the strength of positive weights maintained by each node with every other node in the network. Strength was averaged across all nodes within a module to create a module strength. Thus, module strength describes for nodes contained within a module the strength of informational connections maintained by these nodes. We interpret a module with higher strength as sharing a larger amount of information with the whole-brain network and, therefore, being more important within the representational network.

To investigate our second goal, we calculated between module task-related reconfiguration (similar to first-step reorganization in Geib, Stanley, Wing, et al., 2017). Separately for the semantic and perceptual networks, for each module, we organized the strength of between module connections into a matrix. The semantic and perceptual between module matrices were then correlated (Pearson correlation) with each other to indicate the similarity in the organization of connections between the two tasks. The inverse correlation (1-correlation), which indicates how much the whole pattern of information connectivity changed globally between our two conditions, was our measure of task-related reconfiguration. Thus, higher values indicate greater between module reconfiguration between the two task conditions. For brevity, within the rest of the manuscript, we refer to between module task-related reconfiguration as task-related reconfiguration.

3.2.6. Behavioral and Statistical Analysis

To evaluate memory performance we examined hit rates, false alarm rates, and d’ scores. Hits were considered a response to a previously presented picture of either definitely old or remember. False alarms were considered a response to a novel lure of either definitely old or remember. For the second goal examining the relation between task-related reconfiguration and memory performance, d’ scores were used for memory performance as they account for both hit rates and false alarm rates, thus providing a more accurate measure of memory performance. All statistical analyses (unless otherwise stated) were conducted within StatsModels (Seabold & Perktold, 2010) ran in Python 3 (Python Software Foundation) using linear mixed effects models. Unless stated otherwise, all analyses were corrected for multiple comparisons using a false discovery rate procedure (Benjamini & Hochberg, 1995); multiple comparison correction was conducted on analyses examining sets of modules and on analyses examining the age groups separately.

3.3. Results

3.3.1. Behavior

For the encoding tasks, overall participants performed better on the semantic (M = 0.78, SD = 0.15) than perceptual (M = 0.72, SD = 0.10) task (main effect of task: $\beta = 1.02$, z = 12.73, p-corrected < .0001), but performance did not differ between the younger (M = 0.72, SD = 0.10) and older adults (M = 0.69, SD = 0.16; main effect of age group: $\beta = 0.17$, z = 0.59, p-corrected = .56); also, the age group by task interaction was not statistically significant ($\beta = 0.15$, z = 0.93, p = .93). Regarding memory recognition, overall – collapsing younger and older adults – performance was very good with 56.4% (SD = 18.5%) of hits, 7.44% (SD = 7.58%) of false alarms, and d’ score of 1.80 (SD = 0.51). There was no age-related difference in hit rates (younger adults: M = 0.53, SD = 0.19; older adults: M = 0.60, SD = 0.18; main effect of age group: $\beta = -0.34$, z = 1.02, p-corrected = .31), but compared to the younger adults, older adults had higher false alarm rates (younger adults: M = 0.037, SD = 0.030; older adults: M = 0.12, SD = 0.089; main effect of age group: β = -1.08, z = 8.10, p-corrected < .0001) and lower d’ scores (younger adults: M = 2.00, SD = 0.51; older adults: M = 1.57, SD = 0.40; main effect of age group: β = 0.83, z = 2.71, p-corrected < .05). Also, hit rates (perceptual: M = 0.51, SD = 0.19; semantic: M = 0.62, SD = 0.19; main effect of task: β = 0.52, z = 14.71, p-corrected < .0001) and d’ scores (perceptual: M = 1.65, SD = 0.51; semantic: M = 1.95, SD = 0.51; main effect of task: β = 0.57, z = 14.39, p-corrected < .0001) were higher for images studied during the semantic than perceptual task. However, the age group by task interaction was not statistically significant for both hit rates (β = 0.04, z = 0.54, p-corrected = .80) and d’ scores (β = 0.02, z = 0.26, p-corrected = .80). Lastly, there were not any age-related differences in the number of trials in which participants did not respond for both the encoding (main effect of age group: β = 0.50, z = 0.35, p = .73) and retrieval (main effect of age group: β = -0.84, z = -0.62, p = .54) tasks.

3.3.2. Age-Related Differences in the Strength of Representational Modules

Before addressing our first goal, we had to complete two steps: (1) determine the nodes to be included in representational network construction and (2) identify the representational modules contained within the network. For the first step, we conducted a standard MVPA to identify regions where activation patterns could discriminate between the three image categories significantly above chance. This analysis revealed a set of regions distributed throughout the cortex (Fig. 6-A; Appendix D). These were the regions that were included in representational network construction (see Methods). Activation patterns in medial/lateral prefrontal cortex and occipitotemporal cortex regions could significantly classify pictures into the three image categories, but those in anterior temporal lobe could not, and hence, this region was not included in further analyses. For the second step, we conducted a modularity analysis on the participant-averaged matrix of correlations in representational patterns (Fig. 6-B; note that these correlations are not based on mean activity but on the MVPA output). This analysis revealed four modules: medial/lateral prefrontal cortex, occipitotemporal cortex, frontoparietal, and anterior/posterior midline modules (Fig. 6-C; see Appendix E for a list of modular assignment of each ROI). To examine for possible age-related differences in the modularity partitions, for each participant we calculated the partition distance (via the normalized variation of information; Meilă, 2007) between the participant-averaged modularity partition and each participant's individual modularity partition. We did not find age-group differences in partition distance ($t(32) = 1.79$, $p = 0.08$), indicating that the modularity partitions were similar between the younger and older adults. Lastly, in order to ensure age-related differences in the representational network results described below were not due to age-related differences in classifier accuracy, we compared between the younger and older adults classifier accuracy within each module (averaging across the ROIs within each module); within each module, there were no age-related differences in classifier accuracy (t(32)s < 1.28, ps > 0.21). As our hypotheses emphasized regions associated with perceptual and semantic processing, we focused on the occipitotemporal cortex and medial/lateral prefrontal cortex modules.

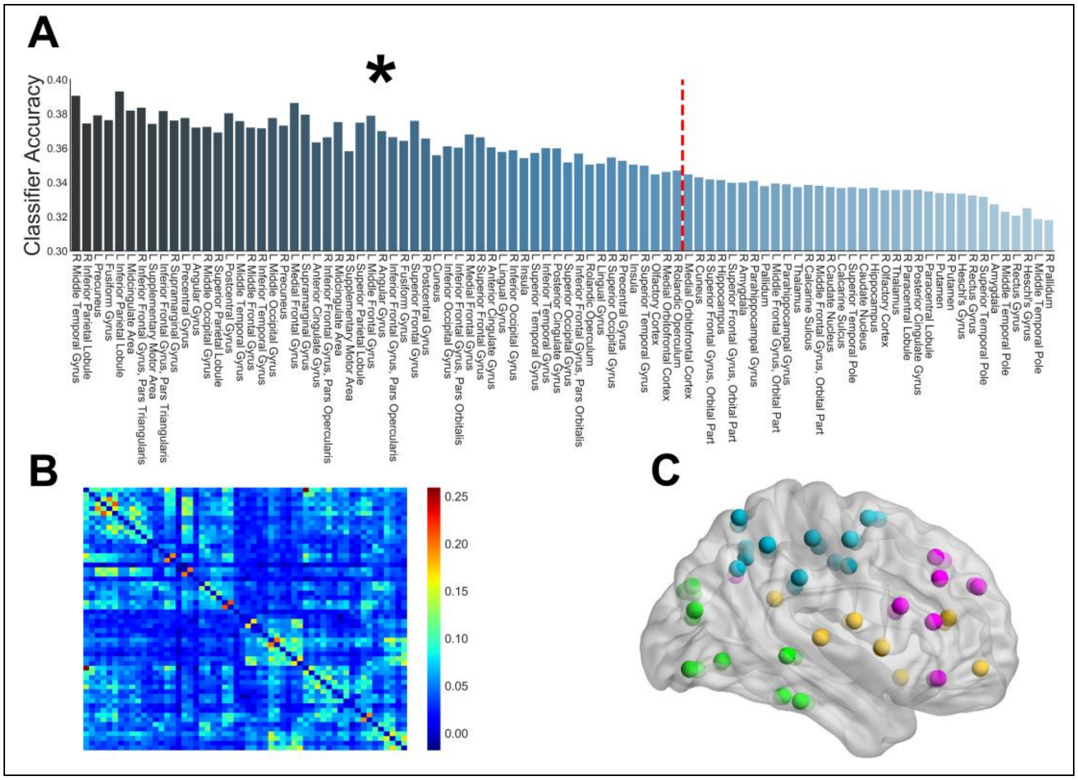


Figure 6: Network-Defining MVPA and Modularity Analysis. Before addressing our first question we had to (1) determine the nodes to be included in representational network construction and (2) identify the representational modules within the network. Panel A shows the MVPA classifier accuracy of all the AAL (Tzourio-Mazoyer et al., 2002) ROIs (sorted from highest to lowest *t*-values). All ROIs to the left of the red line were classified statistically above chance (*p* < .05) and were included in representational network construction. Panel B shows the study participant-averaged representational network (ROIs in ascending AAL ROI number order), which was submitted to the modularity analysis. Panel C shows the module assignment of each ROI over the four identified modules – occipitotemporal cortex

(green), medial/lateral prefrontal cortex (purple), frontoparietal (blue), and anterior/posterior midline (yellow) modules. The brain overlay of the regions of interest (center of mass of the AAL atlas) was visualized with BrainNet Viewer (Xia et al., 2013). * = *p* < .05; AAL = Automated Anatomical Labeling; MVPA = multi-voxel pattern analysis; OTC = occipitotemporal cortex; PFC = prefrontal cortex; ROIs = regions of interest.

Having identified representational modules, we turned to our first goal of examining age-related differences in the strength of informational connections maintained by representational modules. For each participant, we calculated each node's strength and averaged across the nodes within the two modules of interest – the occipitotemporal cortex and medial/lateral prefrontal cortex modules. Partially consistent with our first hypothesis, in the occipitotemporal cortex module, compared to the younger adults, in the older adults we found that the strength of informational connections was lower (main effect of age group: $\beta = -0.34$, $z = 14.16$, p-corrected < .0001), whereas in the medial/lateral prefrontal cortex module, the strength of informational connections was similar (main effect of age group: $\beta = -0.15$, $z = 1.38$, p-corrected = .17; Fig. 7); it should be noted, however, that the age group by module interaction was not statistically significant ($\beta = -0.17$, $z = 1.37$, $p = .17$). Although our hypotheses focused on the occipitotemporal cortex and medial/lateral prefrontal cortex modules, to determine the specificity of these results, we also examined age-related differences in strength in the frontoparietal and anterior/posterior midline modules. We did not find age-related differences in neither the frontoparietal (main effect of age group: $\beta = -0.24$, $z = 1.74$, p-corrected = .16) nor anterior/posterior midline (main effect of age group: β = -0.08, z = 0.47, p-corrected = .64) modules. In sum, these results suggest that there are age-related differences in how information is communicated across the network, where there is an age-related decrease in sensory information being distributed across the network but preservation in semantic information being distributed across the network.

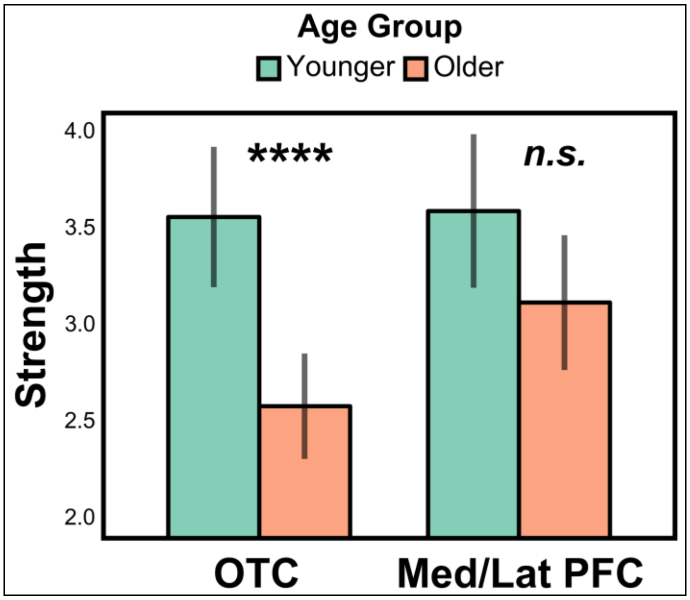


Figure 7: Age-Related Differences in the Strength of Informational Connections. The figure shows age-related differences in the strength of informational connections maintained by the occipitotemporal cortex and medial/lateral prefrontal cortex modules. We found that compared to the YAs, OAs exhibited reduced strength of informational connections maintained by the occipitotemporal cortex module, but similar strength of informational connections maintained by the medial/lateral prefrontal cortex module. Error bars represent the standard error of the mean. ** = *p* < .0001; *n.s.* = non-significant; Lat = Lateral; Med = Medial; OA = older adults; OTC = occipitotemporal cortex; PFC = prefrontal cortex; YA = younger adults.**

3.3.3. Age-Related Differences in Task-Related Reconfiguration

Next, we turned to our second goal, which was to investigate age-related differences in connectivity between informational modules due to attention to semantic vs. perceptual features, and the impact of this network reconfiguration on memory performance. First, we calculated task-related reconfiguration (see Methods) within the occipitotemporal cortex and medial/lateral prefrontal cortex modules and examined age-related differences. Consistent with our second hypothesis, compared to the younger adults, we found that the older adults exhibited increased task-related reconfiguration in the occipitotemporal cortex (main effect of age group: $\beta = 0.26$, $z = 3.98$, p-corrected $< .001$) and medial/lateral prefrontal cortex (main effect of age group: $\beta = 0.31$, $z = 2.16$, p-corrected $< .05$) modules (Fig. 8-A); the module by age group interaction was not statistically significant ($\beta = 0.084$, $z = 0.62$, $p = .53$). It is possible that there are other mechanisms through which older adults may complete the perceptual and semantic tasks, such as through increased univariate activity within the medial/lateral prefrontal cortex modules. Therefore, within each module and each age group, we examined the relation between task-related reconfiguration and univariate activity (difference between semantic and perceptual task); univariate activity was calculated as the mean activation within the modules of interest separately for the semantic and perceptual trials. We did not find any relation between task-related reconfiguration and univariate activity (all rs

< 0.52, ps-corrected > 0.11), indicating that the results presented here were specific to task-related reconfiguration. In sum, compared to younger adults, it appears that older adults utilize greater informational connection reconfiguration in service of the perceptual and semantic tasks.

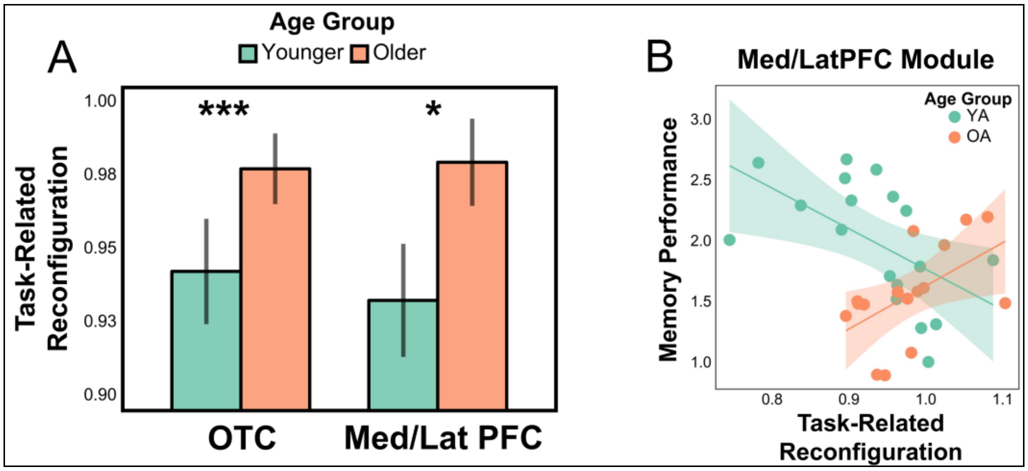


Figure 8: Age-Related Differences in Task-Related Reconfiguration. Panel A shows age-related differences in task-related reconfiguration (between-module informational connection reconfiguration between perceptual and semantic trials). We found that, compared to the YAs, OAs exhibited increased task-related reconfiguration within the occipitotemporal cortex and medial/lateral prefrontal cortex modules. Panel B shows the relation between medial/lateral prefrontal cortex module task-related reconfiguration and memory performance (*d′* scores). Within the OAs, greater medial/lateral prefrontal cortex module task-related reconfiguration was associated with better memory performance and within the YAs, greater medial/lateral prefrontal cortex module task-related reconfiguration was associated with worse memory performance. Error bars represent the standard error of the mean. Translucent bars around the regression lines represent the 95% confidence intervals. * = $p < .05$; **** = $p < .0001$; Med = Medial; Lat = Lateral; OA = older adult; OTC = occipitotemporal cortex; PFC = prefrontal cortex; YA = younger adult.

Second, we examined the relation between task-related reconfiguration and memory performance (d′ scores). As the age group by task interaction for d′ scores was not statistically significant (see section Behavior in the Results), the measure of memory performance used here collapsed across the tasks. Consistent with our second hypothesis, as shown within Fig. 8-B, within the older adults, greater task-related reconfiguration within the medial/lateral prefrontal cortex module was associated with better memory performance ($r(14) = 0.54$, p-corrected $< .05$) and intriguingly, within the younger adults, greater medial/lateral prefrontal cortex module reconfiguration was associated with worse memory performance ($r(16) = -0.55$, p-corrected $< .05$). The medial/lateral prefrontal cortex module reconfiguration by age group interaction was statistically significant ($\beta = 0.53$, $z = 5.13$, $p < .0001$). This relation was specific to the medial/lateral prefrontal cortex module, where within the occipitotemporal cortex module, task-related reconfiguration was not associated with memory performance within both the younger adults ($r(16) = -0.45$, p-corrected $= .12$) and older adults ($r(14) = 0.26$, p-corrected $= .32$). Although our hypotheses focused on the medial/lateral prefrontal cortex and occipitotemporal cortex modules, to determine the specificity of the results, we also examined the relation between task-related reconfiguration and memory performance within the frontoparietal and anterior/posterior midline modules; within these modules within both the younger and older adults we did not find any relation between task-related reconfiguration and memory performance (all absolute rs <

0.46, ps-corrected > .16). In sum, it appears that, consistent with a compensation account, the task-related informational reconfiguration was beneficial to older adults.

3.4. Discussion

In sum, to our knowledge, this is the first study to examine age-related differences in representational networks. The study yielded two main findings. First, we found, compared to the younger adults, older adults exhibited lower strength of informational connections derived from the occipitotemporal cortex module, but similar strength of informational connections derived from the medial/lateral prefrontal cortex module. Second, we found that in response to shifts in attending to semantic vs. perceptual features, compared to the younger adults, the older adults exhibited a greater reorganization of informational connections derived from the medial/lateral prefrontal cortex module, and that effect was associated with better memory performance in the older adults, suggesting compensation. We discuss the two main findings and the overall implication of these results in separate sections below.

3.4.1. Representational Network Regions and Informational Connectivity Strength

Before examining age-related differences in the strength of informational connections, we conducted a standard MVPA to identify brain activation patterns within regions that discriminated between the three image categories. We found brain regions distributed throughout the cortex that represented the stimuli types (Fig. 6-A).

We further ran a modularity analysis on the participant-averaged representational network and found several modules, but of particular interest an occipitotemporal cortex module and medial/lateral prefrontal cortex module. Although this analysis does not indicate the type of information represented in these modules, based upon previous work it is likely the case that the occipitotemporal cortex module represents predominately sensory information and that the medial/lateral prefrontal cortex mainly semantic information (Huth, de Heer, Griffiths, Theunissen, & Gallant, 2016; Miller, Freedman, & Wallis, 2002; Nishimoto et al., 2011; Sreenivasan, Vytlacil, & D'Esposito, 2014; Vandenberghe, Price, Wise, Josephs, & Frackowiak, 1996). Brain regions representing sensory and semantic information are of interest in the study of cognitive aging because sensory processing exhibits a robust decline in aging (Monge & Madden, 2016; Cynthia Owsley, 2011; Sekuler & Sekuler, 2000a), whereas semantic processing is relatively preserved in aging (Balota, Dolan, & Duchek, 2000; Cherry et al., 2012; Mohanty et al., 2016; Denise C Park et al., 2002; Spaniol et al., 2006).

It should be noted, however, that even though the goal of the study was not to investigate emotions, since the MVPA classifier was trained to distinguish between pictures of different valence categories, the classifier may be detecting representations related to emotion. Indeed, previous work using MVPA has found that emotions are represented throughout the cortex (for a review, see Kragel & LaBar, 2016). As emotions are a salient feature in how individuals interpret and represent natural scene stimuli (Sabatinelli et al., 2011; Talmi, Anderson, Riggs, Caplan, & Moscovitch, 2008; van Marle, Hermans, Qin, & Fernandez, 2009), it is not surprising that an emotion classifier detects representations in regions associated with scene processing. However, the classifier was not able to classify brain activation patterns in certain regions typically associated with emotions, such as the amygdala, suggesting that our classifier did not predominately detect emotional representations but rather picture information.

Consistent with our first hypothesis, we found, compared to the younger adults, the older adults exhibited lower strength of informational connections derived from the occipitotemporal cortex module, but similar strength of informational connections derived from the medial/lateral prefrontal cortex module (Fig. 7). It should be noted, however, that the age group by module interaction was not statistically significant, so this finding should be interpreted with some degree of caution. The occipitotemporal cortex finding is consistent with evidence of age-related deficits in representational quality in this region (Carp et al., 2011; Johnson et al., 2015; St-Laurent et al., 2014; Zheng et al., 2017), but extends this work by showing that the deficits also affect the informational connectivity of this region. This finding suggests that, compared to the younger adults, the older adults do not distribute sensory-related information across the brain as well in service of perception. The preservation of medial/lateral prefrontal cortex informational connections is consistent with studies demonstrating that semantic processing is relatively well preserved in aging. Our finding suggests that both the younger and older adults distribute semantic information across the network similarly.

Only one other study, to our knowledge, has examined age-related differences in informational connectivity (Johnson et al., 2015). In the study, a sample of younger and older adults viewed pictures of scenes and objects and later recalled their memories of the scenes and objects. The MVPA classifier was trained to identify brain regions that could distinguish whether the stimulus was a scene or an object. Consistent with our study, they found, compared to the younger adults, older adults exhibited lower informational connectivity strength between posterior regions (e.g., occipital cortex-temporal lobe connections) but similar strength of informational connections derived from the prefrontal cortex. Our study extends these findings by utilizing network-based informational connectivity analyses rather than bivariate informational connections as shown in Johnson et al. (2015). Here, we used a data-driven approach to identify the occipitotemporal cortex and medial/lateral prefrontal cortex modules and we examined how occipitotemporal cortex and prefrontal cortex regions interact with the entire representational network. As brain regions, or even sets of regions such as modules, do not functionally communicate with only one other brain region or a single set of regions, which is an assumption of bivariate connectivity analyses, we believe that multivariate connectivity analyses are necessary to provide a more complete description of informational connectivity patterns. Furthermore, as discussed below, our study also extends Johnson et al. (2015) by examining the effect on informational connectivity patterns of attending to semantic vs. perceptual features.

3.4.2. Task-Related Informational Network Reconfiguration

Consistent with our second hypothesis, in response to shifts in attending to semantic vs. perceptual features, compared to the younger adults, older adults exhibited greater task-related informational connection reconfiguration within the occipitotemporal cortex and medial/lateral prefrontal cortex modules (Fig. 8-A). Our recent work suggests that older adults rely more on semantic-related representations (Monge, Wing, et al., under review), perhaps reflecting a shift in the utilization of different types of representations in response to environmental demands. Here, we demonstrate that indeed older adults in response to environment demands exhibit greater task-related reconfiguration in informational connections derived from the occipitotemporal cortex and medial/lateral prefrontal cortex modules. This finding is somewhat consistent with Gallen et al. (2016), which showed that when comparing resting-state to task-based functional connectivity, compared to the younger adults, older adults exhibited greater task-related network reconfiguration. It should be noted, however, that here we did not examine functional connectivity, which predominately reflects processes, but rather informational connectivity, which predominately reflects representations. Therefore, the interpretation of the reconfiguration of functional vs. informational connections is different.

Also consistent with our second hypothesis, we found in the older adults that greater medial/lateral prefrontal cortex reconfiguration was associated with better memory performance (Fig. 8-B), possibly reflecting a compensatory mechanism. In contrast, the occipitotemporal cortex module reconfiguration was not associated with memory performance in older adults, which further suggests that aging is associated with a greater reliance on semantic rather than sensory representations. Although at a different level of analysis, our results are partially consistent with Johnson et al. (2015), which found within older adults that stronger representational integrity (memory reactivation) within the prefrontal cortex was associated with higher subjective memory vividness ratings. Compensation has traditionally been examined with univariate activity (for reviews, see R. Cabeza et al., 2018; C. L. Grady, 2008, 2012), but more recent evidence has shown evidence for compensation at the level of bivariate functional connectivity (e.g., Simon W Davis, Kragel, Madden, & Cabeza, 2012; Spreng et al., 2018), multivariate connectivity (e.g., Simon W Davis et al., 2017; C. L. Grady et al., 2016; Monge et al., 2017; Zachary A. Monge et al., 2018), and localized representations (Monge, Wing, et al., under review). The current study now extends this literature by demonstrating that age-related compensation also occurs at the level of how information is distributed throughout the cortex.

Intriguingly, within the younger adults, we found that younger adults with greater medial/lateral prefrontal cortex reconfiguration exhibited worse memory performance (Fig. 8-B). Previous work indicates that younger adults utilize both perceptual and semantic representations when viewing visual stimuli (Clarke et al., 2018; Clarke & Tyler, 2014; Barry J. Devereux et al., 2018). Therefore, it may be the case that it is beneficial for younger adults to utilize both types of representations regardless of task demands. Perhaps younger adults exhibiting greater reconfiguration are utilizing an inefficient strategy that is detrimental to task performance. It should be noted that we did not originally predict this relation within the younger adults, so further replication and investigation of this observation is necessary. In sum, from the second goal it appears that how information is organized and utilized within the brain changes with age, where increased age is associated with greater informational connectivity reconfiguration in response to cognitive demands of the environment and this greater reconfiguration may be compensatory.

