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The Effects of Emotion on Dissociable Learning Systems Across the Lifespan

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The Effects of Emotion on Dissociable Learning Systems Across the Lifespan

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Dedication

For my father who encouraged me to know what I don't know, and my mother who reminded me to stop and smell the roses along the way.

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This dissertation would not have been possible without the immense support of my fantastic advisor and mentor, Todd Maddox. Todd showed me how important it is to pay attention to the task when studying cognition to develop a deeper understanding of behavior, which has been the inspiration for much of my graduate research and will serve me well in the years to come. I was also fortunate to have an excellent post-baccalaureate advisor, Mara Mather, who nurtured my early passion for research. Mara showed me how important it is to consider the way emotion influences cognition and how those processes change across the lifespan. Bridging these two lines of work to better understand and improve cognitive outcomes has brought passion and purpose to my research.

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The Effects of Emotion on Dissociable Learning Systems Across the Lifespan

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Contemporary cognitive theory recognizes several dissociable learning systems that are critical in understanding different patterns of performance. *Rule Based* learning is mediated predominantly by the frontal lobe and is available to conscious control. Here executive function and working memory develop verbalizable rules guided by corrective feedback. *Procedural* learning is based on integrating non-verbal information from multiple sources and is predominantly mediated by the striatum. Here habitual stimulus-response associations develop using corrective feedback. *Perceptual Representation* learning is based on passive familiarity predominantly mediated by the visual cortex. Here learning is not guided by on conscious evaluations or feedback. Age-related deficits in learning have been well documented, however dissociable learning systems approaches demonstrated the greatest declines occur in feedback-driven learning.

In the face of declines, older adults maintain several well-persevered aspects of cognition. For example, older adults sometimes show *enhanced* processing of positive emotionally arousing stimuli, but this positivity bias reverses when cognitive control resources are limited becoming a negativity bias. Unlike previous work that explores

emotional stimuli directly, the goal of Chapters 1 and 2 is to use emotional *feedback* to improve learning outcomes.

In addition, older adults have a performance *advantage* over younger adults in perceptual representation learning in the absence of feedback. This suggests that the processes that underlie this mode of learning are relatively intact, however it is unclear what these processes are and how they contribute to performance. The dissociable memory systems that underlie rule based and perceptual representation learning demonstrate asymmetric age-related declines that may be driving these differences. Chapter 3 explores age-related changes processes during learning.

Chapter 3 also highlights a younger adult deficit in perceptual representation learning. Generating rules depends on narrow attention to features, and perceptual representations depend on broad attention to the whole stimulus. Task-irrelevant emotional primes influence the scope of attention where negative arousal narrows and positive arousal broadens, which likely affects rule based and perceptual representation learning systems differently. Chapter 4 explores how task-irrelevant emotional primes influence attention and interact with learning system to enhance performance in younger adults.

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OVERVIEW AND BACKGROUND

The demographics of the world are changing at a rapid pace and people across the United States are living and working longer than ever before. In 2011 the oldest baby boomers started turning 65 and today over 40 million people in the United States are over the age of 65 (Jacobsen, Kent, Lee, & Mather, 2011). This number is slated to more than double over the next 35 years representing 20% of the population in the United States. This increase in longevity places increased economic pressure on our population, which is already being seen as we push back the age of retirement (Reno & Veghte, 2010). Late life participation in the workplace comes with an increased need to learn new skills as we age; however our ability to learn new things shows many declines across the lifespan, though other aspects remain intact or improve.