3.4.3. Representational Networks and Cognitive Aging

Overall, we believe the analysis approach presented here of examining representational networks helps further elucidate the behavioral observation that aging is associated with a preservation of semantic cognition (Denise C Park et al., 2002; Verhaeghen, 2003). The majority of the neuroscience literature investigating this topic has focused on either univariate activity (for a review, see Hoffman & Morcom, 2018) or functional connectivity (e.g., Amer, Giovanello, Nichol, Hasher, & Grady, 2019; Spreng et al., 2018), which only allows for the examination of processes. However, these previous studies still provide vital information on mechanisms underlying the age-related preservation of semantic cognition. Most related to our work presented here is the Default-Executive Coupling Hypothesis of Aging (DECHA; Spreng & Turner, 2019a; Turner & Spreng, 2015). This hypothesis predicts that older adults counteract the age-related decline in cognitive control processes by relying more on semantic processes. In the brain, this is observed by an age-related increase in the coupling between the default mode network (presumably containing prior-knowledge representations) and lateral prefrontal brain regions (presumably important for control-related processes). Somewhat consistent with this interpretation, in a previous publication of this dataset that focused on univariate activity, we found that age-related emotion effects were related to activity in the ventrolateral prefrontal cortex, suggesting the importance of cognitive control processes in age-related differences in emotional processing (M. Ritchey, Bessette-Symons, et al., 2011). We believe the DECHA is helpful, but only tells part of the story. Perhaps the greater reliance on prior knowledge in older adults reflects not only an attempt to counteract deficient cognitive control processes, but also deficient perceptual representations as suggested by our previous work (Monge, Wing, et al., under review) and the data presented here. The DECHA model focuses on functional connectivity, which reflects processes, but the latter possibility that older adults' additional reliance on previous knowledge is counteracting deficient perceptual representations can only be sufficiently tested in the examination of representations, which may be investigated with multivariate analysis techniques such as representational similarity analysis, MVPA and informational connectivity. More work examining the interactions between processes and representations may provide a more complete model, which may benefit from the further examination of representational networks.

3.4.4. Limitations

Even though we believe the study advances the literature investigating age-related differences in neural representations, it does contain a couple limitations. First, although participants were screened for dementia with the MMSE and, overall, exhibited good memory performance on the fMRI task, they were not screened by a clinician for age-related cognitive impairments, such as Mild Cognitive Impairment. Therefore, it is possible that some of the participants reported here may have contained some cognitive impairments. Future studies should provide more thorough participant screening for cognitive impairments. Second, we attempted to equate age-related differences in task difficulty by, within the older adults, reducing the time between the encoding and retrieval sessions and allowing older adult participants more time to respond during the encoding task. Although we believe that minimizing age-related differences in task difficulty facilitates result interpretation, it could be argued that confounding memory performance with task difficultly is more ecologically valid. It may be of interest for future studies to further study the interaction between task difficulty and memory.

3.4.5. Conclusions

In sum, we demonstrated that there are age-related differences in how information is organized and shared across the cortex. The history of the cognitive neuroscience of aging has predominately focused on mechanisms underlying processes within individual brain regions (for reviews, see C. L. Grady, 2008, 2012) and only recently has examined (1) how brain regions interact within a network in service of processes (e.g., Simon W Davis, Szymanski, Boms, Fink, & Cabeza, 2019; Gallen et al., 2016; C. L. Grady et al., 2016; Monge et al., 2017; Zachary A. Monge et al., 2018) and (2) representations within individual brain regions (e.g., Carp et al., 2011; Johnson et al., 2015; St-Laurent et al., 2014). Our study shows the importance of adding another line of research to the discipline of the cognitive neuroscience of aging, which is to examine representations within a networks framework. We believe this investigation will not only expand our knowledge of neural mechanisms underlying normal aging but may also be applied to the investigation of pathological aging (e.g., Alzheimer's disease).

4. The Impact of Visual Signal Loss on Age-Related Differences in Sensory and Semantic Neural Representations

4.1. Introduction

Although cognitively normal older adults show substantial decline in laboratory cognitive tasks assessing speed, episodic memory, attention, and perception (Denise C Park et al., 2002; Timothy A. Salthouse, 2000), many remain highly functional in everyday life, showing little or no decline in productivity in the workplace (e.g., Colonia-Willner, 1998; Hardy & Parasuraman, 1997; Shimamura et al., 1995). One explanation of this discrepancy between laboratory vs. everyday measures of age-related cognitive decline is that in the real world, older adults can take advantage of their wealth of accumulated semantic knowledge to compensate for their cognitive deficits. The current fMRI study investigates the neural mechanisms whereby older adults exploit their spared semantic abilities to compensate for cognitive impairment, in particular perceptual and memory deficits.

Aging is associated with substantial deficits in perception (Greene & Madden, 1987a; Jackson & Owsley, 2003a; C. Owsley, 2011; Owsley et al., 1983) and memory (Friedman, Nessler, & Johnson, 2007; McDaniel, Einstein, & Jacoby, 2015; Michael D. Rugg & Morcom, 2005). These two types of deficits are connected, as there is evidence that older adults impairments in perception are strongly correlated with their impairments in higher-order cognitive abilities, including memory (Paul B Baltes & Ulman Lindenberger, 1997b; Ulman Lindenberger & Paul B Baltes, 1994b). An influential account of this strong correlation is the information degradation hypothesis, which postulates that aging impairs sensory functions, such as vision, leading to a deficit in the sensory input, which cascades through the cognitive system, disrupting downstream cognitive processes, such as memory (Monge & Madden, 2016; Schneider & Pichora-Fuller, 2000). In the case of vision, for example, compared to younger adults, in older adults the crystalline lens of the eye absorbs up to ten times more light, markedly reducing the amount of light available for vision (Sekuler & Sekuler, 2000b), and the optical nerve (Peters, 2002) and primary visual cortex (Peters, Moss, & Sethares, 2001; Peters, Sethares, & Killiany, 2001) show substantial neural and myelin deterioration. In keeping with these anatomical deficits, older adults show significant decline in behavioral visual measures, such as contrast sensitivity (C. Owsley, 2011; Sekuler & Sekuler, 2000b). Consistent with the information degradation hypothesis, there is evidence that these visual deficits predict cognitive decline several years later (Lin et al., 2004). This hypothesis is also supported by the finding that "vision-fair" tests that equate for differences in contrast sensitivity (Toner et al., 2012) can eliminate age-related differences in neuropsychological measures. Also, when visual stimuli are experimentally degraded, younger adults show cognitive deficits that resemble the ones displayed by older adults (Ben-David & Schneider, 2010; Grover C Gilmore, Ruth A Spinks, & Cecil W Thomas, 2006; Laudate et al., 2012). The current fMRI study uses a manipulation of stimuli degradation to test the information degradation hypothesis.

In contrast to perceptual and memory abilities, semantic knowledge is largely preserved in older adults. Behavioral studies have shown that older adults retain and continue to use semantic knowledge from their formal education and experience, and can even outperform younger adults in this domain (Denise C Park et al., 2002; Umanath & Marsh, 2014; Verhaeghen, 2003). According to the semantic compensation hypothesis, because semantic knowledge is generally spared in older adults, they can use this knowledge to compensate for impaired cognitive deficits. Consistent with this hypothesis, there is behavioral evidence that when the laboratory tasks and/or stimuli allow older adults to take advantage of their preserved semantic knowledge, their perception (D. J. Madden, 1988) and memory deficits (Castel, 2005; Donald H. Kausler & Lair, 1966; Zaretsky & Halberstam, 1968a, 1968b) are markedly reduced or even eliminated.

Functional neuroimaging evidence is consistent with both the information degradation and semantic compensation hypotheses. First, univariate fMRI studies have reliably associated aging with decreased activity in visual cortex coupled with an increased activity in anterior brain regions, a pattern known as posterior-anterior shift in aging, or PASA (R. Cabeza et al., 2004; R Cabeza & Dennis, 2013; Simon W Davis et al., 2008). The visual cortex activity decreases have been attributed to visual deficits (R. Cabeza et al., 2004; Cheryl L. Grady et al., 1994), and the anterior activity increase, to functional compensation, including the recruitment of semantic processing (Whiting et al., 2003). Thus, PASA suggests a see-saw mechanism whereby visual processing deficits in visual cortex are compensated by semantic processing recruitment in anterior brain regions. Second, in an fMRI study from our laboratory (Monge, Wing, et al., under review) using representational similarity analysis (RSA; Nikolaus Kriegeskorte & Kievit, 2013; Nikolaus Kriegeskorte et al., 2008) we found that in visual cortex, the link between activation patterns and sensory visual features of the stimuli (henceforth: "sensory representations") was weakened in older adults compared to younger adults (consistent with the information degradation hypothesis), whereas in anterior temporal lobe, the association between activation patterns and semantic features of the stimuli (henceforth: "semantic representations") was, compared to younger adults, enhanced in older adults. Also, encoding-retrieval similarity analysis (ERS), which measures the reinstatement of encoding activation patterns during retrieval (henceforth: "memory reactivation"), revealed a similar effect: an age-related deficit in memory reactivation in visual cortex coupled with an age-related enhancement of memory reactivation in anterior temporal lobe. Moreover, enhanced ERS in the anterior temporal lobe was associated with better memory performance in older adults, consistent with the semantic compensation hypothesis.

In sum, in our previous study, the findings that older adults displayed attenuated sensory representations coupled with enhanced semantic representations are consistent with the information degradation and semantic compensation hypotheses, respectively. However, these two effects were not directly linked to input loss. To address this issue, in the current study, in a sample of younger and older adults undergoing fMRI scanning, we manipulated stimuli degradation as in behavioral studies (Ben-David & Schneider, 2010; Grover C Gilmore et al., 2006; Laudate et al., 2012), comparing pictures of objects in their original format (Clear) to pictures in a degraded format (Blurry). We tested the hypothesis that in younger adults, stimulus degradation will mimic the effects of aging, causing an attenuation of sensory representations and a compensatory enhancement of semantic representations (Hypothesis 1). The effects of the manipulation in older adults are more difficult to predict because their intrinsic input loss could (a) potentiate the experimental degradation effects, (b) obscure these effects, or (c) make the experimental degradation overwhelming. However, we included older adults to examine if the degraded (Blurry) condition in younger adults is similar to the non-degraded (Clear) condition in older adults.

In our previous study, enhanced anterior temporal lobe ERS in the older adults was linked to successful memory performance, consistent with the semantic compensation hypothesis. However, we do not know if the experimental enhancement of semantic representations in younger adults through stimulus degradation would also enhance subsequent memory. Thus, in the current study we tested the hypothesis that in younger adults, the enhancement of semantic representations and ERS in the Blurry condition should be associated with successful memory performance (Hypothesis 2). As in the case of Hypothesis 1 and for the same reasons, the results in older adults are more difficult to predict but older adults provide a useful comparison for the effects in younger adults by showing that the Blurry condition in younger adults is comparable to the Clear condition in older adults.

Turning to the experimental paradigm, we investigated sensory and semantic representations both during encoding (perception) and retrieval. During encoding (Figure 9A), younger and older adults were scanned while viewing pictures of everyday objects, with half of the object pictures in a Clear format and half in a Blurry format. During retrieval (Figure 9B), which occurred the next day, participants read the names of all encoded pictures, responding to each name how well they could recall the corresponding pictures (memory vividness ratings). Immediately upon exiting the scanner, participants completed a self-paced forced-choice recognition task (Figure 9C), in which each encoded object's picture (e.g., a carrot) was paired with a different exemplar of the of the same object (i.e., a different carrot), and they selected the encoded one, indicating also their confidence. Confirming their validity as a memory measure, in-scan memory vividness ratings reliably predicted, in both younger and older adults, post-scan memory recognition scores (Figure 9D; see the Results for more details).

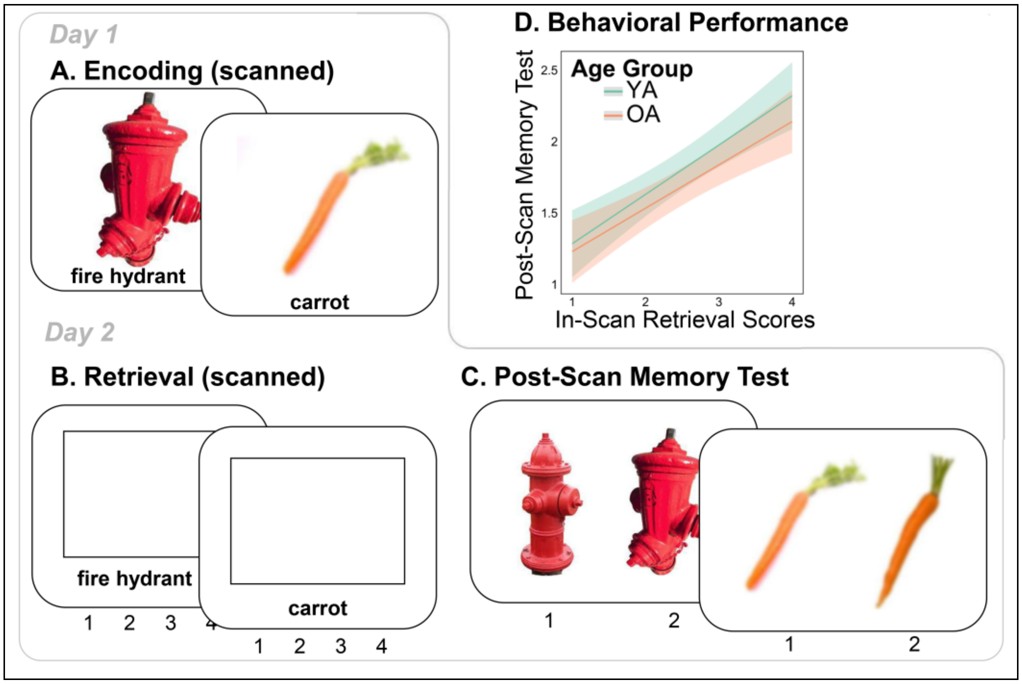


Figure 9: Study Paradigm and Memory Vividness Ratings Validation. The figure shows the study paradigm and memory vividness ratings validation analysis. During the first day, while receiving fMRI scanning (Encoding; Panel A), participants explicitly studied object image stimuli. Half of the images were presented in a *Clear* format and half in a *Blurry* format (Gaussian blur with a radius of 3.0 pixels). The next day, while receiving fMRI scanning (Retrieval; Panel B), participants were presented the names of encoding pictures and participants were instructed to recall the corresponding image from encoding with as much detail as possible (1 = *least amount of detail*, 4 = *highly detailed memory*). Lastly, outside of the scanner (Post-Scan Memory Test; Panel C), participants completed a self-paced forced-choice recognition

task, in which each encoded object's picture (e.g., a carrot) was paired with a different example of the same object (i.e., a different carrot), and they selected the encoded one, indicating also their level of confidence on a 4-point scale (1 = *low confidence*, 4 = *high confidence*). Confirming their validity as a memory measure, in-scan memory vividness reliably predicted, in both YAs and OAs, post-scan memory recognition accuracy (Panel D). Shaded error bars represent 95% confidence intervals; fMRI = functional MRI; OAs = older adults; YAs = younger adults.

In sum, we predict that, compared to the Clear condition, the Blurry condition will show in younger adults (1) an attenuation of sensory representations coupled with an enhancement of semantic representations, and (2) an association of between enhanced semantic representations / ERS and better memory performance. We do not have specific predictions for older adults but they provide a useful comparison for the effects hypothesized in younger adults Given previous findings from our previous RSA/ERS study (Monge, Wing, et al., under review), we examined these effects in ROIs derived from the Harvard-Oxford Atlas (Tzourio-Mazoyer et al., 2002) that were associated with sensory representations (visual cortex) and semantic representations (anterior temporal cortex).

4.2. Methods

4.2.1. Study Participants

Twenty-three younger adults and 22 older adults were recruited and enrolled in the study. Younger adult participants self-reported to be between (inclusive) 18-29 years old and older adult participants 60-79 years old. Participants self-reported to be right-handed, to be native English speakers, to have completed at least 12 years of education, to be free of significant health problems (including atherosclerosis, neurological and psychiatric disorders), and not taking medications known to affect cognitive function or cerebral blood flow (except antihypertensive agents). Participants were screened for depression via the Beck Depression Inventory (Beck, 1978; exclusion criterion > 10) and dementia via the Montreal Cognitive Assessment (MoCA; Nasreddine et al., 2005; exclusion criterion < 26). One younger adult and 1 older adult were excluded due to a MoCA score less than 26; 4 younger adults were excluded due a MRI technical error; 1 younger adult was excluded due to a large number of non-responses during the retrieval task (> 50% non-responses); 1 older adult was excluded due to not making any high memory vividness ratings for Blurry stimuli during the retrieval task; 2 older adults were excluded due to artifacts appearing in functional images; and 2 older adults were excluded due to functional images not properly normalizing into MNI space via DARTEL (Ashburner, 2007). This left a study sample of 17 younger adults and 16 older adults (participant demographics may be viewed in Table 1). The Duke University Institutional Review Board approved all experimental procedures, and participants provided informed consent prior to testing. After study completion, participants were monetarily compensated for their time.

Table 1: Participant Demographics. Table shows participant demographics. All values, except for gender, reflect mean and standard deviation. BDI = Beck

Depression Inventory (Beck, 1978); MoCA = Montreal Cognitive Assessment (Nasreddine et al., 2005); OA = older adult; YA = younger adult.

	YA	OA
Age (years)	21.1 (3.3)	70.4 (3.5)
Gender (# Male / Female)	10 / 7	9 / 7
Education (years)	14.6 (2.5)	17.3 (2.8)
MoCA (score)	28.6 (1.4)	27.9 (1.3)
BDI (score)	2.7 (3.1)	1.9 (2.2)

4.2.2. Experimental Design

Participants completed the encoding task the first day and returned to complete the retrieval tasks on the second day. While undergoing fMRI scanning, participants completed eight encoding runs, where they explicitly studied a total of 240 pictures of objects from a wide variety of living and nonliving categories (30 images per run, order randomized within run). Images were presented on a white background in the center of the screen with the object label below the image. Half of the images were presented in their original high-quality state (Clear images) and the other half were presented blurred (Blurry images; Gaussian blur with a radius of 3.0 pixels). Each image was presented on the screen for 4 sec and participants, via a keypad, either made perceptual (Clear or Blurry; half the runs) or semantic (living or nonliving; half the runs) judgements of the images; all analyses presented here collapse the perceptual and semantic runs to increase statistical power. Each encoding trial was followed by an active baseline interval of 8 sec, in which participants were presented digits from 1 to 4 and pushed the button corresponding to the presented numbers. In half the participants, the order of the runs was reverse counterbalanced to control for possible order effects.

The retrieval runs were identical in format to the encoding runs, except the pictures of the scenes were not presented. During each retrieval trial, participants were presented the object concept label previously presented with the picture of the object, and participants were instructed to recall the corresponding image from encoding with as much detail as possible. Participants then rated, on a four-point scale, the amount of detail with which they could remember the specific picture (1 = least amount of detail, 4 = highly detailed memory). The order of encoding runs was maintained for the retrieval runs.

After the retrieval runs, outside of the scanner, participants completed a post-scan memory recognition task. During each trial (self-paced), participants were presented the original image presented during encoding and a category exemplar lure; both the original image and category exemplar lure were presented in the same state (Clear, Blurry) as the original image was presented during encoding. Participants were instructed to choose the image presented during encoding. After choosing an image, participants rated their level of confidence on a 4-point scale (1 = low confidence, 4 = high confidence). Similar to the encoding and retrieval runs, the task was divided into eight blocks and the order of the blocks was the same as the encoding and retrieval run orders.

4.2.3. MRI Data Acquisition

MRI data were collected on a General Electric 3T Premier UHP MRI scanner and a 48-channel head coil. The MRI session started with a localizer scan, in which 3-plane (straight axial/coronal/sagittal) localizer faster spin echo (FSE) images were collected. Following, a high-resolution anatomical image (162 axial slices parallel to the AC-PC plane with voxel dimensions of 1.0 x 1.0 x 1.0 mm^3) was collected. Afterwards, a resting-state scan was collected, which is not reported here. Then, using a multiband echo-planar imaging (EPI) sequence (repetition time [TR] = 2000 msec, echo time [TE] = 30 msec, field of view [FOV] = 256 mm^2, 69 oblique slices with voxel dimensions of 2.0 x 2.0 x 2.0 mm^3), the functional task images were acquired. The functional images were collected over eight runs – eight encoding runs (day 1) and eight retrieval runs (day 2). Stimuli were projected onto a mirror at the back of the scanner bore, and responses were recorded using a four-button fiber-optic response box (Current Designs, Philadelphia, PA, USA). Lastly, diffusion-weighted imagers were collected, which are not reported here. Participants wore earplugs to reduce scanner noise and foams pads were used to reduce head motion; when necessary, participants wore MRI-compatible lenses to correct vision.

4.2.4. Functional MRI Data Preprocessing

For each run, the first six functional images were discarded to allow for scanner equilibrium. All functional images were preprocessed in a SPM12 (London, United Kingdom) pipeline. Briefly, the functional images were slicing timing corrected (reference slice = first slice), realigned to the first scan in the first session, and subsequently unwarped. Following, the functional images were coregistered to the skull-stripped high-resolution anatomical image (skull-stripped by segmenting the high-resolution anatomical image and only including the gray matter, white matter, and cerebrospinal fluid segments). The functional images were then normalized into MNI space using DARTEL (Ashburner, 2007); the study specific high-resolution anatomical image was created using all of the study participants. The voxel size was maintained at 2.0 x 2.0 x 2.0 mm^3 and the normalized-functional images were not spatially smoothed.

4.2.5. Functional MRI Analysis

4.2.5.1. Single Trial Model Analysis

To conduct both the representational similarity and ERS analyses, it was first necessary to obtain a beta estimate image for each event. These were calculated with a single trial model analysis using a least squares-separate approach (Mumford et al., 2012). With this approach, a first-level general linear model is conducted for each event, where one regressor models a specific event of interest and another regressor models all the other events (each run included a regressor modeling these other trials). Each event was modeled with a stick function placed at stimulus onset convolved with a standard hemodynamic response function with the temporal derivative. Each model also included the six raw motion regressions, a composite motion parameter (derived from the Artifact Detection Tools [ART]), outlier TRs (scan-to-scan motion > 2.0 mm or degrees, scan-to-scan global signal change > 9.0 z score; derived from ART), the white matter timeseries, and cerebrospinal fluid timeseries. In each model we also modeled the temporal derivatives and implemented a 128 sec cutoff high-pass temporal filter. The beta-images were minimally smoothed with a 2 mm full-width at half maximum kernel (similar to Bowman et al., 2019; Clarke et al., 2016; Lee, Samide, Richter, & Kuhl, 2019; Skudlarski, Constable, & Gore, 1999) in order to increase the signal-to-noise ratio but still preserve distributed pattern information (Dimsdale-Zucker & Ranganath, 2018; N. Kriegeskorte, Cusack, & Bandettini, 2010; Op de Beeck, 2010). Trials in which participants did not make a memory vividness rating were excluded from analysis.

4.2.5.2. Representational Similarity Analysis

As mentioned in the Introduction, to investigate representations we conducted representational similarity analyses (Nikolaus Kriegeskorte & Kievit, 2013; Nikolaus Kriegeskorte et al., 2008). For the stimuli models, we used a sensory model and a semantic model. The sensory model was derived from a deep convolutional neural network (DNN; Krizhevsky et al., 2012b; LeCun et al., 2015). DNNs consist of layers of convolutional filters and can be trained to classify images into categories. During model training, DNN convolutional filters learn to detect properties of images that may be used to classify images. Examination of these convolutional filters have revealed that filters from early layers predominately detect sensory-related features (Zeiler & Fergus, 2014). Furthermore, previous work has demonstrated that early DNN layers model representations within posterior visual regions (Güçlü & van Gerven, 2015; Khaligh-Razavi & Kriegeskorte, 2014; Nikolaus Kriegeskorte, 2015; Leeds et al., 2013; Wen et al., 2017) and outperform traditional theoretical models of the ventral visual pathway (e.g., HMAX, object-based models; Cadieu et al., 2014; Groen et al., 2018a). Therefore, we decided to construct our sensory model from an early DNN layer (similar to Monge, Wing, et al., under review). Specifically, we chose the second layer of AlexNet (Krizhevsky et al., 2012b) pretrained on a large database of object images (ImageNet; Russakovsky et al., 2015). Similar to Bruffaerts et al. (2019), we chose to use the second layer, rather than the first layer, because, compared to the first layer, the second layer of AlexNet has previously been shown to map representations in visual cortex better (Cichy, Khosla, Pantazis, Torralba, & Oliva, 2016; Barry J. Devereux et al., 2018). The visual model was constructed by feeding the study stimuli through the pretrained DNN and extracting the activation values from the second layer. Previous work has demonstrated that rather than using large vectors of activation values, model-brain fit is improved by first reducing the number of dimensions through a principal component analysis (PCA; Bruffaerts et al., 2019; Clarke et al., 2018). Therefore, we submitted the raw activation values to the PCA and obtained 100 components; we chose specifically 100 components to be consistent with previous work (Bruffaerts et al., 2019). After conducting the PCA, the component values between stimuli were correlated (Pearson correlation) with each other. This yielded a 240x240 matrix, which represents the similarity of the DNN activation values and is the sensory model.

The semantic model was constructed from object semantic feature norms collected in a separate study. Briefly (full details of object semantic feature norms collection and processing may be viewed in Simon W. Davis et al. (2020)), these semantic norms were collected online via Amazon Mechanical Turk. Participants (n=162, age range: 18-62 years, self-reported native American English speakers) were individually presented object images (from a larger object database) and space to add their features. For the features, participants were asked to add a relation word chosen from a drop-down menu, with presets for is, has, does, made of, and "…" (participants were instructed to use "…" for other relations not listed), and type in a semantic feature associated with the object concept. Data from 30 participants per concept were used to create a feature x concept production frequency matrix. After constructing the matrix, following the procedures used by McRae et al. (2005) and Devereaux et al (2014), feature responses underwent preprocessing. The preprocessing steps included: (1) removal of adverbs, such as really and very; (2) feature-splitting, for example a feature such as has a round face was rewritten as has a round face and has a face; (3) synonym mapping, which involves identifying synonyms both within and across each concept (e.g., "does travel in groups" and "does travel in packs" and "does travel in a flock" were collapsed into "does travel in groups;" (4) correction of spelling mistakes; (5) morphological mapping (e.g., "is used in cooking" and "is used by cooks" were collapsed together into "is used in cooking," (6) removal of plural forms; (7) removal of features not present in at least two concepts; and (8) for each concept, features that were not endorsed by at least three participants were set to zero. Lastly, similar to the sensory model, the object concept feature counts were submitted to a PCA to obtain 100 components. The object concept similarity (cosine similarity) between stimuli were calculated yielding a 240x240 matrix, which represents the similarity of semantic features and is the semantic model.

To investigate the type of information (sensory, semantic) represented in a brain region, for each participant, within individual regions of interest (ROIs), the similarity of activation values from each event were correlated (Fisher-transformed Pearson's r) with each other. This yielded for every participant and ROI, a 240x240 matrix, which represents the similarity of brain activation patterns. Then, each ROI similarity matrix was individually correlated (Spearman's correlation) with the sensory and semantic stimuli models, which is model-brain fit (second-order correlation); all negative correlations were set to zero, as negative model-brain fit correlations are difficult to interpret.

The ROIs were derived from a subset of the Harvard-Oxford Atlas (Tzourio-Mazoyer et al., 2002). Our previous work identified age-related differences in representational quality in early visual cortex and anterior temporal lobe (Monge, Wing, et al., under review), so, therefore, within the current study we chose similar visual processing-related ROIs and semantic processing-related ROIs. Specifically, the visual processing-related ROIs were bilateral occipital pole and the semantic processing-related ROIs were bilateral temporal pole, anterior superior temporal gyrus, anterior middle temporal gyrus, and anterior inferior temporal gyrus.

4.2.5.3. Encoding-Retrieval Similarity

To examine part of our second hypothesis, we calculated ERS for each item. For each item, encoding and retrieval activation values were extracted from the selected ROIs. Then, the encoding and retrieval activation vectors were correlated (Fisher-transformed Pearson's r), which is ERS. In order to investigate item-specific reactivation, from item-level ERS we subtracted set-level ERS (Maureen Ritchey et al., 2013; Wing et al., 2014). Set-level ERS is ERS between an item and every other item within a set.

Therefore, as we subtracted set-level ERS from item-level ERS, in a brain region, an ERS score above zero indicates item-specific reactivation. Before subtracting item- and set-level ERS, all negative values were set to zero because subtracting two negative values may lead to incorrect interpretation and negative ERS values are difficult to interpret.

4.2.6. Statistical Analyses

All statistical analyses (unless otherwise stated) were conducted within StatsModels (Seabold & Perktold, 2010) ran in Python 3 (Python Software Foundation) using two-sided linear mixed effects models. For all ROI analyses, a p-value less than .01 was considered statistically significant, which was determined by Bonferroni correction (each hemisphere contained 5 ROIs; 0.05/5 = 0.01). For analyses comparing high- and low-memory trials, high-memory was defined as in-scanner vividness ratings of 3 and 4 and low-memory as in-scanner vividness ratings of 1 and 2 (similar to Geib, Stanley, Wing, et al., 2017). Lastly, as age-related differences in memory recognition performance are sensitive to confidence levels (Light, Prull, Lavoie, & Healy, 2000; Prull, Dawes, Martin, Rosenberg, & Light, 2006), performance on the post-scan memory recognition task was measured with an 8-point scoring system factoring in confidence levels (4 = hit with a confidence level of 4, -3 = miss with a confidence level of 4).

4.3. Results

4.3.1. Behavior

Average in-scan memory vividness ratings and post-scan recognition performance in younger and older adults are shown in Table 2. First, confirming the validity of in-scan memory vividness ratings as a memory measure, in both the younger adults ($\beta = 0.32$, $z = 10.87$, $p < .0001$) and older adults ($\beta = 0.32$, $z = 9.53$, $p < .0001$), in-scan vividness ratings predicted post-scan memory recognition scores (Figure 9D). For the in-scan memory vividness ratings, there was no significant difference in rating responses between the younger and older adults (main effect of age group: $\beta = -0.09$, $z = -0.69$, $p = .49$), but, compared to Clear stimuli, rating responses were lower for Blurry stimuli (main effect of stimulus type: $\beta = -0.15$, $z = -5.52$, $p < .0001$); the age group by stimulus type interaction was not statistically significant ($\beta = 0.07$, $z = 1.38$, $p = .17$). For the post-scan memory recognition scores, performance was similar between the younger and older adults (main effect of age group: $\beta = 0.02$, $z = 0.09$, $p = .93$), but, compared to the Clear stimuli, participants exhibited worse memory performance for Blurry stimuli (main effect of stimulus type: $\beta = -0.41$, $z = -7.80$, $p < .0001$); the age group by stimulus type interaction was not statistically significant ($\beta = -0.001$, $z = -0.01$, $p = .99$). For post-scan memory recognition reaction times, there was no significant difference in reaction times between Clear and Blurry stimuli (main effect of stimulus type: $\beta = -23.59$, z = -

0.52, $p = .60$), but, compared to younger adults, older adults had higher reaction times (main effect of age group: $\beta = -1023.92$, $z = -3.25$, $p < .01$); the age group by stimulus type interaction was not statistically significant ($\beta = 29.88$, $z = 0.32$, $p = .75$). As can be seen here, in memory scores there was a main effect of stimulus type but not a main effect of age group, but in reaction times there was not a main effect of stimulus type but there was a main effect of age group. This finding is suggestive that examining speed-accuracy tradeoffs may be important, so, therefore, we calculated efficiency scores (reaction time / memory score; higher scores indicate worse performance). Indeed, for efficiency scores we found that, compared to Clear stimuli, participants had worse efficiency scores for Blurry stimuli (main effect of stimulus type: $\beta = 450.26$, $z = 4.09$, $p < .0001$) and, compared to the younger adults, the older adults overall had worse efficiency scores (main effect of age group: $\beta = -778.98$, $z = -2.66$, $p < .01$); the age group by stimulus type interaction was not statistically significant ($\beta = -265.43$, $z = -1.21$, $p = .23$). In sum, we did not find that, compared to younger adults, older adults were disproportionately penalized by Blurry stimuli. However, it should be noted that a lack of behavioral interactions does not imply there could not be age group x stimulus type interactions in the function of some brain regions, as behavioral measures reflect the combined operation of all brain regions.

Table 2: Task Performance. Table shows participants' performance on the in-scanner retrieval and post-scan memory recognition tasks. For the post-scan memory

recognition task, memory scores were scored on an eight-point scale, ranging from 4 to -3 (higher scores = better performance; high-confident [confidence rating of 4] hit = 4, high-confident [confidence rating of 4] miss = -3). RT = reaction time; efficiency score = RT / memory score.

	Younger Adults *M* (*SD*)	Older Adults *M* (*SD*)
In-Scanner Retrieval Responses: Clear Trials		
Response	2.4 (0.4)	2.5 (0.4)
In-Scanner Retrieval Responses: Blurry Trials		
Response	2.3 (0.4)	2.3 (0.4)
Forced-Choice Task: Clear Trials		
Score	1.9 (0.6)	1.8 (0.5)
RT (msec)	2518 (737)	3557 (1044)
Efficiency Score (msec)	1478 (606)	2124 (996)
Forced-Choice Task: Blurry Trials		
Score	1.4 (0.4)	1.4 (0.4)
RT (msec)	2509 (848)	3518 (1014)
Efficiency Score (msec)	1800 (634)	2711 (1236)

4.3.2. Testing the Information Degradation and Semantic Compensation Hypotheses in Younger Adults

We first tested the hypothesis that in younger adults, stimulus degradation will mimic the effects of aging, causing an attenuation of visual representations and a compensatory enhancement of semantic representations (Hypothesis 1). In a first analysis, we measured main effects of stimulus type (younger adults ≈ older adults) on activation patterns linked with visual features of the stimuli (“sensory representations”) or activation patterns associated with semantic features of the stimuli (“semantic representations”). As can be seen in Figure 10, we found that to compared to Clear stimuli, in bilateral occipital pole for Blurry stimuli, participants exhibited lower sensory model-brain fit (Figure 10A), but in right anterior-superior temporal gyrus for Blurry stimuli, participants exhibited higher semantic model-brain fit (Figure 10B; see Appendix F for the detailed results of all ROIs). Thus, in both younger and older adults, the results supported the information degradation hypothesis (weakening of sensory representations) and the semantic compensation hypothesis (counteracting enhancement of semantic representations).

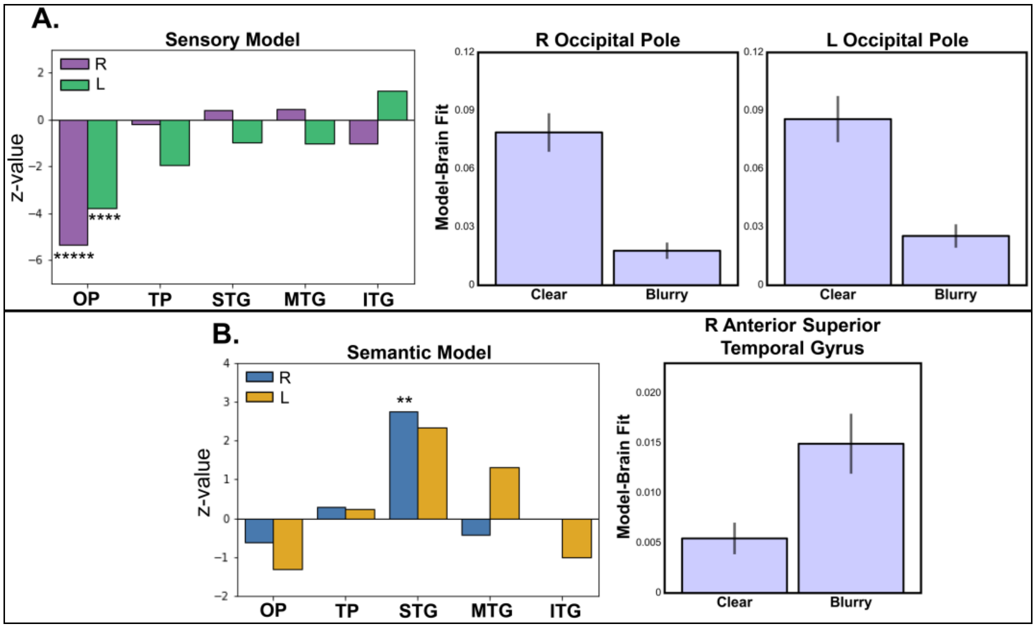


Figure 10: The Effect of Degradation on Representations. The figure shows the representational similarity analysis results related to the main effect of stimulus type, where model-brain fit was statistically different between Clear and Blurry stimuli. Panel A shows sensory model-brain fit (left panel is the z-value outputs for all ROIs), where the main effect of degradation was statistically significant in bilateral occipital pole, reflecting participants exhibiting greater sensory model-brain fit for Clear than

Blurry stimuli. Panel B shows semantic model-brain fit (left panel is the z-value outputs for all ROIs), where the main effect of degradation was statistically significant in right anterior-superior temporal gyrus, reflecting participants exhibiting greater semantic model-brain fit for Blurry than Clear stimuli. ROIs = regions of interest; R = right; L= left; OP = occipital pole; TP = temporal pole; STG = anterior-superior temporal gyrus; MTG = anterior-middle temporal gyrus; ITG = anterior-inferior temporal gyrus; ** = $p < .01$; **** = $p < .001$; ***** = $p < .0001$.

Then, we investigated stimulus type x age group interactions in sensory and semantic representations. In the case of sensory representations (Figure 11A; see Appendix G for the detailed results of all ROIs), significant interactions were found in bilateral occipital pole, where, compared to Clear stimuli, for Blurry stimuli younger adults exhibited lower sensory-model brain fit (post-hoc test: $t(16)$s > 8.08, ps < .0001), mimicking the age-related reduction in the quality of sensory representations (younger adults vs. older adults for Clear stimuli: $t(31) = 2.29$, $p < .05$). This finding provides strong support for the information degradation hypothesis because it shows that stimulus degradation can mimic the effects of aging in younger adults, resulting in attenuated sensory representations. The stimulus degradation also affected sensory representations in older adults in right occipital pole ($t(15) = 2.61$, $p < .05$) but not in left occipital pole ($t(15) = 1.01$, $p = .33$; Figure 11A), possibly because older adults are not as sensitive to the manipulation due to their existing visual limitations (e.g., contrast sensitivity). In the case of semantic representations (Figure 11B), a stimulus type x age group interaction was found in the right temporal pole, where, compared to Clear stimuli, younger adults exhibited higher semantic model-brain fit for Blurry stimuli (t(16) = 2.82, p < .05), at a level similar to the older adults for Clear stimuli (t(31) = 1.71, p = .10). This result provides strong support for the semantic compensation hypothesis because it shows that experimentally creating the need for compensation in younger adults leads to a boost in the quality of semantic representations in semantic-related areas that mimics the results we previously found in older adults (Monge, Wing, et al., under review). In the older adults in right temporal pole, Blurry stimuli did not boost the quality of semantic-related representations, possibly because there is a limit on how much older adults can over-recruit semantic representations to compensate for task demands.

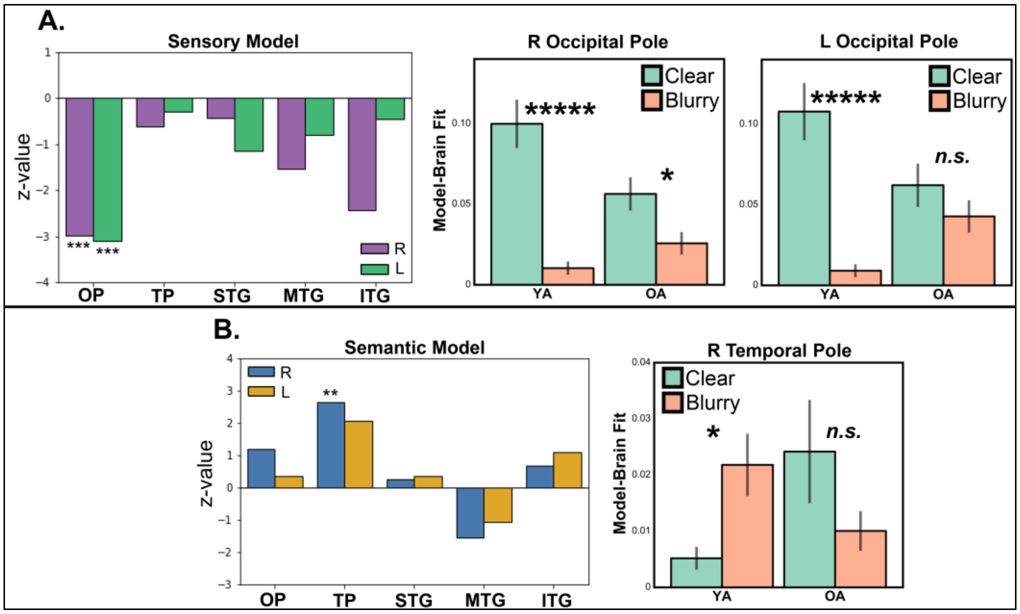


Figure 11: Age-Related Differences in the Effect of Degradation on Representations. The figure shows the representational similarity analysis results

related to the age group x stimulus type interaction, which shows brain regions where model-brain fit exhibited age-related differences in the effect of the degradation manipulation. Panel A shows sensory model-brain fit (left panel is the z-value outputs for all ROIs), where the age group x stimulus type interaction was statistically significant in bilateral occipital pole, predominately reflecting younger adults exhibiting greater sensory model-brain fit for Clear than Blurry stimuli. Panel B shows semantic model-brain fit (left panel is the z-value outputs for all ROIs), where the age group x stimulus type interaction was statistically significant in right temporal pole, where the younger adults exhibited greater semantic model-brain fit for Clear than Blurry stimuli, at a level similar to the older adults. ROIs = regions of interest; R = right; L= left; OP = occipital pole; TP = temporal pole; STG = anterior-superior temporal gyrus; MTG = anterior-middle temporal gyrus; ITG = anterior-inferior temporal gyrus; YA = younger adult; OA = older adult; * = $p < .05$; ** = $p < .01$; *** = $p < .005$; ***** = $p < .0001$; *n.s.* = not significant.

In sum, consistent with our first hypothesis, we found that stimulus degradation mimicked the effects of aging in younger adults, reducing the quality of sensory representations in visual areas and boosting the quality of semantic representations in anterior, semantics-related areas. These results strongly support both the information degradation and the semantic compensation hypotheses. The results from the older adults are also consistent with these hypotheses. The finding that stimulus degradation can impair sensory representations in younger adults, similar to what is observed in older adults during standard viewing conditions, supports the idea that age-related deficits in sensory representation found in our previous study are due to input loss. Conversely, the finding that in response to stimulus degradation younger adults can display a boost in semantic representations that matches the level of semantic representations in older adults (younger adults-Blurry ≈ older adults-Clear) supports the notion that the age-related increase in semantic representations we previously found is a compensatory response to input loss.

4.3.3. Linking Changes in Representations Caused by Stimulus Degradation in Younger Adults to Memory

Having confirmed our first hypothesis, we then tested the hypothesis that in younger adults, the enhancement of semantic representations should be associated with successful memory performance and also reflected in ERS (Hypothesis 2). To identify brain regions where the stimulus degradation manipulation would affect the relation between sensory and semantic representations and subsequent memory differently for younger and older adults, we first examined 3-way stimulus type x age group x memory vividness interactions. Sensory representations did not show significant interactions (Appendix H), but, consistent with Hypothesis 2, semantic representations in right temporal pole showed a significant 3-way interaction (Figure 12; see Appendix I for the detailed results of all ROIs). As can be seen in Figure 12, in younger adults, semantic model-brain fit for Blurry stimuli (but not for Clear stimuli: $t(16) = 0.29$, $p = .78$) was trending toward being associated with enhanced subsequent memory (post-hoc test: $t(16) = 2.06$, $p = .06$). Previously, in the investigation of Hypothesis 1, we found that in response to stimulus degradation, younger adults showed impaired sensory representations coupled with the enhancement of semantic representations. Now, we find that the latter effect is associated with better subsequent memory in younger adults, confirming support for the semantic compensation hypothesis and confirming Hypothesis 2. In contrast to younger adults, in older adults, semantic model-brain fit for Clear stimuli (but not for Blurry stimuli: t(15) = 0.26, p = .79) was trending toward being associated with enhanced subsequent memory (post-hoc test: t(15) = 1.77, p = .10), a result that replicates our previous study.

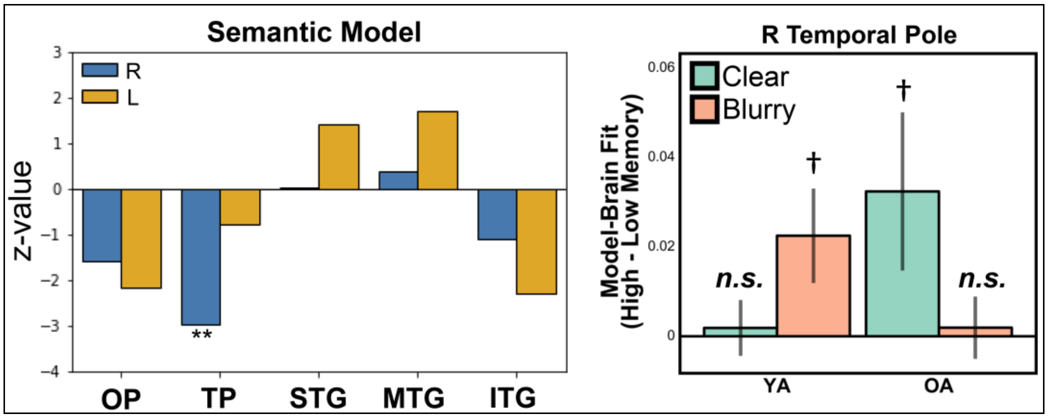


Figure 12: Age-Related Differences in the Effect of Degradation on Mnemonic Representations. The figure shows the semantic model-brain fit results related to the age group x stimulus type x memory vividness interaction (left panel is the z-value outputs for all ROIs), where the three-way interaction was statistically significant in right temporal pole. In the right temporal pole, in the YAs for Blurry stimuli, enhanced semantic-model brain fit was associated with better subsequent memory performance, similar to the OAs for Clear stimuli. ROIs = regions of interest; R = right; L= left; OP = occipital pole; TP = temporal pole; STG = anterior-superior temporal gyrus; MTG = anterior-middle temporal gyrus; ITG = anterior-inferior temporal gyrus; YA = younger adult; OA = older adult; † = *p* < .10; ** = *p* < .01; *n.s.* = not significant.

Next, we investigated a 2-way age group x stimulus type interaction in ERS (item-set; see Methods) to identify the reactivation of mnemonic representations in brain regions in which younger and older adults were differentially affected by the degradation manipulation. The only region in which the interaction was statistically significant was left occipital pole (Figure 13; see Appendix J for the detailed results of all ROIs), but post-hoc tests revealed that in younger adults, for both Clear and Blurry stimuli, item- and set-level ERS were not significantly different from each other making this result difficult to interpret (post-hoc tests: $t(16)$s < 1.82, $ps > .08$). We also found that the interaction was trending toward being statistically significant in the right temporal pole ($p < .05$). As Hypothesis 2 is focused on anterior semantic-related brain regions, as an exploratory analysis, we used a subparcellated version of the HOA (Fornito, Zalesky, & Bullmore, 2010; Tzourio-Mazoyer et al., 2002) to examine subsections of the right temporal pole, which may be more sensitive to the 2-way interaction. Indeed, we found that in a subsection of the right temporal pole, the two-way interaction was statistically significant (Appendix K; statistical significance was considered $p < .005$: Bonferroni correction .05 / 10 ROIs = 0.005). As shown in Figure 13, compared to the Clear stimuli, younger adults exhibited greater ERS for Blurry stimuli (post-hoc test: $t(16) = 2.21$, $p < .05$) at a level similar to older adults for Clear stimuli ($t(31) = 0.47$, $p = .64$); there was no difference between Blurry and Clear stimuli in older adults (post-hoc test: $t(15) = 1.93$, $p = .07$). This finding is consistent with Hypothesis 2 because it shows that, similar to what we found for Clear stimuli in older adults in our previous study and in the current study, semantic representations were reactivated during retrieval demonstrating a clear role in episodic memory.

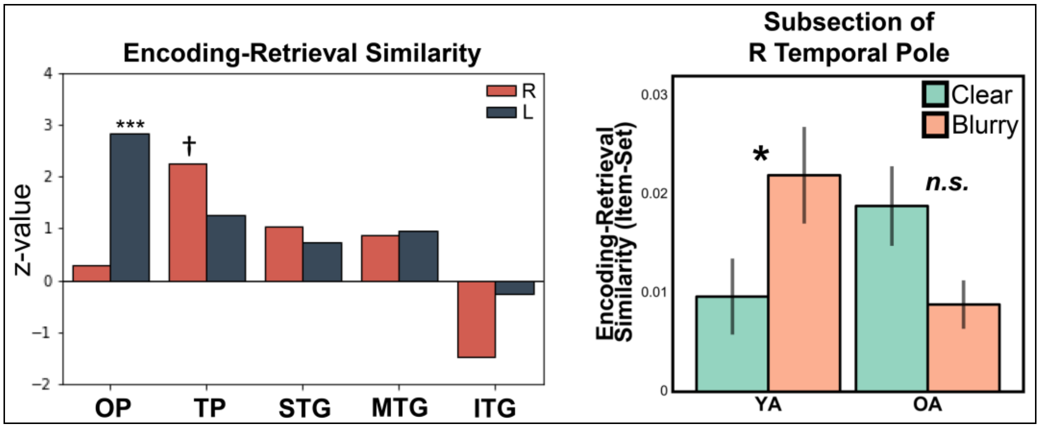


Figure 13: Age-Related Differences in the Effect of Degradation on Encoding-Retrieval Similarity. The figure shows the ERS results related to the age group x stimulus type interaction, which shows brain regions where ERS (item-set) exhibited age-related differences in the effect of the degradation manipulation. The two-way interaction (left panel is the z-value outputs for all ROIs) was statistically significant in the occipital pole, but the item- and set-level ERS was not significantly different in the younger adults, making the result difficult to interpret. The two-way interaction was trending toward beings statistically significant in the right temporal pole and, therefore, we examined subsections of the right temporal pole (subparcellated HOA; Fornito et al., 2010; Tzourio-Mazoyer et al., 2002). As can be seen in the right panel, younger adults exhibited greater ERS for Blurry than Clear stimuli. ERS = encoding-retrieval similarity; ROIs = regions of interest; R = right; L= left; OP = occipital pole; TP = temporal pole; STG = anterior-superior temporal gyrus; MTG = anterior-middle temporal gyrus; ITG = anterior-inferior temporal gyrus; YA = younger adult; OA = older adult; † = $p < .05$ (two-way interaction); * = $p < .05$; *** = $p < .001$; *n.s.* = not significant.

4.4. Discussion

In sum, the overarching goal of this study was to investigate in functional neural representations the coupling between the information degradation and semantic compensation hypotheses, which states that the age-related decline in perceptual signal input, which results in other cognitive deficits, may be compensated for with a greater reliance on semantic knowledge. To test this idea, we experimentally manipulated younger adults’ perceptual signal inputs by having participants study Clear and Blurry images. We had two main findings. First, mimicking the pattern observed in older adults, we found that, compared to Clear stimuli, for Blurry stimuli younger adults exhibited attenuated sensory representations in occipital pole but enhanced semantic representations in anterior temporal cortex. Second, we found these effects to be related to memory, where the younger adults exhibited enhanced semantic representations, which were associated with better subsequent memory and enhanced memory reactivation in temporal pole. These findings are discussed in greater detail below.