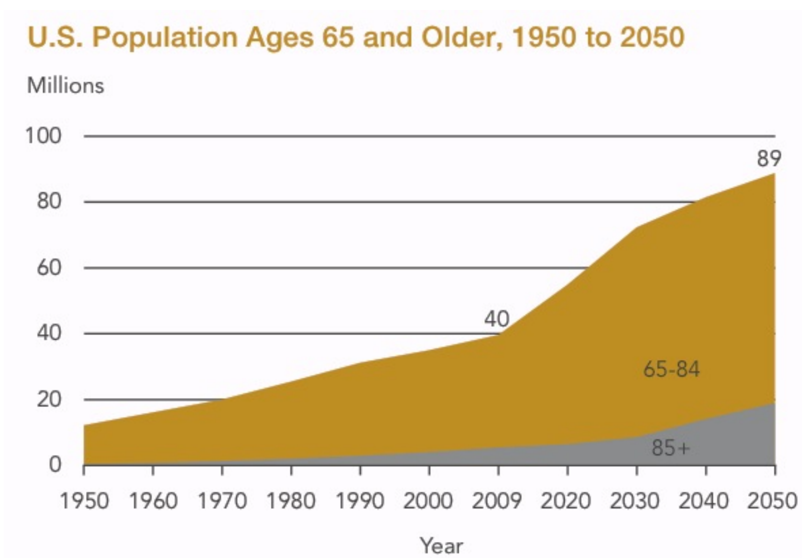

Figure 1. United States' older adult demographic history from 1950 projected through 2050.

Age-related deficits in learning have been well documented and older adults who lack the ability to participate in lifelong learning are becoming increasingly disadvantaged. Though multiple learning systems shows declines across the lifespan, a dissociable learning systems approach has demonstrated that these declines are not unitary and tend to affect feedback-driven processes to a greater degree than learning in the absence of feedback. Despite the declines in learning that occur across the lifespan, both younger adults and older adults report strong emotional experiences and these experiences have been shown to influence concurrent cognitive processes (Bechara & Damasio, 2005; Carstensen & Mikels, 2005; Fredrickson & Branigan, 2005). It is still an open question whether the cognitive changes that result from affective processing can be harnessed to improve learning outcomes within different learning systems and how these processes are affected by age. My dissertation research aims to bridge the dissociable learning systems literature and emotion literature improving our understanding of best practices to optimize learning across the lifespan.

DISSOCIABLE LEARNING SYSTEMS APPROACH TO LEARNING

Contemporary cognitive theory recognizes several dissociable learning systems (Ashby & Maddox, 2005; 2010; Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Beevers, 2005) which have been demonstrated behaviorally (Filoteo, Lauritzen, & Maddox, 2010), functionally (Zeithamova, Maddox, & Schnyer, 2008), and in patient populations (Ashby, Noble, Filoteo, Waldron, & Ell, 2003; Bozoki, Grossman, & Smith, 2006; Schnyer et al., 2009). This dissociable learning systems approach has been critical in explaining mixed findings in the category learning literature over the last 20 years (Ashby et al., 1998; Ashby & Maddox, 2005; 2010; J. D. Smith & Minda, 1998). *Rule Based* tasks are hypothesis driven, utilize feedback, include category structures that are verbalizable and are best learned using executive resources and logic. Here the prefrontal cortex, anterior cingulate, head of the caudate, and the medial temporal lobe mediate learning. For example, in disc golf accuracy increases if you know that short distance throws are more accurate with a thick disc and long distance throws are more accurate with a thin disc. *Procedural* learning, on the other hand, is mediated by the striatum, visual cortex, and dopaminergic cortico-striatal loops. Here learning is accomplished through repeated exposure to stimuli and habitual stimulus-response associations. This includes category structures that are not easily verbalized, such as integrating information from non-verbal mathematical relationships using feedback, and occur at a predecisional level (Ashby et al., 1998; Beevers, 2005; Filoteo et al., 2010; Maddox & Ashby, 2004; Poldrack & Foerde, 2008; Poldrack & Packard, 2003; Schnyer et al., 2009). For example, in disc golf verbal rules are little help in knowing how to move your body to throw a disc to a desired location. Instead, you need to become familiar with the proper technique through repeated attempts over time. *Perceptual Representation* Learning, though also non-verbal, depends on familiarity with a group. Here learning is mediated by the visual cortex and occurs with repeated exposures to stimuli distorted from one exemplar without feedback (Ashby & O'Brien, 2005; Reber, Stark, & Squire, 1998; Zeithamova et al., 2008). For example, as you play disc golf you may familiarize yourself with a set of discs from a particular brand. If you later find an unmarked disc on the course perceptual representations guide whether you classify the disc as a member of the known brand or if it belongs to an unknown brand. Thus, when studying learning it is important to distinguish between these systems and consider which psychological processes support each task (Ashby et al., 1998; Head, Kennedy, Rodrigue, & Raz, 2009).