4.4.1. The Information Degradation and Semantic Compensation Hypotheses

In our previous study we found that aging was associated with an attenuation in sensory-related representations but an enhancement in semantic-related representations (Monge, Wing, et al., under review). The examination of our first hypothesis (in younger adults, stimulus degradation will mimic the effects of aging, causing an attenuation of sensory representations and a compensatory enhancement of semantic representations) provides further insight into our previous finding. Here, we replicated this finding within the younger adults, where, compared to Clear stimuli, for Blurry stimuli younger adults exhibited attenuated sensory representations but enhanced semantic representations (Figure 11). This finding strongly suggests that our previous finding reflects older adults exhibiting deficient perceptual signal input and compensating for this input by relying more on semantic knowledge. Furthermore, it may be the case that the previous literature investigating age-related neural dedifferentiation (e.g., Carp et al., 2011; Chee et al., 2006; Denise C. Park et al., 2004; Payer et al., 2006), which shows that aging is associated with a decline in the differentiation of information in posterior occipitotemporal cortex, may be the result of older adults exhibiting perceptual signal degradation.

This is the first study, to our knowledge, to investigate the effect of a degradation manipulation on representations, but there is previous working investigating this effect on processes. For example, in C. L. Grady, McIntosh, Horwitz, and Rapoport (2000), younger and older adults were presented intact and degraded pictures of faces and found that both age groups exhibited greater prefrontal cortex activity for the degraded faces, which suggests a compensatory mechanism. Our finding extends C. L. Grady et al. (2000), which was focused on processes, by demonstrating a similar pattern in the investigation of neural representations. Therefore, it appears that perceptual signal degradation affects both processes and representations. As it has previously been suggested that the age-related increased reliance on semantic knowledge compensates for deficient cognitive control processes (Spreng & Turner, 2019a; Turner & Spreng, 2015), it will be of interest for future studies, in addition to examining compensatory representations, to also investigate compensatory processes and the interactions between representations and processes.

Regarding the older adults, we did not originally have a hypothesis on how the degradation manipulation would affect the older adults, but, overall, it appears that the experimental degradation did not have a large effect on the older adults. For the sensory representations, only in the right occipital pole was there a significant difference between Clear and Blurry stimuli and, for semantic representations, in the right temporal pole there was no significant difference between Clear and Blurry stimuli (Figure 11). As older adults already contain visual perceptual deficiencies (Greene & Madden, 1987a; Jackson & Owsley, 2003a; C. Owsley, 2011; Owsley et al., 1983), it may be the case that a greater degradation manipulation would be required to see an effect in older adults. It should be noted, however, that in the investigation of the main effect of stimulus type (younger adults ≈ older adults), across all participants, compared to Clear stimuli, semantic representations in the right anterior-superior temporal gyrus were enhanced for Blurry stimuli (Figure 10). This finding combined with the age group by stimulus type interaction finding, suggests that older adults were still affected by the degradation manipulation, but just not to the same extent as the younger adults. In sum, our test of the first hypothesis provides support for both the information degradation and semantic compensation hypotheses, which may explain other observations of age-related differences in neural representations present in the extant literature.

4.4.2. The Effect of Stimulus Degradation on Mnemonic Representations

Our previous study found that in older adults enhanced ERS in anterior temporal lobe was associated with better memory performance (Monge, Wing, et al., under review). Our second hypothesis (in younger adults, the enhancement of semantic representations and ERS in the Blurry condition should be associated with successful memory performance) tested whether this effect was the result of the coupling between the information degradation and semantic compensation hypotheses. Indeed, we found in younger adults for Blurry stimuli, enhanced semantic representations in right temporal pole were associated with better memory performance, similar to the older adults for Clear stimuli (Figure 12). This finding further demonstrates that the enhanced semantic representations are compensatory. Furthermore, the finding that the quality of semantic representations is associated with better subsequent memory only in the Blurry condition for younger adults suggests that the younger adults can remember the stimuli using primarily sensory representations and only when these representations are impaired, memory relies on semantic representations. In older adults, in contrast, memory relies on semantic representations even for Clear stimuli, and perhaps sensory representations do not contribute as much to subsequent memory, possibly because these representations are always of poor quality. However, here and in our previous study (Monge, Wing, et al., under review), we did not find in the younger adults that sensory representations were related to memory. In both studies our sensory model was derived from an early layer of a deep convolutional neural network, which represents low-level visual features (Zeiler & Fergus, 2014), and perhaps the investigation of these low-level visual features is not sensitive enough to detect memory effects related to our study stimuli. Future studies may investigate memory effects using models that represent a range of visual feature types.

In addition to the representational similarity analyses demonstrating that in younger adults enhanced semantic representation for Blurry stimuli was associated with better subsequent memory, compared to Clear stimuli, we also found that younger adults exhibited greater ERS in right temporal pole for Blurry stimuli (Figure 13). This observation may explain our previous study, where the older adults exhibited enhanced ERS in anterior temporal lobe (Monge, Wing, et al., under review). Furthermore, in addition to our previous study, other work has shown that, compared to younger adults, older adults exhibit attenuated memory reactivation in occipitotemporal cortex (Johnson et al., 2015; St-Laurent et al., 2014). Our work here suggests that this observation is the result of older adults exhibiting deficient perceptual signal input.

Overall, our findings from the investigation of the second hypothesis help explain the behavioral literature demonstrating that (1) degrading task stimuli detrimentally affects memory (Dickinson & Rabbitt, 1991) and (2) increased semantic demands improves older adults' memory performance (Donald H. Kausler & Lair, 1966; M. Naveh-Benjamin, 2000; Zaretsky & Halberstam, 1968a, 1968b). Here, we clearly demonstrate that in younger adults degrading task stimuli attenuates the quality of sensory representations but enhances the quality of semantic representations, which is associated with better memory performance.

4.4.3. Conclusions

In sum, the current study provides a mechanism explaining our previous findings of an age-related attenuation in sensory representations and enhancement in semantic representations. As semantic compensation ameliorates many age-related memory deficits (M. Naveh-Benjamin, 2000) and is perhaps responsible for adults remaining highly functional in advanced age (e.g., Colonia-Willner, 1998; Hardy & Parasuraman, 1997; Shimamura et al., 1995), it is vital to understand mechanisms underlying this semantic compensation. The discipline of the cognitive neuroscience of aging is largely focused on the aspects of cognition that decline with age, but this work and research from many others demonstrate the importance of also investigating the aspects of cognition preserved in aging and how they can be harnessed to compensate for cognitive deficiencies. This investigation is still in its infancy and will hopefully lead to successful intervention development with the goal of ameliorating age-related cognitive deficiencies.

5. Conclusion

The studies presented here provide further insight into age-related differences in neural representational quality and how the quality of these representations relate to memory. In the first study we found that, compared to younger adults, older adults exhibited attenuated sensory representations in visual cortex but enhanced categorical representations in anterior temporal lobe. This same pattern was present in the examination of ERS and in the older adults greater ERS in the anterior temporal lobe was associated with better memory performance. In the second study we found that, compared to younger adults, older adults exhibited lower strength of informational connections derived from the occipitotemporal cortex module, but similar strength of informational connections derived from the medial/lateral prefrontal cortex module. We also found that in response to shifts in attending to semantic vs. perceptual features, compared to younger adults, older adults exhibited greater reorganization of informational connections derived from the medial/lateral prefrontal cortex module, and that this effect was associated with better memory performance in the older adults. Lastly, in the third study we found that the effects found in the first two studies were likely the result of older adults exhibiting degraded visual signal inputs, which are compensated by greater use of semantic-enhancing mechanisms. This was reflected by younger adults, in response to visually degraded stimuli, exhibited attenuated sensory representations in visual cortex but enhanced semantic representations in anterior temporal cortex; this same pattern was also present in the examination of memory reactivation. In the rest of the Conclusion I discuss the original key questions, methodological considerations, and future directions.

5.1. Key Questions, Revisited

As mentioned in the Introduction, the extant literature only presents preliminary evidence that there are age-related differences in neural representational quality and that the quality of these representations is related to memory. It is specifically unclear what types of representations younger and older adults differentially represent (i.e., perceptual vs. semantic representations). In the first study presented in Chapter 2, we directly addressed this issue by answering the question are there age-related differences in perceptual and semantic-related neural representations and does the quality of these representations also impact mnemonic representations? Our finding that the quality of sensory representations in visual cortex was, compared to younger adults, lower in older adults is suggestive that the finding in the extant literature of age-related neural dedifferentiation in occipitotemporal cortex (Chee et al., 2006; Denise C. Park et al., 2004; Payer et al., 2006) reflects older adults not differentiating sensory features as well as younger adults. Although in general the discipline of the cognitive neuroscience of aging largely focuses on aspects of cognition that decline with age, we found in anterior temporal lobe that categorical representations were enhanced in older adults. We termed this observation as age-related hyperdifferentiation. It may be the case that this finding explains the observation that many older adults remain highly functional well into advanced age. This same pattern was present in the examination of memory reactivation, which suggests that the quality of perceptual representations may also impact downstream mnemonic representations.

The first study focused on representations in individual brain regions, but it is also believed that representations are shared between brain regions (Anzellotti & Coutanche, 2018; Coutanche & Thompson-Schill, 2013) and it may be the case that examining how representations are shared between brain regions is important for further understanding cognitive aging. In the second study presented in Chapter 3 we addressed this issue by answering the question are there age-related differences in how perceptual and semantic information are shared across the whole brain network? To answer this question, we developed a new method that investigates how representations are shared across the whole-brain network, which we call representational networks. Our finding that, compared to younger adults, older adults exhibited lower strength of informational connections derived from the occipitotemporal cortex module suggests that not only is aging associated with a decline in the quality of perceptual representations in individual brain regions, as shown in the first study, but is also associated with a decline in how perceptual information is distributed across the whole-brain network. Our finding in the first study of age-related hyperdifferentiation in the anterior temporal lobe is also similar to what was observed in the second study where we found that, compared to younger adults, older adults exhibited similar strength of information connections derived from the medial/lateral prefrontal cortex module. This finding suggests that aging is associated with a preservation in how semantic information is distributed across the whole brain network. Lastly, the finding in Chapter 3 that, compared to younger adults, older adults exhibited greater reorganization of informational connections derived from the medial/lateral prefrontal cortex module and that this reorganization was associated with better memory performance further suggests that greater use of semantic representations in older adults is compensatory.

Together Chapters 2 and 3 provide evidence that aging is associated with a decline in both the quality and distribution of perceptual representations but a preservation and even an enhancement of semantic representations. The goal of the third study, presented in Chapter 4, was to investigate mechanisms underlying these effects. Specifically, I examined the question does visual signal loss and compensatory semantic-enhancing mechanisms explain age-related differences in mnemonic neural representations? We found when participants viewed visually degraded stimuli, younger adults exhibited attenuated sensory representations in visual cortex, but enhanced semantic representations in anterior temporal cortex, similar to the older adults during normal viewing conditions (i.e., Clear stimuli). We also found for the visually degraded stimuli that in the younger adults that enhanced semantic representations was associated with better subsequent memory and younger adults exhibited greater ERS in anterior temporal cortex. These findings suggest that the age-related effects found in the first two studies were the result an age-related attenuation of perceptual signal strength (the information degradation hypothesis), which is compensated for with the greater use of semantic knowledge (semantic compensation hypothesis).

5.2. Methodological Considerations

I believe the studies presented here advance our knowledge of the cognitive neuroscience of aging and memory, but there are some methodological limitations that should be considered when interpreting study results. Below, I discuss a few of these considerations and how they can be further addressed in future studies.

5.2.1. Study Sample Demographics

In all three studies presented here, the samples of older adults completed a relatively large number of years of education. This brings into question whether the study samples are representative of the general population. Indeed, in the United States in individuals 65 years and older, only 26.7% of individuals attained a Bachelor’s or more advanced degree (Ryan & Bauman, 2016), whereas in the studies presented here, the majority of individuals had at least achieved a Bachelor's degree. Overall, we found that older adults exhibited an additional reliance on semantic representations and that this additional reliance was compensatory, but it is unclear if this effect would be present in individuals who attained less education. Perhaps to observe the effects seen in the current studies it is necessary for older adults to have a large knowledge base, which may be attained through education. It will be important for future studies to include more diverse study samples and investigate individual differences.

5.2.2. Functional Neural Representations Analysis Approach

In Studies 1 and 3, we investigated neural representations with the use of representational similarity analyses (Nikolaus Kriegeskorte & Kievit, 2013; Nikolaus Kriegeskorte et al., 2008). As mentioned in the Introduction, an advantage of representational similarity analyses over other approaches, such as multi-voxel pattern analysis, is that representational similarity analyses allow for further insight into the types of information being represented in a brain region by correlating similarity in brain activation patterns with stimuli models. This is an informative method, but the interpretation of representational similarity analysis results is highly dependent upon the interpretation of the stimuli model and stimuli model interpretation may be difficult at times. For example, in Study 1, we used different layers of a DNN to model sensory and categorical representations. When inputting an image through a DNN, depending on the model and layer, it outputs thousands of activation values. Therefore, interpreting these outputs may be difficult. Although we believe the DNN was an appropriate model for this study, we recognized that the complexity makes it difficult to interpret and also provided less complex alternative models (HMAX (Serre et al., 2007) and indoor vs. outdoor pattern similarity), which were easier to interpret. Perhaps to avoid this issue of misinterpreting a model, studies should run representational similarity analyses with multiple models that likely represent similar types of information. If the result is replicated with multiple models, then the result will have a clearer interpretation.

Another limitation of representational similarity analyses, related to the limitation above, is that they are correlational. Therefore, representational similarity analyses should always be interpreted with some degree of caution. The only method to definitively determine the type of information being represented in a brain region is through experimental manipulation. For example, in Study 3 we experimentally manipulated the amount of visual information available. This experimental manipulation not only allowed us to investigate the main goals of the study but also provided a method to confirm the validity of our interpretation of sensory representations. We expected that manipulating the amount of visual information available would have a direct impact on sensory representations and, indeed, in Study 3 we found that it does have an impact, which further confirms that the representational similarity analysis was detecting sensory-related representations. Future studies may further rely on the combination of representational similarity analyses and experimental manipulation to investigate the type of information represented in a brain region.

Lastly, with the use of fMRI, it is assumed that representations can be detected at the level of voxels. Voxels contain thousands of neurons (Herculano-Houzel, 2009; Lent, Azevedo, Andrade-Moraes, & Pinto, 2012), so, therefore, it may be the case that some representations are only detectable at a smaller scale. Indeed, a general observation within the field is that model-brain fit from representational similarity analyses is relatively low. It is likely that part of the issue is that the stimuli models typically used are not ideal, but it may be the case that the scale in which representations are being examined is not sufficient. A benefit of representational similarity analyses is that after constructing the representational dissimilarity matrices, whether the matrix is from an image model, fMRI activation patterns or single-cell recordings, the matrices are in the same space and can be easily compared (Nikolaus Kriegeskorte et al., 2008). Future work may investigate this issue by utilizing representational similarity analyses derived from multiple modalities (e.g., fMRI, single-cell recordings, MEG) and compare and combine these modalities to test the impact of modality on model-brain fit.

5.2.3. Measures of Memory Reactivation

In Studies 1 and 3, memory reactivation was measured using ERS analyses. Unlike representational similarity analyses, a limitation of ERS analyses is that they do not indicate what type of information (e.g., sensory, semantic) is being reactivated. In the studies presented here, we used a combination of the representational similarity analysis results and reverse inference to infer what type of information was being reactivated. This approach is not ideal as it does not directly test what type of information is being reactivated. A possible solution is to further combine ERS with representational similarity analyses. Representational similarity analyses are typically conducted on data in which participants are viewing stimuli. However, there is no reason the image model cannot be correlated with brain activation pattern similarity matrices for trials in which the participants are not viewing the stimuli, which in the case of the studies presented here is during memory retrieval. Perhaps in regions that exhibit significant ERS, to determine what type of information is being reactivated, an image model can be correlated with the similarity in brain activation patterns. This method may be further tested in future studies.

5.3. Future Directions

The investigation of age-related differences in representations is still in its infancy. Just like with most areas of the cognitive neuroscience of aging and memory, there is still much not know. Below I highly a few areas of research that I believe are important future directions.

5.3.1. Interactions Between Representations and Processes

The studies presented here largely focused on representations and did not investigate interactions between representations and cognitive processes. The interaction between representations and cognitive processes has been demonstrated in other lines of research, such as in the working memory literature, where it is largely believed that the information stored in working memory is represented in sensory-related cortices and that the prefrontal cortex exerts top-down executive control processes on these representations in service of maintenance and other processes (for a review, see Serences, 2016). As many processes decline with age (for reviews, see Roberto Cabeza, Nyberg, & Park, 2016), it is likely the case that the examination of the interactions between processes and interactions is another important line of research in the discipline of the cognitive neuroscience of aging. Most related to this idea, as mentioned in Chapter 3, is the Default-Executive Coupling Hypothesis of Aging (DECHA; Spreng & Turner, 2019a; Turner & Spreng, 2015). This hypothesis predicts that older adults counteract the age-related decline in cognitive control processes by relying more on semantic processes. In the brain, this is observed by an age-related increase in the coupling between the default mode network (presumably containing prior-knowledge representations) and lateral prefrontal brain regions (presumably important for control-related processes). It is likely the case that DECHA and the ideas presented in this thesis are both only telling part of the story. Here, I presented evidence demonstrating that the increased age-related dependence on semantic representations is compensating for perceptual representational deficits. Perhaps a more complete model will also consider that in addition to semantic representations compensating for perceptual representational deficits, they are also compensating for cognitive control deficiencies. It will be important for future studies to investigate not only age-related differences in representations but also how top-down processes interact with these representations.

5.3.2. When Is Greater Use of Semantic Cognition Not Beneficial?

The studies presented in this thesis suggest that the age-related increase in the use of semantic representations is compensatory. However, there are also likely cases that the additional reliance on semantic representations is detrimental. For example, it is likely in scenarios in which perceptual discrimination is required, this additional reliance on semantic representations is detrimental. This effect can be seen in studies in which participants discriminate between category exemplar lures, which, therefore, requires discriminating between perceptual details. It is generally found that, compared to younger adults, older adults exhibit a higher false alarm rate (Koutstaal et al., 1999; K. A. Norman & Schacter, 1997; Tun et al., 1998). Further work is needed in the investigation of age-related differences in false memories and the impact of semantic representations. In addition to scenarios in which perceptual discrimination is required, it may be the case that when older adults are required to go against their prior knowledge that the greater use of semantic representations is detrimental. Behaviorally, this can be seen where, compared to younger adults, older adults exhibit worse memory for words spelled incorrectly (MacKay et al., 1999) and incorrect math equations (Ruch, 1934). As previously mentioned, even though there is the observation that older adults remain highly proficient within the workplace (e.g., Colonia-Willner, 1998; Hardy & Parasuraman, 1997; Shimamura et al., 1995), perhaps this would not be the case for professions that require learning new skills. The role of semantic representations and accumulating new knowledge in aging is another area of research that requires further investigation.

5.3.3. Pathological Aging

All three studies presented here contained samples of cognitively normal older adults. It is unknown, to my knowledge, how neural representations change in pathological aging (e.g., mild cognitive impairment, Alzheimer’s disease). As the studies presented here and others have demonstrated that the investigation of neural representations is crucial for providing a more comprehensive understanding of normal cognitive aging, this investigation is very well also important in the study of pathological aging. It will especially be interesting to compare between normal and pathological aging perceptual and semantic representations. For example, unlike what is observed in normal aging, amnesic mild cognitive impairment (MCI) is associated with a decline in semantic performance (Gardini et al., 2013; Gardini et al., 2015; Hirni, Kivisaari, Monsch, & Taylor, 2013). Also, relative to cognitively normal older adults, MCI patients do not exhibit a semantic support effect in memory (Froger, Taconnat, Landre, Beigneux, & Isingrini, 2009; Hudon, Villeneuve, & Belleville, 2011; Mandzia, McAndrews, Grady, Graham, & Black, 2009), but for MCI patients who display a preservation of semantic cognition, they also exhibit a slower conversion to Alzheimer's disease (Quaranta et al., 2014). This literature and the studies presented here suggest that a preservation or enhancement of semantic cognition in aging is protective against displaying some symptoms of pathological aging. Therefore, it is likely imperative for intervention development to understand how semantic information is represented in MCI patients. Perhaps interventions that strengthen the quality of semantic representations will ameliorate some symptoms of MCI.

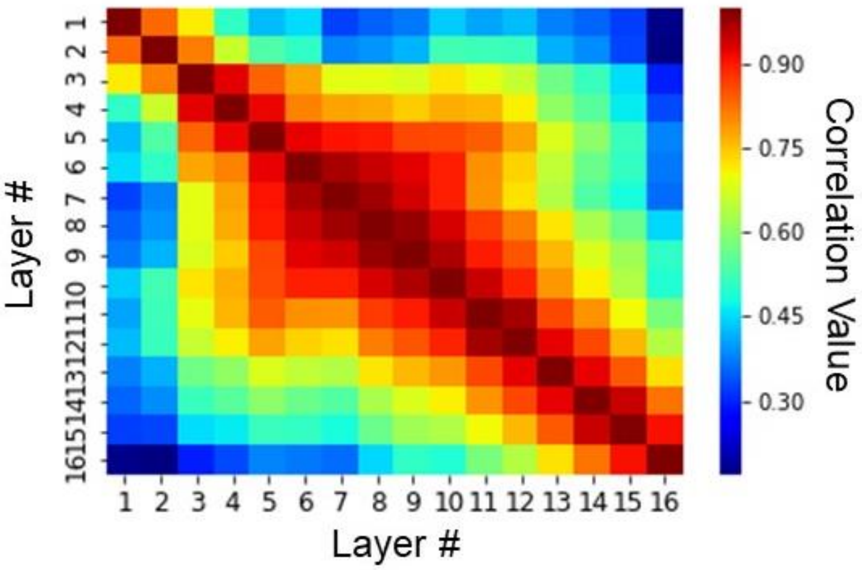
5.4. Concluding Thoughts

Until recently, the role of neural representations in cognitive aging was relatively unstudied. The studies reported here demonstrate the importance of studying age-related differences in functional neural representations, which appear to have a direct impact on episodic memory.

Overall, the three studies reported provide evidence for an age-related attenuation in perceptual representations but enhancement in semantic representations at various levels of analysis. In the first study, I showed that, compared to younger adults, the quality of sensory-related representations in visual cortex was attenuated in older adults but the quality of semantic-related representations in anterior temporal lobe was enhanced in older adults; these effects were also present in memory reactivation. In the second study, I extended this finding by showing that, compared to younger adults, older adults exhibited a deficit in distributing perceptual representations across the whole- brain network but a preservation in distributing semantic representations. Lastly, in the third study, I found that the age-related increased reliance on semantic representations is likely the result of semantic representations compensating for visual signal loss.

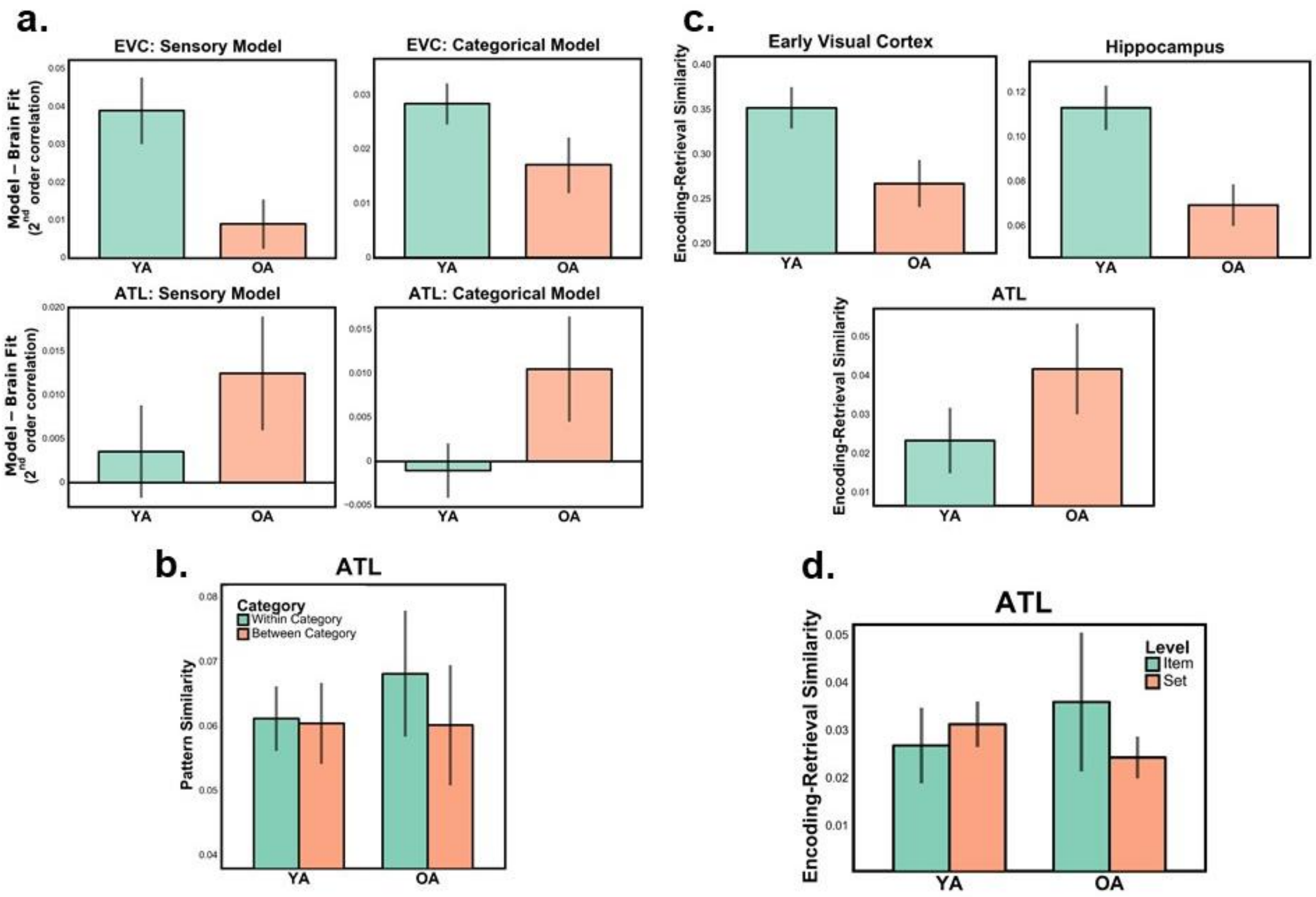
Taken together, these studies contribute to the literature investigating the cognitive neuroscience of aging. Historically, this discipline of the cognitive neuroscience of aging has focused on cognitive processes leaving age-related differences in representations relatively unclear. Now, as mentioned in the Future Directions, this line of research can be taken into several directions. Most clinically urgent is the investigation of neural representations in pathological aging. As knowledge and technology advances, I hope to see greater study of age-related differences in neural representations in directions that I cannot currently imagine and the use of this work toward intervention development with the goal of promoting healthy cognitive aging.

Appendix A



Correlation Matrix of DNN Stimuli Models. The figure shows the correlation matrix of stimuli models derived from every layer of the VGG16. DNN = deep convolutional neural network.

Appendix B


a.
EVC: Sensory Model
Model – Brain Fit (2nd order correlation)
0
0.01
0.02
0.03
0.04
0.05
YA
OA
EVC: Categorical Model
0
0.01
0.02
0.03
YA
OA
ATL: Sensory Model
Model – Brain Fit (2nd order correlation)
0
0.005
0.010
0.015
0.020
YA
OA
ATL: Categorical Model
-0.005
0
0.005
0.010
0.015
YA
OA
b.
ATL
Pattern Similarity
Category
🟩 Within Category
🟥 Between Category
0.04
0.05
0.06
0.07
0.08
YA
OA
c.
Early Visual Cortex
Encoding-Retrieval Similarity
0.20
0.25
0.30
0.35
0.40
YA
OA
Hippocampus
0.06
0.08
0.10
0.12
YA
OA
ATL
Encoding-Retrieval Similarity
0.01
0.02
0.03
0.04
0.05
YA
OA
d.
ATL
Encoding-Retrieval Similarity
Level
🟩 Item
🟥 Set
0.01
0.02
0.03
0.04
0.05
YA
OA

Panel a shows within the early visual cortex and anterior temporal lobe the raw values of the image model (sensory and categorical)-brain fit. Panel b shows the brain activation pattern similarity for within and between categories (categories = indoor vs. outdoor scenes) in the ATL. Panel c shows in the early visual cortex, hippocampus and ATL raw ERS values. Panel d shows in the ATL raw ERS values for trials that were subsequently remembered on the post-scan memory recognition task separately for item- and set-level ERS. Error bars represent the standard error of the mean. ATL = anterior temporal lobe; ERS = encoding-retrieval similarity; EVC = early visual cortex; OA = older adults; YA = younger adults.

Appendix C

Shows coordinates of peaks and subpeaks within clusters (thresholded at *p*<.005, k=12; determined by 3dClust-Sim in AFNI version 17.0; only positive-values are shown). BA = Brodmann area; Hem = Hemisphere; L = Left; R = Right; mprefrontal cortex = medial prefrontal cortex.

Cluster	Hem	BA	MNI Coordinates (mm)			*t*-value	Size (voxels)
			x	*y*	*z*		
Younger Adults							
Sensory Model							
Calcarine Cortex	L	17	-23	-64	15	6.70	1452
	R	17	19	-68	11	6.25	
	R	23	26	-60	11	5.76	
Categorical Model							
Occipitotemporal Cortex	L	17	-26	-71	4	12.81	2171
	L	17	-15	-68	8	9.99	
	R	23	26	-56	11	8.87	
Midline	R	8	23	11	30	4.34	54
	R	-	23	-4	15	3.36	
Cerebellum	L	-	-4	-60	-30	4.10	21
Older Adults							
Sensory Model							
Inferior Lateral Occipital Cortex	R	19	41	-71	11	6.61	324
	R	19	41	-75	4	5.98	

	R	19	45	-68	-4	5.09	
Inferior Lateral Occipital Cortex/Calcarine Cortex	L	18	-34	-75	8	4.49	149
	L	17	-15	-68	15	3.72	
	R	18	4	-74	23	3.15	
Categorical Model							
Inferior Lateral Occipital Cortex	L	19	-45	-64	8	6.22	1123
	R	39	45	-60	11	5.34	
	R	19	45	-64	0	5.18	
Dorsal/Ventral mPFC	L	9	-26	30	27	5.86	833
	R	10	23	53	4	5.25	
	R	10	26	45	8	5.06	
Midline	R	-	30	-11	30	4.35	106
	R	4	38	-15	42	3.94	
	R	24	11	-11	42	3.30	
Anterior Parahippocampal Gyrus	L	36	-34	-15	-27	4.17	29
Midline	L	8	-15	19	46	3.95	90
	L	-	-19	4	38	3.36	
	L	6	-15	-15	42	3.28	
Temporal Pole	L	21	-60	-8	-23	3.64	20
	L	21	-53	-11	-27	3.27	
	L	20	-45	-8	-30	3.24	
	R	8	26	23	38	3.45	13

Appendix D

MVPA Classifier Accuracy of All AAL ROIs. Shows the MVPA classifier accuracy of all AAL ROIs sorted from highest to lowest *t*-values. AAL = Automated Anatomical Labeling; L = Left; MVPA = multi-voxel pattern analysis; R = Right; ROIs = regions of interest.

ROI Number	ROI Name	*t-value*	*p*-value	Average Classifier Accuracy
86	R Middle Temporal Gyrus	8.066022	2.62E-09	0.390507
62	R Inferior Parietal Lobule	7.896862	4.18E-09	0.374385
67	L Precuneus	7.464453	1.40E-08	0.379139
55	L Fusiform Gyrus	7.361127	1.88E-08	0.376299
61	L Inferior Parietal Lobule	7.07848	4.20E-08	0.393075
33	L Midcingulate Area	6.779768	9.91E-08	0.381886
14	R Inferior Frontal Gyrus, Pars Triangularis	6.726856	1.16E-07	0.383629
19	L Supplementary Motor Area	6.533356	2.03E-07	0.374175
13	L Inferior Frontal Gyrus, Pars Triangularis	6.372699	3.23E-07	0.38159
64	R Supramarginal Gyrus	5.995272	9.78E-07	0.376089

1	L Precentral Gyrus	5.842919	1.53E-06	0.37756
65	L Angular Gyrus	5.691036	2.40E-06	0.372043
52	R Middle Occipital Gyrus	5.606332	3.08E-06	0.372448
60	R Superior Parietal Lobule	5.546092	3.68E-06	0.369157
57	L Postcentral Gyrus	5.47272	4.57E-06	0.380322
85	L Middle Temporal Gyrus	5.458179	4.77E-06	0.375833
8	R Middle Frontal Gyrus	5.414843	5.42E-06	0.372035
90	R Inferior Temporal Gyrus	5.361994	6.34E-06	0.371584
51	L Middle Occipital Gyrus	5.351238	6.54E-06	0.377622
68	R Precuneus	5.253904	8.72E-06	0.373117
23	L Medial Frontal Gyrus	5.236854	9.17E-06	0.386352
63	L Supramarginal Gyrus	5.233482	9.26E-06	0.379552
31	L Anterior Cingulate Gyrus	5.213923	9.82E-06	0.363305
12	R Inferior Frontal Gyrus, Pars Opercularis	5.151895	1.18E-05	0.366332
34	R Midcingulate Area	5.143936	1.21E-05	0.375187
20	R Supplementary Motor Area	5.000203	1.84E-05	0.358217
59	L Superior Parietal Lobule	4.99246	1.89E-05	0.374876

7	L Middle Frontal Gyrus	4.973429	1.99E-05	0.378906
66	R Angular Gyrus	4.74023	3.96E-05	0.369896
11	L Inferior Frontal Gyrus, Pars Opercularis	4.729792	4.08E-05	0.366457
56	R Fusiform Gyrus	4.499827	7.99E-05	0.364255
3	L Superior Frontal Gyrus	4.48054	8.45E-05	0.375926
58	R Postcentral Gyrus	4.425604	9.91E-05	0.365647
45	L Cuneus	4.387875	0.000111	0.355867
53	L Inferior Occipital Cortex	4.246126	0.000166	0.361088
15	L Inferior Frontal Gyrus, Pars Orbitalis	4.168435	0.000208	0.360247
24	R Medial Frontal Gyrus	4.076459	0.000271	0.367982
4	R Superior Frontal Gyrus	4.029387	0.00031	0.36634
32	R Anterior Cingulate Gyrus	3.990179	0.000346	0.360434
47	L Lingual Gyrus	3.843785	0.000523	0.35782
54	R Inferior Occipital Cortex	3.694589	0.000793	0.358769
30	R Insula	3.562095	0.001144	0.354194
81	L Superior Temporal Gyrus	3.516202	0.001297	0.357166
89	L Inferior Temporal Gyrus	3.515753	0.001298	0.360045

35	L Posterior Cingulate Gyrus	3.508005	0.001326	0.359812
49	L Superior Occipital Gyrus	3.326971	0.002164	0.351727
16	R Inferior Frontal Gyrus, Pars Orbitalis	3.281618	0.002443	0.356839
17	L Rolandic Operculum	3.252238	0.002641	0.350405
48	R Lingual Gyrus	3.161083	0.00336	0.351012
50	R Superior Occipital Gyrus	3.044806	0.00455	0.35456
2	R Precentral Gyrus	2.983094	0.005334	0.352638
29	L Insula	2.892022	0.006726	0.35042
82	R Superior Temporal Gyrus	2.384913	0.022984	0.349852
21	L Olfactory Cortex	2.225149	0.03302	0.344616
26	R Medial Orbitofrontal Cortex	2.070323	0.046321	0.346117
18	R Rolandic Operculum	2.059611	0.047396	0.346888
25	L Medial Orbitofrontal Cortex	1.906977	0.065261	0.344616
46	R Cuneus	1.878691	0.069145	0.343005
6	R Superior Frontal Gyrus, Orbital Part	1.443004	0.158445	0.341682
38	R Hippocampus	1.35951	0.183203	0.34141
5	L Superior Frontal Gyrus, Orbital Part	1.187144	0.243647	0.339753

42	R Amygdala	1.118961	0.271236	0.339924
40	R Parahippocampal Gyrus	1.110568	0.274781	0.340896
75	L Pallidum	0.945128	0.351463	0.337784
9	L Middle Frontal Gyrus, Orbital Part	0.859858	0.396071	0.33934
39	L Parahippocampal Gyrus	0.835329	0.40954	0.33892
77	L Thalamus	0.800413	0.429197	0.337247
44	R Calcarine Sulcus	0.796138	0.431642	0.338531
10	R Middle Frontal Gyrus, Orbital Part	0.707649	0.484132	0.338103
72	R Caudate Nucleus	0.619295	0.539975	0.337247
43	L Calcarine Sulcus	0.558105	0.58054	0.336664
83	L Superior Temporal Pole	0.54836	0.587136	0.337185
71	L Caudate Nucleus	0.543005	0.590776	0.336531
37	L Hippocampus	0.5198	0.606672	0.336889
22	R Olfactory Cortex	0.411376	0.683456	0.335512
78	R Thalamus	0.37718	0.708455	0.335629
70	R Paracentral Lobule	0.352671	0.726577	0.335652
36	R Posterior Cingulate Gyrus	0.303993	0.763042	0.335683

69	L Paracentral Lobule	0.218893	0.828081	0.334781
73	L Putamen	0.081447	0.935579	0.333808
74	R Putamen	0.069269	0.945193	0.333691
79	L Transverse Temporal Gyrus	0.009564	0.992427	0.333396
28	R Rectus Gyrus	-0.14686	0.884137	0.332446
84	R Superior Temporal Pole	-0.35566	0.724358	0.331606
41	L Amygdala	-1.04565	0.30332	0.327171
88	R Middle Temporal Pole	-1.24648	0.221363	0.322915
27	L Rectus Gyrus	-1.52759	0.136143	0.320619
80	R Transverse Temporal Gyrus	-1.69454	0.099581	0.324961
87	L Middle Temporal Pole	-2.56545	0.015035	0.318557
76	R Pallidum	-2.73421	0.009977	0.317982

Appendix E

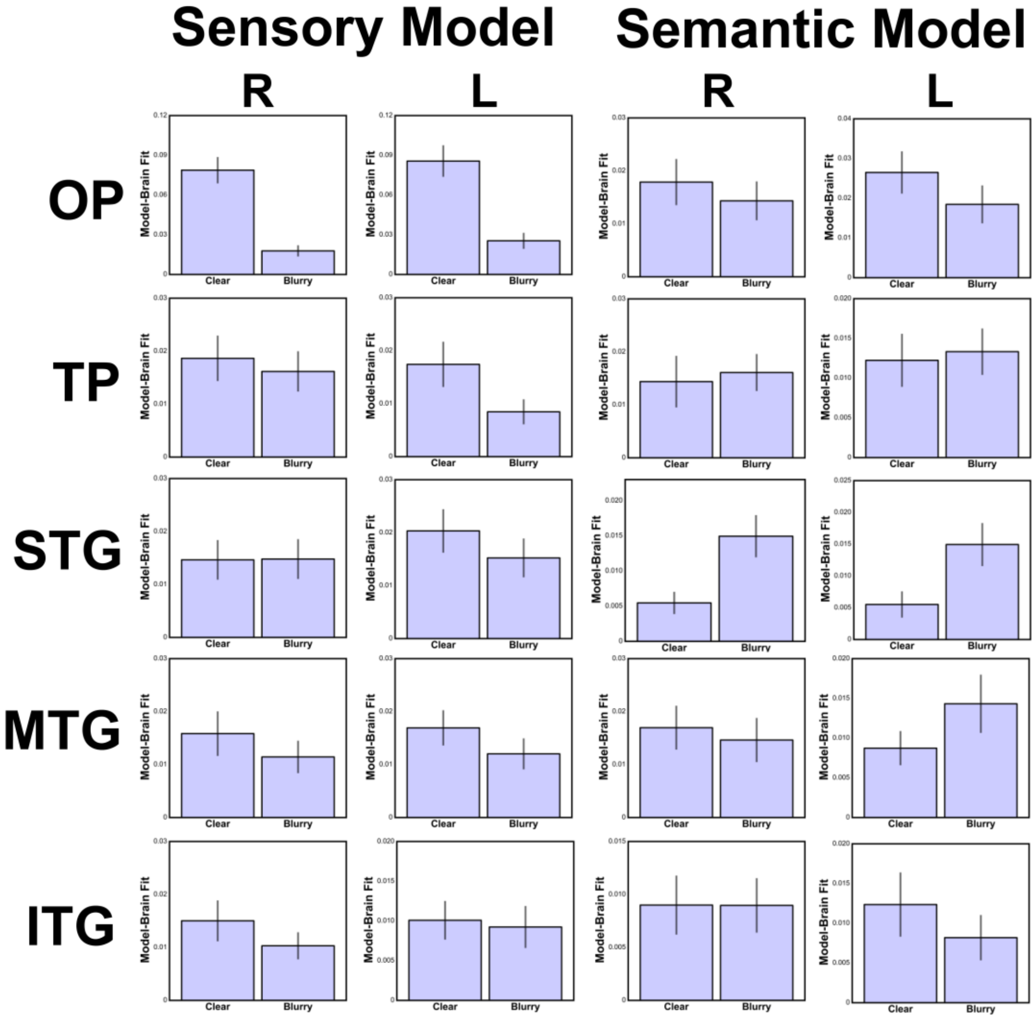
Modular Assignment of AAL ROIs. Shows the modular assignment of the AAL ROIs included in the representational networks. AAL = Automated Anatomical Labeling; L = Left; OTC = occipitotemporal cortex; PFC = prefrontal cortex; R = Right; ROIs = regions of interest.

ROI Number	ROI Name	Module
3	L Superior Frontal Gyrus	Medial/Lateral PFC
4	R Superior Frontal Gyrus	Medial/Lateral PFC
7	L Middle Frontal Gyrus	Medial/Lateral PFC
8	R Middle Frontal Gyrus	Medial/Lateral PFC
11	L Inferior Frontal Gyrus, Pars Opercularis	Medial/Lateral PFC
12	R Inferior Frontal Gyrus, Pars Opercularis	Medial/Lateral PFC
13	L Inferior Frontal Gyrus, Pars Triangularis	Medial/Lateral PFC
14	R Inferior Frontal Gyrus, Pars Triangularis	Medial/Lateral PFC
15	L Inferior Frontal Gyrus, Orbital Part	Medial/Lateral PFC
16	R Inferior Frontal Gyrus, Orbital Part	Medial/Lateral PFC
23	L Medial Frontal Gyrus	Medial/Lateral PFC
24	R Medial Frontal Gyrus	Medial/Lateral PFC
65	L Angular Gyrus	Medial/Lateral PFC
45	L Cuneus	OTC
47	L Lingual Gyrus	OTC
48	R Lingual Gyrus	OTC
49	L Superior Occipital Gyrus	OTC
50	R Superior Occipital Gyrus	OTC
51	L Middle Occipital Gyrus	OTC
52	R Middle Occipital Gyrus	OTC

53	L Inferior Occipital Gyrus	OTC
54	R Inferior Occipital Gyrus	OTC
55	L Fusiform Gyrus	OTC
56	R Fusiform Gyrus	OTC
85	L Middle Temporal Gyrus	OTC
86	R Middle Temporal Gyrus	OTC
89	L Inferior Temporal Gyrus	OTC
90	R Inferior Temporal Gyrus	OTC
17	L Rolandic Operculum	Anterior/Posterior Midline
18	R Rolandic Operculum	Anterior/Posterior Midline
21	L Olfactory Cortex	Anterior/Posterior Midline
26	R Medial Orbitofrontal Cortex	Anterior/Posterior Midline
29	L Insula	Anterior/Posterior Midline
30	R Insula	Anterior/Posterior Midline
31	L Anterior Cingulate Gyrus	Anterior/Posterior Midline
32	R Anterior Cingulate Gyrus	Anterior/Posterior Midline
35	L Posterior Cingulate Gyrus	Anterior/Posterior Midline
81	L Superior Temporal Gyrus	Anterior/Posterior

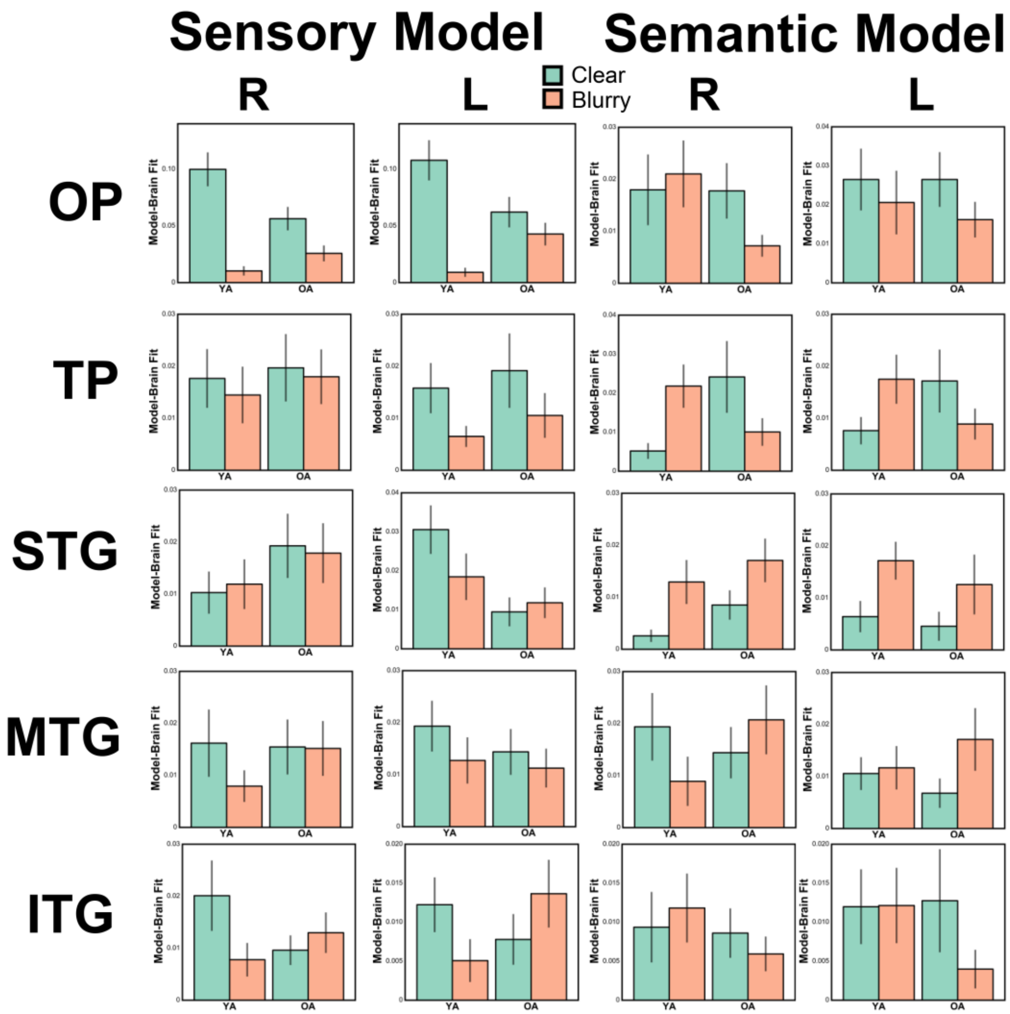
		Midline
82	R Superior Temporal Gyrus	Anterior/Posterior Midline
1	L Precentral Gyrus	Frontoparietal
2	R Precentral Gyrus	Frontoparietal
19	L Supplementary Motor Area	Frontoparietal
20	R Supplementary Motor Area	Frontoparietal
33	L Midcingulate Area	Frontoparietal
34	R Midcingulate Area	Frontoparietal
57	L Postcentral Gyrus	Frontoparietal
58	R Postcentral Gyrus	Frontoparietal
59	L Superior Parietal Lobule	Frontoparietal
60	R Superior Parietal Lobule	Frontoparietal
61	L Inferior Parietal Lobule	Frontoparietal
62	R Inferior Parietal Lobule	Frontoparietal
63	L Supramarginal Gyrus	Frontoparietal
64	R Supramarginal Gyrus	Frontoparietal
66	R Angular Gyrus	Frontoparietal
67	L Precuneus	Frontoparietal
68	R Precuneus	Frontoparietal

Appendix F



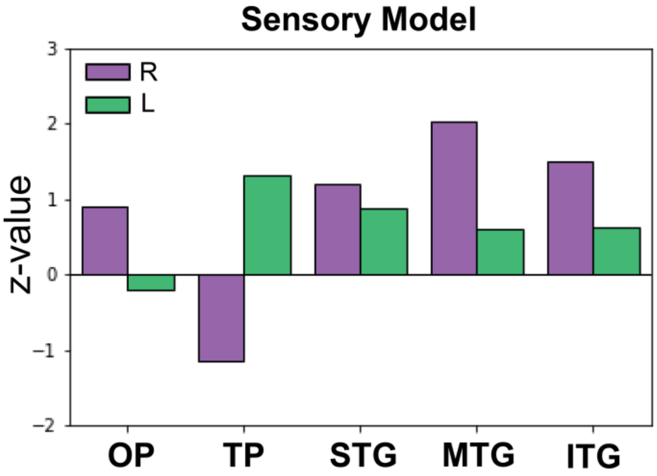
The Effect of Degradation on Representations. The figure shows the representational similarity analysis results related to the main effect of stimulus type for all ROIs. ROIs = regions of interest; R = right; L= left; OP = occipital pole; TP = temporal pole; STG = anterior-superior temporal gyrus; MTG = anterior-middle temporal gyrus; ITG = anterior-inferior temporal gyrus.

Appendix G



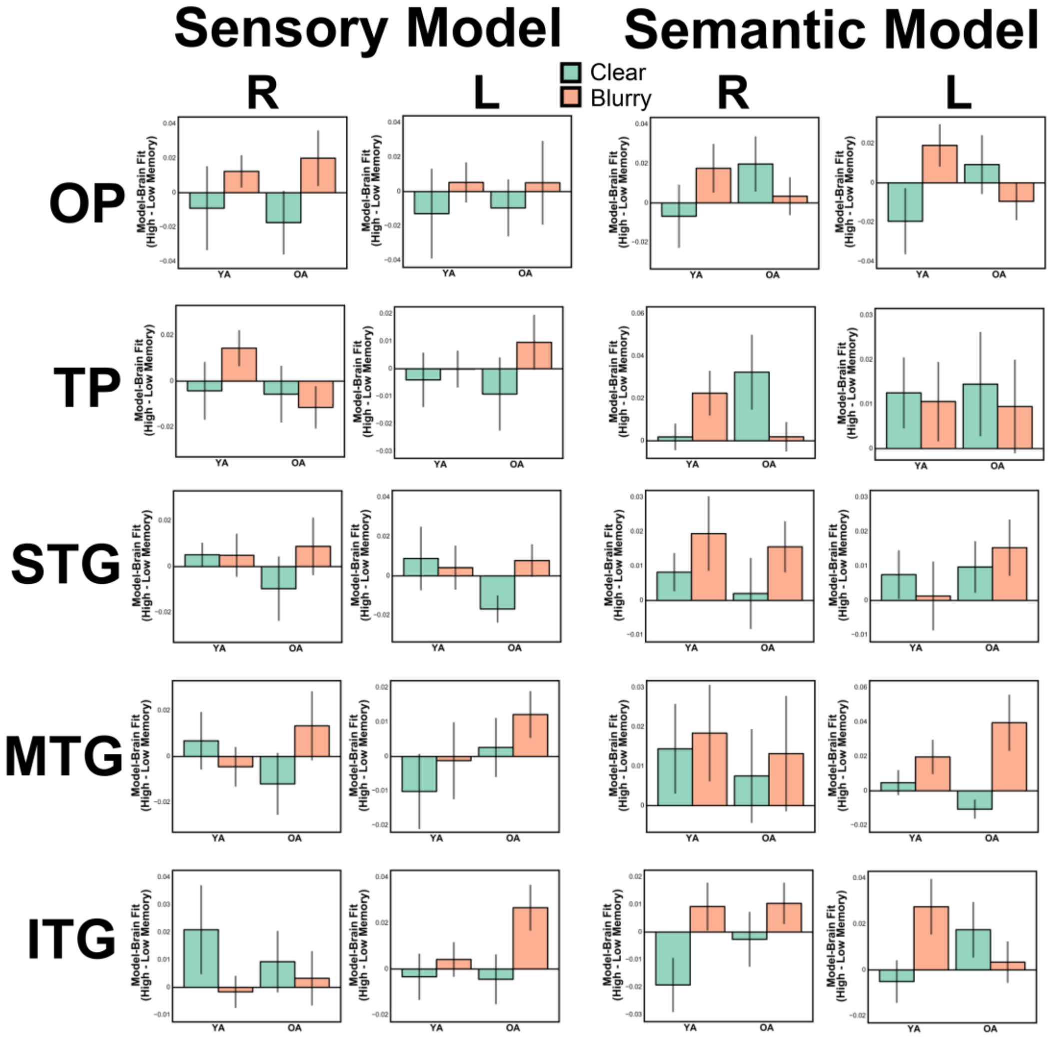
Age-Related Differences in the Effect of Degradation on Representations. The figure shows the representational similarity analysis results related to the age group x stimulus type interaction for all ROIs. ROIs = regions of interest; R = right; L= left; OP = occipital pole; TP = temporal pole; STG = anterior-superior temporal gyrus; MTG = anterior-middle temporal gyrus; ITG = anterior-inferior temporal gyrus; YA = younger adult; OA = older adult.

Appendix H



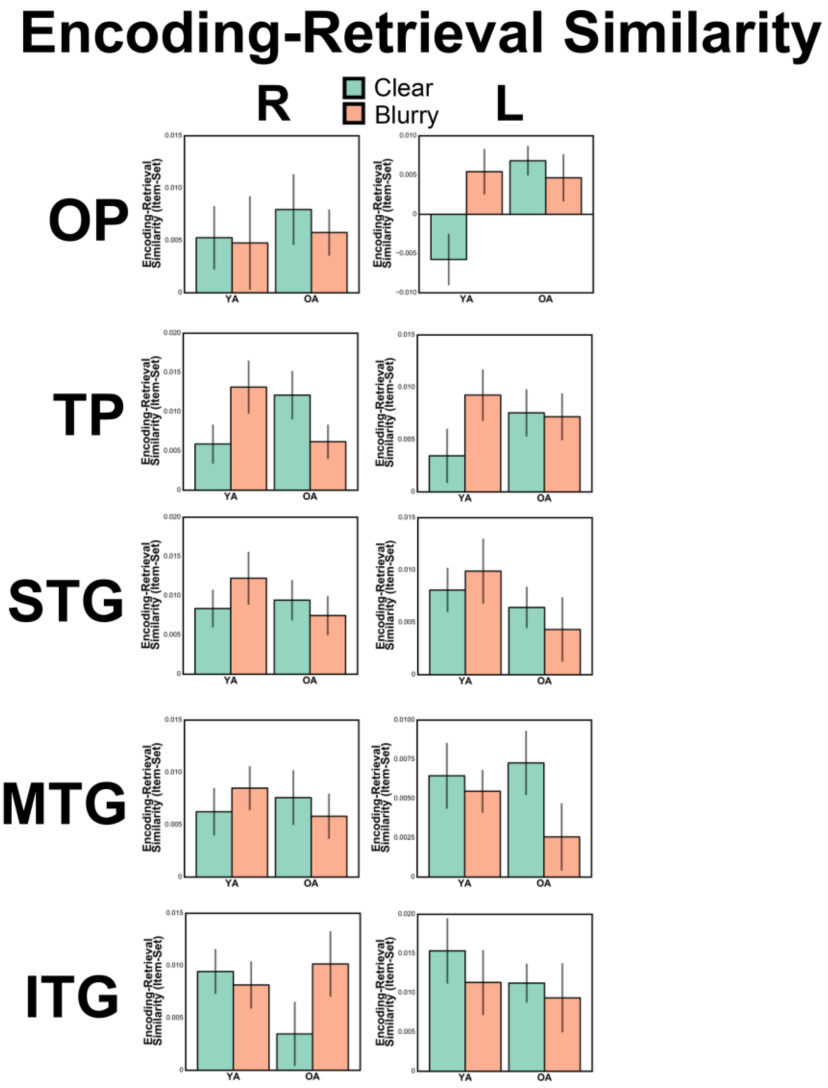
Age-Related Differences in the Effect of Degradation on Sensory-Mnemonic Representations. The figure shows the sensory model-brain fit results related to the age group x stimulus type x memory vividness interaction. R = right; L= left; OP = occipital pole; TP = temporal pole; STG = anterior-superior temporal gyrus; MTG = anterior-middle temporal gyrus; ITG = anterior-inferior temporal gyrus.

Appendix I



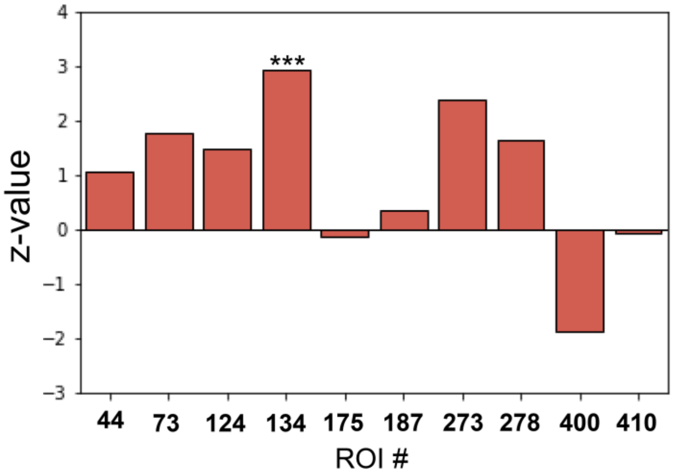
Age-Related Differences in the Effect of Degradation on Mnemonic Representations. The figure shows the representational similarity analysis results related to the age group x stimulus type x memory vividness interaction for all ROIs. ROIs = regions of interest; R = right; L= left; OP = occipital pole; TP = temporal pole; STG = anterior-superior temporal gyrus; MTG = anterior-middle temporal gyrus; ITG = anterior-inferior temporal gyrus; YA = younger adult; OA = older adult.

Appendix J



Age-Related Differences in the Effect of Degradation on Memory Reactivation. The figure shows the ERS results related to the age group x stimulus type interaction for all ROIs. ERS = encoding-retrieval similarity; ROIs = regions of interest; R = right; L= left; OP = occipital pole; TP = temporal pole; STG = anterior-superior temporal gyrus; MTG = anterior-middle temporal gyrus; ITG = anterior-inferior temporal gyrus; YA = younger adult; OA = older adult.

Appendix K



Age-Related Differences in the Effect of Degradation on Memory Reactivation in Right Temporal Pole. The figure shows the ERS results related to the age group x stimulus type interaction for all ROIs in subsections of the right temporal pole derived from the subparcellated HOA (Fornito et al., 2010; Tzourio-Mazoyer et al., 2002). ERS = encoding-retrieval similarity; ROIs = regions of interest; HOA = Harvard-Oxford Atlas.

References

Abdulrahman, H., Fletcher, P. C., Bullmore, E., & Morcom, A. M. (2017). Dopamine and memory dedifferentiation in aging. *NeuroImage, 153*, 211-220. doi:10.1016/j.neuroimage.2015.03.031

Aguirre, G. K., Zarahn, E., & D'Esposito, M. (1998). An area within human ventral cortex sensitive to "building" stimuli: evidence and implications. *Neuron, 21*(2), 373-383.

Aldwin, C. (1990). The elder's life stress inventory: egocentric and non-egocentric stress. In S. E. H. Stephens, J. H. Crowther, & D. L. Tennenbaum (Eds.), *Stress and coping in late life families* (pp. 49-69). New York: Hemisphere.

Alvarez, P., & Squire, L. R. (1994). Memory consolidation and the medial temporal lobe: a simple network model. *Proc Natl Acad Sci U S A, 91*(15), 7041-7045.

Alwin, D. F., & McCammon, R. J. (1999). Aging versus cohort interpretations of intercohort differences in GSS vocabulary scores. *Am Sociol Rev, 64*(2), 272-286. doi:10.2307/2657532

Alwin, D. F., & McCammon, R. J. (2001). Aging, cohorts, and verbal ability. *J Gerontol B Psychol Sci Soc Sci, 56*(3), S151-S161. doi:10.1093/geronb/56.3.s151

Amer, T., Giovanello, K. S., Nichol, D. R., Hasher, L., & Grady, C. L. (2019). Neural correlates of enhanced memory for meaningful associations with age. *Cereb Cortex*. doi:10.1093/cercor/bhy334

Anstey, K. J., Butterworth, P., Borzycki, M., & Andrews, S. (2006). Between-and within-individual effects of visual contrast sensitivity on perceptual matching, processing speed, and associative memory in older adults. *Gerontology, 52*(2), 124-130.

Anzellotti, S., & Coutanche, M. N. (2018). Beyond functional connectivity: investigating networks of multivariate representations. *Trends Cogn Sci, 22*(3), 258-269. doi:10.1016/j.tics.2017.12.002

Ashburner, J. (2007). A fast diffeomorphic image registration algorithm. *NeuroImage, 38*(1), 95-113. doi:10.1016/j.neuroimage.2007.07.007

Babcock, R. L., Laguna, K. D., & Roesch, S. C. (1997). A comparison of the factor structure of processing speed for younger and older adults: testing the assumption of measurement equivalence across age groups. *Psychol Aging, 12*(2), 268-276.

Bäckman, L., Small, B. J., & Fratiglioni, L. (2001). Stability of the preclinical episodic memory deficit in Alzheimer's disease. *Brain, 124*(1), 96-102. doi:10.1093/brain/124.1.96

Badre, D., & Wagner, A. D. (2002). Semantic retrieval, mnemonic control, and prefrontal cortex. *Behav Cogn Neurosci Rev, 1*(3), 206-218. doi:10.1177/1534582302001003002

Bahrick, H. P., & Hall, L. K. (1991). Lifetime maintenance of high school mathematics content. *J Exp Psychol Gen, 120*(1), 20-33. doi:10.1037/0096-3445.120.1.20

Balota, D. A., Dolan, P. O., & Duchek, J. M. (2000). Memory changes in healthy older adults. In E. Tulving & F. I. M. Craik (Eds.), *The Oxford handbook of memory* (pp. 395-409). New York, NY: Oxford University Press.

Baltes, P. B., & Lindenberger, U. (1997a). Emergence of a powerful connection between sensory and cognitive functions across the adult life span: A new window to the study of cognitive aging? *Psychology and Aging, 12*(1), 12. doi:10.1037/0882-7974.12.1.12

Baltes, P. B., & Lindenberger, U. (1997b). Emergence of a powerful connection between sensory and cognitive functions across the adult life span: a new window to the study of cognitive aging? *Psychol Aging, 12*(1), 12-21.

Baltes, P. B., & Lindenberger, U. (1997). Emergence of a powerful connection between sensory and cognitive functions across the adult life span: A new window to the study of cognitive aging? *Psychology and Aging, 12*, 12-21.

Bankson, B. B., Hebart, M. N., Groen, I. I. A., & Baker, C. I. (2018). The temporal evolution of conceptual object representations revealed through models of behavior, semantics and deep neural networks. *NeuroImage, 178*, 172-182. doi:10.1016/j.neuroimage.2018.05.037

Beck, A. T. (1978). *The Beck Depression Inventory*. New York: Psychological Corporation.

Ben-David, B. M., & Schneider, B. A. (2010). A sensory origin for color-word Stroop effects in aging: Simulating age-related changes in color-vision mimics age-related changes in Stroop. *Aging, Neuropsychology, and Cognition, 17*(6), 730-746.

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *J R Stat Soc Series B Stat Methodol, 57*(1), 289-300.

Blondel, V. D., Guillaume, J. L., Hendrickx, J. M., de Kerchove, C., & Lambiotte, R. (2008). Local leaders in random networks. *Phys Rev E Stat Nonlin Soft Matter Phys, 77*(3 Pt 2), 036114. doi:10.1103/PhysRevE.77.036114

Bowman, C. R., Chamberlain, J. D., & Dennis, N. A. (2019). Sensory representations supporting memory specificity: age effects on behavioral and neural discriminability. *J Neurosci, 39*(12), 2265-2275. doi:10.1523/jneurosci.2022-18.2019

Bruffaerts, R., Tyler, L. K., Shafto, M., Tsvetanov, K. A., & Clarke, A. (2019). Perceptual and conceptual processing of visual objects across the adult lifespan. *Sci Rep, 9*(1), 13771. doi:10.1038/s41598-019-50254-5

Buckner, R. L., Andrews-Hanna, J. R., & Schacter, D. L. (2008). The brain's default network: anatomy, function, and relevance to disease. *Ann N Y Acad Sci, 1124*, 1-38.

Buckner, R. L., Snyder, A. Z., Sanders, A. L., Raichle, M. E., & Morris, J. C. (2000). Functional brain imaging of young, nondemented, and demented older adults. *Journal of Cognitive Neuroscience, 12*(Suppl. 2), 24-34. doi:10.1162/089892900564046

Buckner, R. L., & Wheeler, M. E. (2001). The cognitive neuroscience of remembering. *Nat Rev Neurosci, 2*(9), 624-634.

Bussey, T. J., Saksida, L. M., & Murray, E. A. (2005). The perceptual-mnemonic/feature conjunction model of perirhinal cortex function. *Q J Exp Psychol B, 58*(3-4), 269-282. doi:10.1080/02724990544000004

Cabeza, R., Albert, M., Belleville, S., Craik, F. I. M., Duarte, A., Grady, C. L., . . . Rajah, M. N. (2018). Maintenance, reserve and compensation: the cognitive neuroscience of healthy ageing. *Nat Rev Neurosci, 19*(11), 701-710. doi:10.1038/s41583-018-0068-2

Cabeza, R., Daselaar, S. M., Dolcos, F., Prince, S., Budde, M., & Nyberg, L. (2004). Age-related changes in brain activity during working memory, attention, and episodic memory: Task-independent vs. task-specific effects. *Cereb Cortex, 14*, 365-375.

Cabeza, R., & Dennis, N. A. (2012). Frontal lobes and aging: Deterioration and compensation. In D. T. Stuss & R. T. Knight (Eds.), *Principles of Frontal Lobe*

Function, Second Edition (pp. 628-652). New York, New York, United States: Oxford University Press.

Cabeza, R., & Dennis, N. A. (2013). Frontal lobes and aging: Deterioration and Compensation. In D. T. Stuss & R. T. Knight (Eds.), *Principles of frontal lobe function* (Second ed.). New York: Oxford University Press.

Cabeza, R., Nyberg, L., & Park, D. C. (2016). *Cognitive neuroscience of aging: Linking cognitive and cerebral aging*. Oxford, United Kingdom: Oxford University Press.

Cadieu, C. F., Hong, H., Yamins, D. L., Pinto, N., Ardila, D., Solomon, E. A., . . . DiCarlo, J. J. (2014). Deep neural networks rival the representation of primate IT cortex for core visual object recognition. *PLoS Comput Biol, 10*(12), e1003963. doi:10.1371/journal.pcbi.1003963

Carp, J., Park, J., Polk, T. A., & Park, D. C. (2011). Age differences in neural distinctiveness revealed by multi-voxel pattern analysis. *NeuroImage, 56*(2), 736-743. doi:10.1016/j.neuroimage.2010.04.267

Castel, A. D. (2005). Memory for grocery prices in younger and older adults: the role of schematic support. *Psychol Aging, 20*(4), 718-721. doi:10.1037/0882-7974.20.4.718

Chan, M. Y., Park, D. C., Savalia, N. K., Petersen, S. E., & Wig, G. S. (2014). Decreased segregation of brain systems across the healthy adult lifespan. *Proc Natl Acad Sci U S A, 111*(46), E4997-5006. doi:10.1073/pnas.1415122111

Chee, M. W. L., Goh, J. O. S., Venkatraman, V., Tan, J. C., Gutchess, A., Sutton, B., . . . Park, D. (2006). Age-related changes in object processing and contextual binding revealed using fMR adaptation. *J Cogn Neurosci, 18*(4), 495-507. doi:10.1162/jocn.2006.18.4.495

Chen, J., Myerson, J., & Hale, S. (2002). Age-related dedifferentiation of visuospatial abilities. *Neuropsychologia, 40*(12), 2050-2056.

Cherry, K. E., Silva Brown, J., Jackson Walker, E., Smitherman, E. A., Boudreaux, E. O., Volaufova, J., & Michal Jazwinski, S. (2012). Semantic encoding enhances the pictorial superiority effect in the oldest-old. *Neuropsychol Dev Cogn B Aging Neuropsychol Cogn, 19*(1-2), 319-337. doi:10.1080/13825585.2011.619645

Cichy, R. M., Khosla, A., Pantazis, D., Torralba, A., & Oliva, A. (2016). Comparison of deep neural networks to spatio-temporal cortical dynamics of human visual object recognition reveals hierarchical correspondence. *Sci Rep, 6*, 27755. doi:10.1038/srep27755

Clarke, A., Devereux, B. J., & Tyler, L. K. (2018). Oscillatory dynamics of perceptual to conceptual transformations in the ventral visual pathway. *J Cogn Neurosci, 30*(11), 1590-1605. doi:10.1162/jocn_a_01325

Clarke, A., Pell, P. J., Ranganath, C., & Tyler, L. K. (2016). Learning warps object representations in the ventral temporal cortex. *J Cogn Neurosci, 28*(7), 1010-1023. doi:10.1162/jocn_a_00951

Clarke, A., & Tyler, L. K. (2014). Object-specific semantic coding in human perirhinal cortex. *J Neurosci, 34*(14), 4766-4775. doi:10.1523/jneurosci.2828-13.2014

Cohen-Shikora, E. R., Diede, N. T., & Bugg, J. M. (2018). The flexibility of cognitive control: age equivalence with experience guiding the way. *Psychol Aging, 33*(6), 924-939. doi:10.1037/pag0000280

Cohen, J. R., & D'Esposito, M. (2016). The segregation and integration of distinct brain networks and their relationship to cognition. *J Neurosci, 36*(48), 12083-12094. doi:10.1523/jneurosci.2965-15.2016

Cole, M. W., Reynolds, J. R., Power, J. D., Repovs, G., Anticevic, A., & Braver, T. S. (2013). Multi-task connectivity reveals flexible hubs for adaptive task control. *Nat Neurosci, 16*(9), 1348-1355. doi:10.1038/nn.3470

Colonia-Willner, R. (1998). Practical intelligence at work: relationship between aging and cognitive efficiency among managers in a bank environment. *Psychol Aging, 13*(1), 45-57. doi:10.1037//0882-7974.13.1.45

Cornelius, S. W., & Caspi, A. (1987). Everyday problem solving in adulthood and old age. *Psychol Aging, 2*(2), 144-153. doi:10.1037//0882-7974.2.2.144

Coutanche, M. N., & Thompson-Schill, S. L. (2013). Informational connectivity: identifying synchronized discriminability of multi-voxel patterns across the brain. *Front Hum Neurosci, 7*, 15. doi:10.3389/fnhum.2013.00015

Craik, F. I. M. (1986). A functional account of age differences in memory. In F. Klix & H. Hagendorf (Eds.), *Human memory and cognitive capabilities* (pp. 181-211). New York: Elsevier Science Publishers.

Cronin-Golomb, A., Gilmore, G. C., Neargarder, S., Morrison, S. R., & Laudate, T. M. (2007). Enhanced stimulus strength improves visual cognition in aging and Alzheimer's disease. *Cortex, 43*(7), 952-966. doi:10.1016/S0010-9452(08)70693-2

Dagli, M. S., Ingeholm, J. E., & Haxby, J. V. (1999). Localization of cardiac-induced signal change in fMRI. *Neuroimage, 9*(4), 407-415. doi:10.1006/nimg.1998.0424

Danker, J. F., & Anderson, J. R. (2010). The Ghosts of Brain States Past: Remembering Reactivates the Brain Regions Engaged During Encoding. *Psychological Bulletin, 136*(1), 87-102. doi:10.1037/a0017937

Davis, S. W., Dennis, N. A., Daselaar, S. M., Fleck, M. S., & Cabeza, R. (2008). Qué PASA? The posterior–anterior shift in aging. *Cerebral Cortex, 18*(5), 1201-1209. doi:10.1093/cercor/bhm155

Davis, S. W., Geib, B. R., Wing, E. A., Wang, W.-C., Hovhannisyan, M., Monge, Z. A., & Cabeza, R. (2020). Visual and semantic representations predict subsequent memory in perceptual and conceptual memory tests. *bioRxiv*, 2020.2002.2011.944801. doi:10.1101/2020.02.11.944801

Davis, S. W., Kragel, J. E., Madden, D. J., & Cabeza, R. (2012). The architecture of cross-hemispheric communication in the aging brain: linking behavior to functional and structural connectivity. *Cereb Cortex, 22*(1), 232-242. doi:10.1093/cercor/bhr12

Davis, S. W., Luber, B., Murphy, D. L., Lisanby, S. H., & Cabeza, R. (2017). Frequency-specific neuromodulation of local and distant connectivity in aging & episodic memory function. *Hum Brain Mapp, 38*(12), 5987–6004.

Davis, S. W., Szymanski, A., Boms, H., Fink, T., & Cabeza, R. (2019). Cooperative contributions of structural and functional connectivity to successful memory in aging. *Network Neuroscience, 3*(1), 173-194. doi:10.1162/netn_a_00064

Dennis, N. A., Overman, A. A., Gerver, C. R., McGraw, K. E., Rowley, M. A., & Salerno, J. M. (2019). Different types of associative encoding evoke differential processing in both younger and older adults: Evidence from univariate and multivariate analyses. *Neuropsychologia*, 107240. doi:10.1016/j.neuropsychologia.2019.107240

Devereux, B. J., Clarke, A. D., & Tyler, L. K. (2018). Integrated deep visual and semantic attractor neural networks predict fMRI pattern-information along the ventral object processing pathway. *Sci Rep, 8*(1), 10636. doi:10.1101/302406

Devereux, B. J., Tyler, L. K., Geertzen, J., & Randall, B. (2014). The Centre for Speech, Language and the Brain (CSLB) concept property norms. *Behav Res Methods, 46*(4), 1119-1127. doi:10.3758/s13428-013-0420-4

Devlin, J. T., Russell, R. P., Davis, M. H., Price, C. J., Wilson, J., Moss, H. E., . . . Tyler, L. K. (2000). Susceptibility-induced loss of signal: comparing PET and fMRI on a semantic task. *NeuroImage, 11*(6 Pt 1), 589-600. doi:10.1006/nimg.2000.0595

Dew, I. T., Ritchey, M., LaBar, K. S., & Cabeza, R. (2014). Prior perceptual processing enhances the effect of emotional arousal on the neural correlates of memory retrieval. *Neurobiol Learn Mem, 112*, 104-113. doi:10.1016/j.nlm.2013.12.012

Diana, R. A., Yonelinas, A. P., & Ranganath, C. (2007). Imaging recollection and familiarity in the medial temporal lobe: a three-component model. *Trends Cogn Sci, 11*(9), 379-386. doi:10.1016/j.tics.2007.08.001

Dickinson, C., & Rabbitt, P. (1991). Simulated visual impairment: Effects on text comprehension and reading speed. *Clinical Vision Sciences, 6*(4), 301-308.

Dimsdale-Zucker, H. R., & Ranganath, C. (2018). Representational similarity analyses: A practical guide for functional MRI applications *Handbook of Behavioral Neuroscience* (Vol. 28, pp. 509-525): Elsevier.

Dubois, B., Feldman, H. H., Jacova, C., Dekosky, S. T., Barberger-Gateau, P., Cummings, J., . . . Scheltens, P. (2007). Research criteria for the diagnosis of Alzheimer's disease: revising the NINCDS-ADRDA criteria. *Lancet Neurol, 6*(8), 734-746. doi:10.1016/s1474-4422(07)70178-3

Duchek, J. M., Balota, D. A., & Thessing, V. C. (1998). Inhibition of visual and conceptual information during reading in healthy aging and Alzheimer's disease. *Neuropsychol Dev Cogn B Aging Neuropsychol Cogn, 5*(3), 169-181. doi:10.1076/anec.5.3.169.616

Duncan, J. (2010). The multiple-demand (MD) system of the primate brain: mental programs for intelligent behaviour. *Trends Cogn Sci, 14*(4), 172-179. doi:10.1016/j.tics.2010.01.004

Epstein, R., & Kanwisher, N. (1998). A cortical representation of the local visual environment. *Nature, 392*(6676), 598-601. doi:10.1038/33402

Evans, D. W., & Ginsburg, A. P. (1985). Contrast sensitivity predicts age-related differences in highway-sign discriminability. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 27*(6), 637-642.

Faust, M. E., Balota, D. A., Spieler, D. H., & Ferraro, F. R. (1999). Individual differences in information-processing rate and amount: Implications for group differences in response latency. *Psychological Bulletin, 125*(6), 777-799.

Fedorenko, E., Duncan, J., & Kanwisher, N. (2013). Broad domain generality in focal regions of frontal and parietal cortex. *Proc Natl Acad Sci U S A, 110*(41), 16616-16621. doi:10.1073/pnas.1315235110

Folstein, M. F., Folstein, S. E., & McHugh, P. R. (1975). "Mini-mental state". A practical method for grading the cognitive state of patients for the clinician. *J Psychiatr Res, 12*(3), 189-198.

Fornito, A., Zalesky, A., & Bullmore, E. T. (2010). Network scaling effects in graph analytic studies of human resting-state FMRI data. *Front Syst Neurosci, 4*, 22. doi:10.3389/fnsys.2010.00022

Friedman, D., Nessler, D., & Johnson, R., Jr. (2007). Memory encoding and retrieval in the aging brain. *Clin EEG Neurosci, 38*(1), 2-7. doi:10.1177/155005940703800105

Froger, C., Taconnat, L., Landre, L., Beigneux, K., & Isingrini, M. (2009). Effects of level of processing at encoding and types of retrieval task in mild cognitive impairment and normal aging. *J Clin Exp Neuropsychol, 31*(3), 312-321. doi:10.1080/13803390802112554

Gallen, C. L., Turner, G. R., Adnan, A., & D'Esposito, M. (2016). Reconfiguration of brain network architecture to support executive control in aging. *Neurobiol Aging, 44*, 42-52. doi:10.1016/j.neurobiolaging.2016.04.003

Gardini, S., Cuetos, F., Fasano, F., Ferrari Pellegrini, F., Marchi, M., Venneri, A., & Caffarra, P. (2013). Brain structural substrates of semantic memory decline in mild cognitive impairment. *Curr Alzheimer Res, 10*(4), 373-389.

Gardini, S., Venneri, A., Sambataro, F., Cuetos, F., Fasano, F., Marchi, M., . . . Caffarra, P. (2015). Increased functional connectivity in the default mode network in mild cognitive impairment: a maladaptive compensatory mechanism associated with poor semantic memory performance. *Journal of Alzheimer's Disease, 45*(2), 457-470.

Geerligs, L., Renken, R. J., Saliasi, E., Maurits, N. M., & Lorist, M. M. (2015). A brain-wide study of age-related changes in functional connectivity. *Cereb Cortex, 25*(7), 1987-1999. doi:10.1093/cercor/bhu012

Geib, B. R., Stanley, M. L., Dennis, N. A., Woldorff, M. G., & Cabeza, R. (2017). From hippocampus to whole-brain: the role of integrative processing in episodic memory retrieval. *Hum Brain Mapp, 38*(4), 2242-2259. doi:10.1002/hbm.23518

Geib, B. R., Stanley, M. L., Wing, E. A., Laurienti, P. J., & Cabeza, R. (2017). Hippocampal contributions to the large-scale episodic memory network predict vivid visual memories. *Cereb Cortex, 27*(1), 680-693. doi:10.1093/cercor/bhv272

Gilmore, G. C., Spinks, R. A., & Thomas, C. W. (2006). Age effects in coding tasks: Componential analysis and test of the sensory deficit hypothesis. *Psychology and Aging, 21*(1), 7-18. doi:10.1037/0882-7974.21.1.7

Gilmore, G. C., Spinks, R. A., & Thomas, C. W. (2006). Age effects in coding tasks: Componential analysis and test of the sensory deficit hypothesis. *Psychology and Aging, 21*(1), 7.

Goh, J. O., Suzuki, A., & Park, D. C. (2010). Reduced neural selectivity increases fMRI adaptation with age during face discrimination. *NeuroImage, 51*(1), 336-344. doi:10.1016/j.neuroimage.2010.01.107

Grady, C. (2012a). The cognitive neuroscience of ageing. *Nature Reviews Neuroscience, 13*(7), 491-505. doi:10.1038/nrn3256

Grady, C. (2012b). The cognitive neuroscience of ageing. *Nat Rev Neurosci, 13*(7), 491-505. doi:10.1038/nrn3256

Grady, C. L. (2008). Cognitive neuroscience of aging. *Annals of the New York Academy of Sciences, 1125*(1), 127-144. doi:10.1196/annals.1440.009

Grady, C. L. (2012). The cognitive neuroscience of ageing. *Nat Rev Neurosci, 13*(7), 491-505. doi:10.1038/nrn3256

Grady, C. L., Maisog, J. M., Horwitz, B., Ungerleider, L. G., Mentis, M. J., Salerno, J. A., . . . Haxby, J. V. (1994). Age-related changes in cortical blood flow activation during visual processing of faces and location. *Journal of Neuroscience, 14*(3, Pt 2), 1450-1462.

Grady, C. L., McIntosh, A. R., Horwitz, B., & Rapoport, S. I. (2000). Age-related changes in the neural correlates of degraded and nondegraded face processing. *Cogn Neuropsychol, 17*(1), 165-186. doi:10.1080/026432900380553

Grady, C. L., Sarraf, S., Saverino, C., & Campbell, K. (2016). Age differences in the functional interactions among the default, frontoparietal control, and dorsal attention networks. *Neurobiol Aging, 41*, 159-172. doi:10.1016/j.neurobiolaging.2016.02.020

Greene, H. A., & Madden, D. J. (1987a). Adult age differences in visual acuity, stereopsis, and contrast sensitivity. *Am J Optom Physiol Opt, 64*(10), 749-753.

Greene, H. A., & Madden, D. J. (1987b). Adult age differences in visual acuity, stereopsis, and contrast sensitivity. *Optometry & Vision Science, 64*(10), 749-753.

Groen, II, Greene, M. R., Baldassano, C., Fei-Fei, L., Beck, D. M., & Baker, C. I. (2018a). Distinct contributions of functional and deep neural network features to representational similarity of scenes in human brain and behavior. *Elife, 7*. doi:10.7554/eLife.32962

Groen, II, Greene, M. R., Baldassano, C., Fei-Fei, L., Beck, D. M., & Baker, C. I. (2018b). Distinct contributions of functional and deep neural network features to representational similarity of scenes in human brain and behavior. *Elife, 7*, e32962. doi:10.7554/eLife.32962

Güçlü, U., & van Gerven, M. A. J. (2015). Deep neural networks reveal a gradient in the complexity of neural representations across the ventral stream. *J Neurosci, 35*(27), 10005-10014. doi:10.1523/jneurosci.5023-14.2015

Haller, S., Badoud, S., Nguyen, D., Barnaure, I., Montandon, M. L., Lovblad, K. O., & Burkhard, P. R. (2013). Differentiation between Parkinson disease and other forms of Parkinsonism using support vector machine analysis of susceptibility-weighted imaging (SWI): initial results. *Eur Radiol, 23*(1), 12-19. doi:10.1007/s00330-012-2579-y

Hanke, M., Halchenko, Y. O., Sederberg, P. B., Hanson, S. J., Haxby, J. V., & Pollmann, S. (2009). PyMVPA: A python toolbox for multivariate pattern analysis of fMRI data. *Neuroinformatics, 7*(1), 37-53. doi:10.1007/s12021-008-9041-y

Hardy, D. J., & Parasuraman, R. (1997). Cognition and flight performance in older pilots. *J Exp Psychol Appl, 3*(4), 313-348. doi:10.1037/1076-898X.3.4.313

Haxby, J. V., Connolly, A. C., & Guntupalli, J. S. (2014). Decoding neural representational spaces using multivariate pattern analysis. *Annu Rev Neurosci, 37*, 435-456. doi:10.1146/annurev-neuro-062012-170325

Herculano-Houzel, S. (2009). The human brain in numbers: a linearly scaled-up primate brain. *Front Hum Neurosci, 3*, 31. doi:10.3389/neuro.09.031.2009

Hirni, D. I., Kivisaari, S. L., Monsch, A. U., & Taylor, K. I. (2013). Distinct neuroanatomical bases of episodic and semantic memory performance in Alzheimer's disease. *Neuropsychologia, 51*(5), 930-937. doi:10.1016/j.neuropsychologia.2013.01.013

Hodges, J. R., Patterson, K., Oxbury, S., & Funnell, E. (1992). Semantic dementia. Progressive fluent aphasia with temporal lobe atrophy. *Brain, 115 (Pt 6)*, 1783-1806.

Hoffman, P. (2019). Divergent effects of healthy ageing on semantic knowledge and control: Evidence from novel comparisons with semantically impaired patients. *J Neuropsychol, 13*(3), 462-484. doi:10.1111/jnp.12159

Hoffman, P., Jefferies, E., & Lambon Ralph, M. A. (2010). Ventrolateral prefrontal cortex plays an executive regulation role in comprehension of abstract words: convergent neuropsychological and repetitive TMS evidence. *J Neurosci, 30*(46), 15450-15456. doi:10.1523/jneurosci.3783-10.2010

Hoffman, P., & Morcom, A. M. (2018). Age-related changes in the neural networks supporting semantic cognition: A meta-analysis of 47 functional neuroimaging studies. *Neurosci Biobehav Rev, 84*, 134-150. doi:10.1016/j.neubiorev.2017.11.010

Houston, J. R., Bennett, I. J., Allen, P. A., & Madden, D. J. (2016). Visual acuity does not moderate effect sizes of higher-level cognitive tasks. *Experimental Aging Research, 42*(3), 221-263. doi:10.1080/0361073X.2016.1156964

Hudon, C., Villeneuve, S., & Belleville, S. (2011). The effect of semantic orientation at encoding on free-recall performance in amnestic mild cognitive impairment and probable Alzheimer's disease. *J Clin Exp Neuropsychol, 33*(6), 631-638. doi:10.1080/13803395.2010.547663

Huettel, S. A., Singerman, J. D., & McCarthy, G. (2001). The effects of aging upon the hemodynamic response measured by functional MRI. *NeuroImage, 13*(1), 161-175. doi:10.1006/nimg.2000.0675

Huth, A. G., de Heer, W. A., Griffiths, T. L., Theunissen, F. E., & Gallant, J. L. (2016). Natural speech reveals the semantic maps that tile human cerebral cortex. *Nature, 532*(7600), 453-458. doi:10.1038/nature17637

Jackson, G. R., & Owsley, C. (2003a). Visual dysfunction, neurodegenerative diseases, and aging. *Neurologic Clinics of North America, 21*(3), 709-728. doi:10.1016/S0733-8619(02)00107-X

Jackson, G. R., & Owsley, C. (2003b). Visual dysfunction, neurodegenerative diseases, and aging. *Neurol Clin, 21*(3), 709-728.

Jacoby, L. L., Hessels, S., & Bopp, K. (2001). Proactive and retroactive effects in memory performance: Dissociating recollection and accessibility bias *The nature of remembering: Essays in honor of Robert G. Crowder.* (pp. 35-54). Washington, DC, US: American Psychological Association.

Johnson, M. K., Kuhl, B. A., Mitchell, K. J., Ankudowich, E., & Durbin, K. A. (2015). Age-related differences in the neural basis of the subjective vividness of memories: evidence from multivoxel pattern classification. *Cogn Affect Behav Neurosci, 15*(3), 644-661. doi:10.3758/s13415-015-0352-9

Jung-Beeman, M. (2005). Bilateral brain processes for comprehending natural language. *Trends Cogn Sci, 9*(11), 512-518. doi:10.1016/j.tics.2005.09.009

Kanwisher, N., McDermott, J., & Chun, M. M. (1997). The fusiform face area: a module in human extrastriate cortex specialized for face perception. *J Neurosci, 17*(11), 4302-4311.

Kausler, D. H. (1994). *Learning and memory in normal aging.* San Diego, CA: Academic Press.

Kausler, D. H., & Lair, C. V. (1966). Associative strength and paired-associate learning in elderly subjects. *J Gerontol, 21*(2), 278-280. doi:10.1093/geronj/21.2.278

Kennedy, K. M., Boylan, M. A., Rieck, J. R., Foster, C. M., & Rodrigue, K. M. (2017). Dynamic range in BOLD modulation: lifespan aging trajectories and association with performance. *Neurobiol Aging, 60*, 153-163. doi:10.1016/j.neurobiolaging.2017.08.027

Khaligh-Razavi, S. M., & Kriegeskorte, N. (2014). Deep supervised, but not unsupervised, models may explain IT cortical representation. *PLoS Comput Biol, 10*(11), e1003915. doi:10.1371/journal.pcbi.1003915

Koen, J. D., & Rugg, M. D. (2016). Memory reactivation predicts resistance to retroactive interference: evidence from multivariate classification and pattern similarity analyses. *J Neurosci, 36*(15), 4389-4399. doi:10.1523/jneurosci.4099-15.2016

Koutstaal, W., Schacter, D. L., Galluccio, L., & Stofer, K. A. (1999). Reducing gist-based false recognition in older adults: encoding and retrieval manipulations. *Psychol Aging, 14*(2), 220-237. doi:10.1037//0882-7974.14.2.220

Kragel, P. A., Carter, R. M., & Huettel, S. A. (2012). What makes a pattern? Matching decoding methods to data in multivariate pattern analysis. *Front Neurosci, 6*, 162. doi:10.3389/fnins.2012.00162

Kragel, P. A., & LaBar, K. S. (2016). Decoding the nature of emotion in the brain. *Trends Cogn Sci, 20*(6), 444-455. doi:10.1016/j.tics.2016.03.011

Kriegeskorte, N. (2015). Deep neural networks: a new framework for modeling biological vision and brain information processing. *Annu Rev Vis Sci, 1*(1), 417-446. doi:10.1146/annurev-vision-082114-035447

Kriegeskorte, N., Cusack, R., & Bandettini, P. (2010). How does an fMRI voxel sample the neuronal activity pattern: compact-kernel or complex spatiotemporal filter? *NeuroImage, 49*(3), 1965-1976. doi:10.1016/j.neuroimage.2009.09.059

Kriegeskorte, N., & Douglas, P. K. (2018). Cognitive computational neuroscience. *Nat Neurosci, 21*(9), 1148-1160. doi:10.1038/s41593-018-0210-5

Kriegeskorte, N., Goebel, R., & Bandettini, P. (2006). Information-based functional brain mapping. *Proc Natl Acad Sci U S A, 103*(10), 3863-3868. doi:10.1073/pnas.0600244103

Kriegeskorte, N., & Kievit, R. A. (2013). Representational geometry: integrating cognition, computation, and the brain. *Trends Cogn Sci, 17*(8), 401-412. doi:10.1016/j.tics.2013.06.007

Kriegeskorte, N., Mur, M., & Bandettini, P. (2008). Representational similarity analysis–connecting the branches of systems neuroscience. *Front Syst Neurosci, 2*, 4. doi:10.3389/neuro.06.004.2008

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012a). *Imagenet classification with deep convolutional neural networks.* Paper presented at the Advances in Neural Information Processing Systems.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012b). *Imagenet classification with deep convolutional neural networks.* Paper presented at the Neural Information Processing Systems Conference.

Ksander, J. C., Paige, L. E., Johndro, H. A., & Gutchess, A. H. (2018). Cultural specialization of visual cortex. *Soc Cogn Affect Neurosci, 13*(7), 709-718. doi:10.1093/scan/nsy039

Kuhl, B. A., Rissman, J., Chun, M. M., & Wagner, A. D. (2011). Fidelity of neural reactivation reveals competition between memories. *Proc Natl Acad Sci U S A, 108*(14), 5903-5908. doi:10.1073/pnas.1016939108

La Fleur, C. G., & Salthouse, T. A. (2014). Out of sight, out of mind? Relations between visual acuity and cognition. *Psychonomic Bulletin & Review, 21*(5), 1202-1208. doi:10.3758/s13423-014-0594-5

Lambon Ralph, M. A., Jefferies, E., Patterson, K., & Rogers, T. T. (2017). The neural and computational bases of semantic cognition. *Nat Rev Neurosci, 18*(1), 42-55.

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (2008). *International affective picture system (IAPS): affective ratings of pictures and instruction manual*. Retrieved from University of Florida, Gainesville, FL:

Laudate, T. M., Neargarder, S., Dunne, T. E., Sullivan, K. D., Joshi, P., Gilmore, G. C., . . . Cronin-Golomb, A. (2012). Bingo! Externally supported performance intervention for deficient visual search in normal aging, Parkinson's disease, and Alzheimer's disease. *Aging, Neuropsychology, and Cognition, 19*, 102-121. doi:10.1080/13825585.2011.621930

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436-444. doi:10.1038/nature14539

Lee, H., Samide, R., Richter, F. R., & Kuhl, B. A. (2019). Decomposing parietal memory reactivation to predict consequences of remembering. *Cereb Cortex, 29*(8), 3305–3318. doi:10.1093/cercor/bhy200

Leeds, D. D., Seibert, D. A., Pyles, J. A., & Tarr, M. J. (2013). Comparing visual representations across human fMRI and computational vision. *J Vis, 13*(13), 25-25. doi:10.1167/13.13.25

Lent, R., Azevedo, F. A., Andrade-Moraes, C. H., & Pinto, A. V. (2012). How many neurons do you have? Some dogmas of quantitative neuroscience under revision. *Eur J Neurosci, 35*(1), 1-9. doi:10.1111/j.1460-9568.2011.07923.x

Levine, B., Svoboda, E., Hay, J. F., Winocur, G., & Moscovitch, M. (2002). Aging and autobiographical memory: dissociating episodic from semantic retrieval. *Psychol Aging, 17*(4), 677-689. doi:10.1037/0882-7974.17.4.677

Li, K. Z., Lindenberger, U., Freund, A. M., & Baltes, P. B. (2001). Walking while memorizing: Age-related differences in compensatory behavior. *Psychological Science, 12*(3), 230-237.

Light, L. L., Prull, M. W., Lavoie, D. J., & Healy, M. R. (2000). Dual-process theories of memory in old age. In T. J. Perfect & E. A. Maylor (Eds.), *Models of Cognitive Aging* (pp. 238-300). Oxford, UK: Oxford University Press.

Lin, M. Y., Gutierrez, P. R., Stone, K. L., Yaffe, K., Ensrud, K. E., Fink, H. A., . . . Mangione, C. M. (2004). Vision impairment and combined vision and hearing impairment predict cognitive and functional decline in older women. *Journal of the American Geriatrics Society, 52*(12), 1996-2002. doi:10.1111/j.1532-5415.2004.52554.x

Lindenberger, U., & Baltes, P. B. (1994a). Sensory functioning and intelligence in old age: A strong connection. *Psychology and Aging, 9*(3), 339.

Lindenberger, U., & Baltes, P. B. (1994b). Sensory functioning and intelligence in old age: a strong connection. *Psychol Aging, 9*(3), 339-355.

Lindenberger, U., & Baltes, P. B. (1994). Sensory functioning and intelligence in old age: A strong connection. *Psychology and Aging, 9*, 339-355.

Lindenberger, U., & Baltes, P. B. (1997). Intellectual functioning in old and very old age: cross-sectional results from the Berlin Aging Study. *Psychol Aging, 12*(3), 410-432.

Lindenberger, U., Marsiske, M., & Baltes, P. B. (2000). Memorizing while walking: increase in dual-task costs from young adulthood to old age. *Psychology and Aging, 15*(3), 417.

Long, L. L., & Shaw, R. J. (2000). Adult age differences in vocabulary acquisition. *Educational Gerontology, 26*(7), 651-664.

Lord, S. R., Clark, R. D., & Webster, I. W. (1991). Visual acuity and contrast sensitivity in relation to falls in an elderly population. *Age Ageing, 20*(3), 175-181. doi:10.1093/ageing/20.3.175

MacKay, D. G., Abrams, L., & Pedroza, M. J. (1999). Aging on the input versus output side: theoretical implications of age-linked asymmetries between detecting versus retrieving orthographic information. *Psychol Aging, 14*(1), 3-17. doi:10.1037//0882-7974.14.1.3

Madden, D. J. (1988). Adult age differences in the effects of sentence context and stimulus degradation during visual word recognition. *Psychol Aging, 3*(2), 167-172. doi:10.1037//0882-7974.3.2.167

Madden, D. J. (2001). Speed and timing of behavioral processes. In J. E. Birren & K. W. Schaie (Eds.), *Handbook of the Psychology of Aging, Fifth Edition* (Vol. 5, pp. 288-312). San Diego, California, United States: Academic Press.

Madden, D. J., Whiting, W. L., & Huettel, S. A. (2005). Age-related changes in neural activity during visual perception and attention. In R. Cabeza, L. Nyberg, & D. C. Park (Eds.), *Cognitive Neuroscience of Aging: Linking Cognitive and Cerebral aging* (pp. 157-185). New York, New York, United States: Oxford University Press.

Mandzia, J. L., McAndrews, M. P., Grady, C. L., Graham, S. J., & Black, S. E. (2009). Neural correlates of incidental memory in mild cognitive impairment: an fMRI study. *Neurobiol Aging, 30*(5), 717-730. doi:10.1016/j.neurobiolaging.2007.08.024

Martin, C. B., Douglas, D., Newsome, R. N., Man, L. L., & Barense, M. D. (2018). Integrative and distinctive coding of visual and conceptual object features in the ventral visual stream. *Elife, 7*. doi:10.7554/eLife.31873

Mayeux, R. (2010). Early Alzheimer's disease. *N Engl J Med, 362*(23), 2194-2201. doi:10.1056/NEJMcp0910236

McDaniel, M. A., Einstein, G. O., & Jacoby, L. L. (2015). New considerations in aging and memory: the glass may be half full. In F. I. M. Craik & T. A. Salthouse (Eds.), *The handbook of aging and cognition* (pp. 251-310). New York, NY: Psychology Press.

McGillivray, S., Murayama, K., & Castel, A. D. (2015). Thirst for knowledge: the effects of curiosity and interest on memory in younger and older adults. *Psychol Aging, 30*(4), 835-841. doi:10.1037/a0039801

McRae, K., Cree, G. S., Seidenberg, M. S., & McNorgan, C. (2005). Semantic feature production norms for a large set of living and nonliving things. *Behav. Res. Methods, 37*(4), 547-559.

McRae, K., Cree, G. S., Seidenberg, M. S., & McNorgan, C. (2005). Semantic feature production norms for a large set of living and nonliving things. *Behav Res Methods, 37*(4), 547-559.

Meilă, M. (2007). Comparing clusterings—an information based distance. *Journal of Multivariate Analysis, 98*(5), 873-895. doi:10.1016/j.jmva.2006.11.013

Miller, E. K., Freedman, D. J., & Wallis, J. D. (2002). The prefrontal cortex: categories, concepts and cognition. *Philos Trans R Soc Lond B Biol Sci, 357*(1424), 1123-1136. doi:10.1098/rstb.2002.1099

Mišić, B., & Sporns, O. (2016). From regions to connections and networks: new bridges between brain and behavior. *Curr Opin Neurobiol, 40*, 1-7. doi:10.1016/j.conb.2016.05.003

Mohanty, P., Naveh-Benjamin, M., & Ratneshwar, S. (2016). Beneficial effects of semantic memory support on older adults' episodic memory: differential patterns of support of item and associative information. *Psychol Aging, 31*(1), 25-36. doi:10.1037/pag0000059

Monge, Z. A., Davis, S. W., Hovhannisyan, M., & Cabeza, R. (in preparation). The impact of visual signal loss on age-related differences in sensory and semantic neural representations.

Monge, Z. A., Geib, B. R., Siciliano, R. E., Packard, L. E., Tallman, C. W., & Madden, D. J. (2017). Functional modular architecture underlying attentional control in aging. *NeuroImage, 155*, 257-270. doi:10.1016/j.neuroimage.2017.05.002

Monge, Z. A., & Madden, D. J. (2016). Linking cognitive and visual perceptual decline in healthy aging: the information degradation hypothesis. *Neurosci Biobehav Rev, 69*, 166-173. doi:10.1016/j.neubiorev.2016.07.031

Monge, Z. A., Ritchey, M., & Cabeza, R. (under review). Age-related differences in memory representational networks.

Monge, Z. A., Stanley, M. L., Geib, B. R., Davis, S. W., & Cabeza, R. (2018). Functional networks underlying item and source memory: shared and distinct network components and age-related differences. *Neurobiol Aging, 69*, 140-150. doi:10.1016/j.neurobiolaging.2018.05.016

Monge, Z. A., Wing, E. A., Geib, B. R., Davis, S. W., Raghunandan, A., & Cabeza, R. (under review). Age-related dedifferentiation and hyperdifferentiation of perceptual and mnemonic representations.

Monge, Z. A., Wing, E. A., Stokes, J., & Cabeza, R. (2018). Search and recovery of autobiographical and laboratory memories: shared and distinct neural components. *Neuropsychologia, 110*, 44-54. doi:10.1016/j.neuropsychologia.2017.07.030

Mumford, J. A., Turner, B. O., Ashby, F. G., & Poldrack, R. A. (2012). Deconvolving BOLD activation in event-related designs for multivoxel pattern classification analyses. *NeuroImage, 59*(3), 2636-2643. doi:10.1016/j.neuroimage.2011.08.076

Murphy, D. R., Craik, F. I., Li, K. Z., & Schneider, B. A. (2000). Comparing the effects of aging and background noise on short-term memory performance. *Psychol Aging, 15*(2), 323-334.

Nameda, N., Kawara, T., & Ohzu, H. (1989a). Human visual spatio-temporal frequency performance as a function of age. *Optom Vis Sci, 66*(11), 760-765.

Nameda, N., Kawara, T., & Ohzu, H. (1989b). Human visual spatio-temporal frequency performance as a function of age. *Optometry & Vision Science, 66*(11), 760-765.

Nasreddine, Z. S., Phillips, N. A., Bedirian, V., Charbonneau, S., Whitehead, V., Collin, I., . . . Chertkow, H. (2005). The Montreal Cognitive Assessment, MoCA: a brief screening tool for mild cognitive impairment. *J Am Geriatr Soc, 53*(4), 695-699. doi:10.1111/j.1532-5415.2005.53221.x

Naveh-Benjamin, M. (2000). Adult age differences in memory performance: Tests of an associative deficit hypothesis. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 26*(5), 1170-1187.

Naveh-Benjamin, M. (2000). Adult age differences in memory performance: tests of an associative deficit hypothesis. *J Exp Psychol Learn Mem Cogn, 26*(5), 1170-1187.

Nishimoto, S., Vu, A. T., Naselaris, T., Benjamini, Y., Yu, B., & Gallant, J. L. (2011). Reconstructing visual experiences from brain activity evoked by natural movies. *Curr Biol, 21*(19), 1641-1646. doi:10.1016/j.cub.2011.08.031

Noonan, K. A., Jefferies, E., Visser, M., & Lambon Ralph, M. A. (2013). Going beyond inferior prefrontal involvement in semantic control: evidence for the additional contribution of dorsal angular gyrus and posterior middle temporal cortex. *J Cogn Neurosci, 25*(11), 1824-1850. doi:10.1162/jocn_a_00442

Norman, K. A., & O'Reilly, R. C. (2003). Modeling hippocampal and neocortical contributions to recognition memory: a complementary-learning-systems approach. *Psychol Rev, 110*(4), 611-646. doi:10.1037/0033-295X.110.4.611

Norman, K. A., Polyn, S. M., Detre, G. J., & Haxby, J. V. (2006). Beyond mind-reading: multi-voxel pattern analysis of fMRI data. *Trends Cogn Sci, 10*(9), 424-430. doi:10.1016/j.tics.2006.07.005

Norman, K. A., & Schacter, D. L. (1997). False recognition in younger and older adults: exploring the characteristics of illusory memories. *Mem Cognit, 25*(6), 838-848. doi:10.3758/bf03211328

Nyberg, L. (2017). Functional brain imaging of episodic memory decline in ageing. *J Intern Med, 281*(1), 65-74. doi:10.1111/joim.12533

Op de Beeck, H. P. (2010). Against hyperacuity in brain reading: spatial smoothing does not hurt multivariate fMRI analyses? *NeuroImage, 49*(3), 1943-1948. doi:10.1016/j.neuroimage.2009.02.047

Owsley, C. (2011). Aging and vision. *Vision Res, 51*(13), 1610-1622.

Owsley, C. (2011). Aging and vision. *Vision Res, 51*(13), 1610-1622.

Owsley, C., Sekuler, R., & Siemsen, D. (1983). Contrast sensitivity throughout adulthood. *Vision Res, 23*(7), 689-699.

Owsley, C., & Sloane, M. E. (1987). Contrast sensitivity, acuity, and the perception of 'real-world' targets. *British Journal of Ophthalmology, 71*(10), 791-796. doi:10.1136/bjo.71.10.791

Park, D. C., Lautenschlager, G., Hedden, T., Davidson, N. S., Smith, A. D., & Smith, P. K. (2002). Models of visuospatial and verbal memory across the adult life span. *Psychol Aging, 17*(2), 299-3320.

Park, D. C., Polk, T. A., Park, R., Minear, M., Savage, A., & Smith, M. R. (2004). Aging reduces neural specialization in ventral visual cortex. *Proc Natl Acad Sci U S A, 101*(35), 13091-13095. doi:10.1073/pnas.0405148101

Park, D. C., & Reuter-Lorenz, P. (2009). The adaptive brain: aging and neurocognitive scaffolding. *Annual Review of Psychology, 60*, 173-196. doi:10.1146/annurev.psych.59.103006.093656

Payer, D., Marshuetz, C., Sutton, B., Hebrank, A., Welsh, R. C., & Park, D. C. (2006). Decreased neural specialization in old adults on a working memory task. *NeuroReport, 17*(5), 487-491. doi:10.1097/01.wnr.0000209005.40481.31

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., . . . Dubourg, V. (2011). Scikit-learn: machine learning in Python. *Journal of machine learning research, 12*(Oct), 2825-2830.

Peters, A. (2002). The effects of normal aging on myelin and nerve fibers: A review. *Journal of Neurocytology, 31*(8-9), 581-593.

Peters, A., Moss, M. B., & Sethares, C. (2001). The effects of aging on layer 1 of primary visual cortex in the rhesus monkey. *Cereb Cortex, 11*(2), 93-103.

Peters, A., Sethares, C., & Killiany, R. J. (2001). Effects of age on the thickness of myelin sheaths in monkey primary visual cortex. *Journal of Comparative Neurology, 435*(2), 241-248.

Pichora-Fuller, M. K., Schneider, B. A., & Daneman, M. (1995). How young and old adults listen to and remember speech in noise. *J Acoust Soc Am, 97*(1), 593-608.

Polk, T. A., Stallcup, M., Aguirre, G. K., Alsop, D. C., D'Esposito, M., Detre, J. A., & Farah, M. J. (2002). Neural specialization for letter recognition. *J Cogn Neurosci, 14*(2), 145-159. doi:10.1162/089892902317236803

Prull, M. W., Dawes, L. L., Martin, A. M., 3rd, Rosenberg, H. F., & Light, L. L. (2006). Recollection and familiarity in recognition memory: adult age differences and neuropsychological test correlates. *Psychol Aging, 21*(1), 107-118. doi:10.1037/0882-7974.21.1.107

Quaranta, D., Vita, M. G., Spinelli, P., Scaricamazza, E., Castelli, D., Lacidogna, G., . . . Marra, C. (2014). Does semantic memory impairment in amnestic MCI with hippocampal atrophy conform to a distinctive pattern of progression? *Curr Alzheimer Res, 11*(4), 399-407. doi:10.2174/1567205011666140317104051

Raichle, M. E. (2015). The brain's default mode network. *Annu Rev Neurosci, 38*, 433-447. doi:10.1146/annurev-neuro-071013-014030

Rasmussen, P. M., Madsen, K. H., Lund, T. E., & Hansen, L. K. (2011). Visualization of nonlinear kernel models in neuroimaging by sensitivity maps. *NeuroImage, 55*(3), 1120-1131. doi:10.1016/j.neuroimage.2010.12.035

Raz, N., Lindenberger, U., Rodrigue, K. M., Kennedy, K. M., Head, D., Williamson, A., . . . Acker, J. D. (2005). Regional brain changes in aging healthy adults: general trends, individual differences and modifiers. *Cerebral Cortex, 15*(11), 1676-1689.

Riesenhuber, M., & Poggio, T. (1999). Hierarchical models of object recognition in cortex. *Nat Neurosci, 2*(11), 1019-1025. doi:10.1038/14819

Ritchey, M., Bessette-Symons, B., Hayes, S. M., & Cabeza, R. (2011). Emotion processing in the aging brain is modulated by semantic elaboration. *Neuropsychologia, 49*(4), 640-650. doi:10.1016/j.neuropsychologia.2010.09.009

Ritchey, M., LaBar, K. S., & Cabeza, R. (2011). Level of processing modulates the neural correlates of emotional memory formation. *J Cogn Neurosci, 23*(4), 757-771. doi:10.1162/jocn.2010.21487

Ritchey, M., Libby, L. A., & Ranganath, C. (2015). Cortico-hippocampal systems involved in memory and cognition: the PMAT framework. *Prog Brain Res, 219*, 45-64. doi:10.1016/bs.pbr.2015.04.001

Ritchey, M., Wing, E. A., LaBar, K. S., & Cabeza, R. (2013). Neural similarity between encoding and retrieval is related to memory via hippocampal interactions. *Cereb Cortex, 23*(12), 2818-2828. doi:10.1093/cercor/bhs258

Ross, M., Yurgelun-Todd, D. A., Renshaw, P. F., Maas, L., Mendelson, J., Mello, N., . . . Levin, J. (1997). Age-related reduction in functional MRI response to photic stimulation. *Neurology, 48*(1), 173-176. doi:10.1212/WNL.48.1.173

Rubin, G. S., Roche, K. B., Prasada-Rao, P., & Fried, L. P. (1994). Visual impairment and disability in older adults. *Optometry & Vision Science, 71*(12), 750-760.

Rubinov, M., & Sporns, O. (2010). Complex network measures of brain connectivity: uses and interpretations. *NeuroImage, 52*(3), 1059-1069. doi:10.1016/j.neuroimage.2009.10.003

Ruch, F. L. (1934). The differentiative effects of age upon human learning. *J Gen Psychol, 11*(2), 261-286. doi:10.1080/00221309.1934.9917838

Rugg, M. D., & Morcom, A. M. (2005). The relationship between brain activity, cognitive performance, and aging: the case of memory. In R. Cabeza, L. Nyberg, & D. Park (Eds.), *Cognitive neuroscience of aging: linking cognitive and cerebral aging* (pp. 132-154). New York, NY: Oxford University Press.

Rugg, M. D., & Vilberg, K. L. (2013). Brain networks underlying episodic memory retrieval. *Current Opinion in Neurobiology, 23*(2), 255-260. doi:10.1016/j.conb.2012.11.005

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., . . . Fei-Fei, L. (2015). ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision, 115*(3), 211-252. doi:10.1007/s11263-015-0816-y

Ryan, C. L., & Bauman, K. (2016). *Educational attainment in the United States: 2015*. U.S. Census Bureau Retrieved from https://www.census.gov/content/dam/Census/library/publications/2016/demo/p20-578.pdf.

Sabatinelli, D., Fortune, E. E., Li, Q., Siddiqui, A., Krafft, C., Oliver, W. T., . . . Jeffries, J. (2011). Emotional perception: meta-analyses of face and natural scene processing. *NeuroImage, 54*(3), 2524-2533. doi:10.1016/j.neuroimage.2010.10.011

Salthouse, T. A. (1990). Working memory as a processing resource in cognitive aging. *Dev Rev, 10*(1), 101-124. doi:10.1016/0273-2297(90)90006-P

Salthouse, T. A. (1996). The processing-speed theory of adult age differences in cognition. *Psychological Review, 103*(3), 403.

Salthouse, T. A. (2000). Aging and measures of processing speed. *Biological Psychology, 54*(1), 35-54.

Salthouse, T. A. (2000). Aging and measures of processing speed. *Biol Psychol, 54*(1–3), 35-54. doi:10.1016/S0301-0511(00)00052-1

Sarkka, S., Solin, A., Nummenmaa, A., Vehtari, A., Auranen, T., Vanni, S., & Lin, F. H. (2012). Dynamic retrospective filtering of physiological noise in BOLD fMRI: DRIFTER. *NeuroImage, 60*(2), 1517-1527. doi:10.1016/j.neuroimage.2012.01.067

Schlichting, M. L., & Preston, A. R. (2014). Memory reactivation during rest supports upcoming learning of related content. *Proc Natl Acad Sci U S A, 111*(44), 15845-15850. doi:10.1073/pnas.1404396111

Schmitter-Edgecombe, M., Woo, E., & Greeley, D. R. (2009). Characterizing multiple memory deficits and their relation to everyday functioning in individuals with mild cognitive impairment. *Neuropsychology, 23*(2), 168-177. doi:10.1037/a0014186

Schneider, B. A., & Pichora-Fuller, M. K. (2000). Implications of perceptual deterioration for cognitive aging research. In F. I. M. Craik & T. A. Salthouse (Eds.), *The Handbook of Aging and Cognition (2nd ed.)* (pp. 755). Mahwah, New Jersey, United States: Lawrence Erlbaum Associates Publishers.

Scialfa, C. T. (2002). The role of sensory factors in cognitive aging research. *Canadian Journal of Experimental Psychology/Revue canadienne de psychologie expérimentale, 56*(3), 153-163. doi:10.1037/h0087393

Seabold, S., & Perktold, J. (2010). *Statsmodels: econometric and statistical modeling with Python.* Paper presented at the Proceedings of the 9th Python in Science Conference.

Seghier, M. L., & Price, C. J. (2012). Functional heterogeneity within the default network during semantic processing and speech production. *Front Psychol, 3*, 281. doi:10.3389/fpsyg.2012.00281

Sekuler, R., & Sekuler, A. B. (2000a). Vision and aging. In A. Kazdin (Ed.), *Encyclopedia of Psychology* (Vol. 8, pp. 180-183): American Psychological Association and Cambridge University Press.

Sekuler, R., & Sekuler, A. B. (2000b). Vision and aging. . In A. Kazdin (Ed.), *Encyclopedia of Psychology* (Vol. 8, pp. 180-183): American Psychological Association and Cambridge University Press.

Serences, J. T. (2016). Neural mechanisms of information storage in visual short-term memory. *Vision Res, 128*(Supplement C), 53-67. doi:10.1016/j.visres.2016.09.010

Serre, T., Wolf, L., Bileschi, S., Riesenhuber, M., & Poggio, T. (2007). *Robust object recognition with cortex-like mechanisms*. Paper presented at the IEEE Trans Pattern Anal Mach Intell.

Shimamura, A. P., Berry, J. M., Mangels, J. A., Rusting, C. L., & Jurica, P. J. (1995). Memory and cognitive abilities in university professors: Evidence for successful aging. *Psychol Sci, 6*(5), 271-277. doi:10.1111/j.1467-9280.1995.tb00510.x

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv*, 1409.1556.

Skeel, R. L., Nagra, A., VanVoorst, W., & Olson, E. (2003). The relationship between performance-based visual acuity screening, self-reported visual acuity, and neuropsychological performance. *The Clinical Neuropsychologist, 17*(2), 129-136. doi:10.1076/clin.17.2.129.16509

Skeel, R. L., Schutte, C., van Voorst, W., & Nagra, A. (2006). The relationship between visual contrast sensitivity and neuropsychological performance in a healthy elderly sample. *J Clin Exp Neuropsychol, 28*(5), 696-705.

Skudlarski, P., Constable, R. T., & Gore, J. C. (1999). ROC analysis of statistical methods used in functional MRI: individual subjects. *NeuroImage, 9*(3), 311-329. doi:10.1006/nimg.1999.0402

Spaniol, J., Madden, D. J., & Voss, A. (2006). A diffusion model analysis of adult age differences in episodic and semantic long-term memory retrieval. *J Exp Psychol Learn Mem Cogn, 32*(1), 101-117. doi:10.1037/0278-7393.32.1.101

Spencer, W. D., & Raz, N. (1995). Differential effects of aging on memory for content and context: a meta-analysis. *Psychol Aging, 10*(4), 527-539. doi:10.1037/0882-7974.10.4.527

Spieler, D. H., Balota, D. A., & Faust, M. E. (1996). Stroop performance in healthy younger and older adults and in individuals with dementia of the Alzheimer's type. *J Exp Psychol Hum Percept Perform, 22*(2), 461-479. doi:10.1037//0096-1523.22.2.461

Sporns, O., & Betzel, R. F. (2016). Modular brain networks. *Annu Rev Psychol, 67*(1), 613-640. doi:10.1146/annurev-psych-122414-033634

Spreng, R. N., Lockrow, A. W., DuPre, E., Setton, R., Spreng, K. A. P., & Turner, G. R. (2018). Semanticized autobiographical memory and the default - executive coupling hypothesis of aging. *Neuropsychologia, 110*, 37-43. doi:10.1016/j.neuropsychologia.2017.06.009

Spreng, R. N., & Turner, G. R. (2019a). The Shifting Architecture of Cognition and Brain Function in Older Adulthood. *Perspect Psychol Sci*, 1745691619827511. doi:10.1177/1745691619827511

Spreng, R. N., & Turner, G. R. (2019b). The shifting architecture of cognition and brain function in older adulthood. *Perspect Psychol Sci, 14*(4), 523-542. doi:10.1177/1745691619827511

Sreenivasan, K. K., Vytlacil, J., & D'Esposito, M. (2014). Distributed and dynamic storage of working memory stimulus information in extrastriate cortex. *J Cogn Neurosci, 26*(5), 1141-1153. doi:10.1162/jocn_a_00556

St-Laurent, M., Abdi, H., Bondad, A., & Buchsbaum, B. R. (2014). Memory reactivation in healthy aging: evidence of stimulus-specific dedifferentiation. *J Neurosci, 34*(12), 4175-4186. doi:10.1523/jneurosci.3054-13.2014

Stanley, M. L., Dagenbach, D., Lyday, R. G., Burdette, J. H., & Laurienti, P. J. (2014). Changes in global and regional modularity associated with increasing working memory load. *Front Hum Neurosci, 8*. doi:10.3389/fnhum.2014.00954

Stanley, M. L., Moussa, M. N., Paolini, B. M., Lyday, R. G., Burdette, J. H., & Laurienti, P. J. (2013). Defining nodes in complex brain networks. *Front Comput Neurosci, 7*, 169. doi:10.3389/fncom.2013.00169

Staudinger, U. M., Cornelius, S. W., & Baltes, P. B. (1989). The aging of intelligence: potential and limits. *Ann Am Acad Pol Soc Sci, 503*, 43-59.

Talmi, D., Anderson, A. K., Riggs, L., Caplan, J. B., & Moscovitch, M. (2008). Immediate memory consequences of the effect of emotion on attention to pictures. *Learn Mem, 15*(3), 172-182. doi:10.1101/lm.722908

Taylor, K. I., Devereux, B. J., Acres, K., Randall, B., & Tyler, L. K. (2012). Contrasting effects of feature-based statistics on the categorisation and basic-level identification of visual objects. *Cognition, 122*(3), 363-374. doi:10.1016/j.cognition.2011.11.001

Thakral, P. P., Wang, T. H., & Rugg, M. D. (2019). Effects of age on across-participant variability of cortical reinstatement effects. *NeuroImage, 191*, 162-175. doi:10.1016/j.neuroimage.2019.02.005

Tielsch, J. M., Sommer, A., Witt, K., Katz, J., & Royall, R. M. (1990). Blindness and visual impairment in an American urban population: The Baltimore Eye Survey. *Archives of Ophthalmology, 108*(2), 286-290. doi:10.1001/archopht.1990.01070040138048

Toner, C. K., Reese, B. E., Neargarder, S., Riedel, T. M., Gilmore, G. C., & Cronin-Golomb, A. (2012). Vision-fair neuropsychological assessment in normal aging, Parkinson's disease and Alzheimer's disease. *Psychology and Aging, 27*(3), 785.

Tulving, E. (1972). Episodic and semantic memory. In E. Tulving & W. Donaldson (Eds.), *Organization of memory* (pp. 381–403). New York, NY: Academic Press.

Tulving, E. (1985a). *Elements of episodic memory*. New York, NY: Oxford University Press.

Tulving, E. (1985b). Memory and consciousness. *Can Psychol, 26*, 1-12.

Tun, P. A., Wingfield, A., Rosen, M. J., & Blanchard, L. (1998). Response latencies for false memories: gist-based processes in normal aging. *Psychol Aging, 13*(2), 230-241. doi:10.1037/0882-7974.13.2.230

Turner, G. R., & Spreng, R. N. (2015). Prefrontal engagement and reduced default network suppression co-occur and are dynamically coupled in older adults: the default-executive coupling hypothesis of aging. *J Cogn Neurosci, 27*(12), 2462-2476. doi:10.1162/jocn_a_00869

Tyler, L. K., Stamatakis, E. A., Bright, P., Acres, K., Abdallah, S., Rodd, J. M., & Moss, H. E. (2004). Processing objects at different levels of specificity. *J Cogn Neurosci, 16*(3), 351-362. doi:10.1162/089892904322926692

Tzourio-Mazoyer, N., Landeau, B., Papathanassiou, D., Crivello, F., Etard, O., Delcroix, N., . . . Joliot, M. (2002). Automated anatomical labeling of activations in SPM using a macroscopic anatomical parcellation of the MNI MRI single-subject brain. *NeuroImage, 15*(1), 273-289. doi:10.1006/nimg.2001.0978

Umanath, S., & Marsh, E. J. (2014). Understanding how prior knowledge influences memory in older adults. *Perspect Psychol Sci, 9*(4), 408-426. doi:10.1177/1745691614535933

Ungerleider, L. G., & Haxby, J. V. (1994). 'What' and 'where' in the human brain. *Curr Opin Neurobiol, 4*(2), 157-165. doi:10.1016/0959-4388(94)90066-3

van den Heuvel, M. P., & Sporns, O. (2013). Network hubs in the human brain. *Trends Cogn Sci, 17*(12), 683-696. doi:10.1016/j.tics.2013.09.012

van Marle, H. J., Hermans, E. J., Qin, S., & Fernandez, G. (2009). From specificity to sensitivity: how acute stress affects amygdala processing of biologically salient stimuli. *Biol Psychiatry, 66*(7), 649-655. doi:10.1016/j.biopsych.2009.05.014

Vandenberghe, R., Price, C., Wise, R., Josephs, O., & Frackowiak, R. S. (1996). Functional anatomy of a common semantic system for words and pictures. *Nature, 383*(6597), 254-256. doi:10.1038/383254a0

Verhaeghen, P. (2003). Aging and vocabulary scores: a meta-analysis. *Psychol Aging, 18*(2), 332-339.

Voss, M. W., Erickson, K. I., Chaddock, L., Prakash, R. S., Colcombe, S. J., Morris, K. S., . . . Kramer, A. F. (2008). Dedifferentiation in the visual cortex: an fMRI investigation of individual differences in older adults. *Brain Res, 1244*, 121-131. doi:10.1016/j.brainres.2008.09.051

Wang, T. H., Johnson, J. D., de Chastelaine, M., Donley, B. E., & Rugg, M. D. (2016). The effects of age on the neural correlates of recollection success, recollection-related cortical reinstatement, and post-retrieval monitoring. *Cereb Cortex, 26*(4), 1698-1714. doi:10.1093/cercor/bhu333

Wang, W. C., Brashier, N. M., Wing, E. A., Marsh, E. J., & Cabeza, R. (2018). Neural basis of goal-driven changes in knowledge activation. *Eur J Neurosci, 48*(11), 3389-3396. doi:10.1111/ejn.14196

Ward, L. M., Aitchison, R. T., Tawse, M., Simmers, A. J., & Shahani, U. (2015). Reduced haemodynamic response in the ageing visual cortex measured by absolute fNIRS. *PLOS ONE, 10*(4), e0125012. doi:10.1371/journal.pone.0125012

Warrington, E. K., & McCarthy, R. (1983). Category specific access dysphasia. *Brain, 106 (Pt 4)*, 859-878.

Weale, R. A. (1961). Retinal illumination and age. *Lighting Research & Technology, 26*, 95-100. doi:10.1177/147715356102600204

Wen, H., Shi, J., Zhang, Y., Lu, K. H., Cao, J., & Liu, Z. (2017). Neural encoding and decoding with deep Learning for dynamic natural vision. *Cereb Cortex*, 1-25. doi:10.1093/cercor/bhx268

Whiting, W. L., Madden, D. J., Langley, L. K., Denny, L. L., Turkington, T. G., Provenzale, J. M., . . . Coleman, R. E. (2003). Lexical and sublexical components of age-related changes in neural activation during visual word identification. *J Cogn Neurosci, 15*(3), 475-487. doi:10.1162/089892903321593171

Whitney, C., Kirk, M., O'Sullivan, J., Lambon Ralph, M. A., & Jefferies, E. (2011). The neural organization of semantic control: TMS evidence for a distributed network in left inferior frontal and posterior middle temporal gyrus. *Cereb Cortex, 21*(5), 1066-1075. doi:10.1093/cercor/bhq180

Windischberger, C., Langenberger, H., Sycha, T., Tschernko, E. M., Fuchsjager-Mayerl, G., Schmetterer, L., & Moser, E. (2002). On the origin of respiratory artifacts in BOLD-EPI of the human brain. *Magn Reson Imaging, 20*(8), 575-582.

Wing, E. A., Ritchey, M., & Cabeza, R. (2014). Reinstatement of individual past events revealed by the similarity of distributed activation patterns during encoding and retrieval. *J Cogn Neurosci, 27*(4), 679-691. doi:10.1162/jocn_a_00740

Wirth, M., Jann, K., Dierks, T., Federspiel, A., Wiest, R., & Horn, H. (2011). Semantic memory involvement in the default mode network: a functional neuroimaging study using independent component analysis. *NeuroImage, 54*(4), 3057-3066. doi:10.1016/j.neuroimage.2010.10.039

Wood, J. M., & Owens, D. A. (2005). Standard measures of visual acuity do not predict drivers' recognition performance under day or night conditions. *Optometry & Vision Science, 82*(8), 698-705.

Xia, M., Wang, J., & He, Y. (2013). BrainNet Viewer: a network visualization tool for human brain connectomics. *PLOS ONE, 8*(7), e68910. doi:10.1371/journal.pone.0068910

Zaretsky, H. H., & Halberstam, J. L. (1968a). Age differences in paired-associate learning. *J Gerontol, 23*(2), 165-168. doi:10.1093/geronj/23.2.165

Zaretsky, H. H., & Halberstam, J. L. (1968b). Effects of aging, brain-damage, and associative strength on paired-associate learning and relearning. *J Genet Psychol, 112*(2), 149-163. doi:10.1080/00221325.1968.10533791

Zeiler, M. D., & Fergus, R. (2014). *Visualizing and understanding convolutional networks.* Paper presented at the European Conference on Computer Vision, Cham.

Zhao, Y., Song, L., Ding, J., Lin, N., Wang, Q., Du, X., . . . Han, Z. (2017). Left anterior temporal lobe and bilateral anterior cingulate cortex are semantic hub regions: Evidence from behavior-nodal degree mapping in brain-damaged patients. *Journal of Neuroscience, 37*(1), 141-151.

Zheng, L., Gao, Z., Xiao, X., Ye, Z., Chen, C., & Xue, G. (2017). Reduced fidelity of neural representation underlies episodic memory decline in normal aging. *Cereb Cortex*, 1-14. doi:10.1093/cercor/bhx130

Zhou, B., Lapedriza, A., Khosla, A., Oliva, A., & Torralba, A. (2017). Places: A 10 million image database for scene recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*(99).

Biography

Zachary A. Monge received his Bachelor of Arts in Biology and Psychology from Boston University in 2013. Afterwards, he worked at the University of Pennsylvania investigating neural mechanisms underlying drug addiction relapse. In 2020 he received his Doctor of Philosophy in Psychology & Neuroscience from Duke University. During his time at Duke University he received a NIH Ruth L. Kirschstein National Research Service Award and was the first-place winner of Duke University's Artificial Intelligence for Art Competition.

Representative Publications:

Monge, Z. A., Stanley, M. L., Geib, B. R., Davis, S. W., & Cabeza, R. (2018). Functional networks underlying item and source memory: shared and distinct network components and age-related differences. *Neurobiology of Aging, 69,* 140-150.

Monge, Z. A., Wing, E. A., Stokes, J., & Cabeza, R. (2018). Search and recovery of autobiographical and laboratory memories: shared and distinct neural components. *Neuropsychologia, 110,* 44-54.

Monge, Z. A., Geib, B. R., Siciliano, R. E., Packard, L. E., Tallman, C. W., & Madden, D. J. (2017). Functional modular architecture underlying attentional control in aging. *NeuroImage, 155,* 257-270.

Monge, Z. A., & Madden, D. J. (2016). Linking cognitive and visual perceptual decline in healthy aging: The information degradation hypothesis. *Neuroscience and Biobehavioral Reviews, 69,* 166-173.

Monge, Z. A., Greenwood, P. M., Parasuraman, R., & Strenziok, M. (2016). Individual differences in reasoning and visuospatial attention are associated with prefrontal and parietal white matter tracts in healthy older adults. *Neuropsychology, 30(5),* 558-567.