RULE-BASED CATEGORY LEARNING WITH FEEDBACK ACROSS THE LIFESPAN

Age-related performance deficits are seen across a multitude of cognitive domains including inductive reasoning, spatial orientation, perceptual speed, numeric ability, verbal ability, and memory (Schaie, 1996). In the realm of learning, age-related deficits in rule-based processing are well documented. Older adults often have particular trouble learning tasks that rely on executive function and cognitive control mechanisms (Braver & Barch, 2002; Park et al., 2002; however see Verhaeghen, 2011; 2011; Verhaeghen & Cerella, 2002; Verhaeghen, Steitz, Sliwinski, & Cerella, 2003). These include many forms of rule-based category learning (Maddox, Chandrasekaran, Smayda, & Yi, 2013; Maddox, Pacheco, Reeves, Zhu, & Schnyer, 2010), as well as tasks that require set shifting such as the classic Wisconsin Card Sorting Task (Gorlick et al., 2013; Gunning-Dixon & Raz, 2003; Head et al., 2009; MacPherson, Phillips, & Sala, 2002).

Evidence from anatomical studies suggests that dopaminergic and volumetric declines in the prefrontal cortex may hinder older adults' performance during rule-based tasks (Bãckman et al., 2000; Gunning-Dixon & Raz, 2003). The prefrontal cortex, which shows the greatest volume declines in white and gray matter with age (Raz, 2005; Raz, Williamson, Gunning-Dixon, Head, & Acker, 2000), has been linked with impairments in working memory and executive function (MacPherson et al., 2002). These cognitive abilities are important for rule-based learning, where flexibility and maintenance of contingencies in working memory is critical to optimize performance (Filoteo et al., 2010; Gunning-Dixon & Raz, 2003; Schnyer et al., 2009). In support of this hypothesis, rule-based learning deficits have been induced in younger adults using behavioral manipulations that tax frontal systems such as a dual tasks that limit working memory resources (Filoteo et al., 2010; Maddox et al., 2011; Maddox, Love, Glass, & Filoteo, 2008).

PROCEDURAL CATEGORY LEARNING WITH FEEDBACK ACROSS THE LIFESPAN

Age-related deficits are also seen in procedural non-verbalizable tasks that include feedback processing during learning (Glass, Chotibut, Pacheco, Schnyer, & Maddox, 2012; J. H. Howard, Howard, Dennis, Yankovich, & Vaidya, 2004; Maddox et al., 2010; 2013; Simon, Vaidya, Howard, & Howard, 2012). Here feedback is critical in facilitating the integration of mathematical relationships in the striatum over time. For example, age-related deficits are seen during a procedural categorization task where non-verbal mathematical information about binary features is learned slowly over time with corrective feedback. Here older adults use simple suboptimal strategies or when they do use appropriate strategies they use them inconsistently which is related to poor performance. These declines could also be influenced by changes in dopamine and the way the striatum processes feedback across the lifespan (Mell, 2009; Mell et al., 2005).

Age-Related Changes in Feedback Processing

Research has shown that older adults respond to reward and punishment differently than younger adults and these differences may depend on the processes underlying learning (Eppinger & Kray, 2011; Eppinger, Schuck, Nystrom, & Cohen, 2013; Guitart-Masip et al., 2013; Lighthall, Gorlick, Schoeke, Frank, & Mather, 2013; Mell et al., 2005; Pietschmann, Endrass, Czerwon, & Kathmann, 2011; Samanez-Larkin, Hollon, Carstensen, & Knutson, 2008; Samanez-Larkin, Levens, Perry, Dougherty, & Knutson, 2012; Simon, Howard, & Howard, 2010). During rule-based tasks, older adults have demonstrated a greater sensitivity to the anticipation of rewards than punishment (Samanez-Larkin et al., 2007). For example, while trying to explicitly respond to the presence of a target associated with monetary gains or monetary losses, older adults demonstrate reduced neural activation and subjective affective response while anticipating monetary losses and intact neural activation and subjective affective response while anticipating monetary gains relative to younger adults. While this study suggests that older adults are processing positive monetary feedback differently than negative monetary feedback, it is unclear how anticipatory biases affect learning outcomes in older adults.

During procedural learning, on the other hand, older adults have been shown to be better at avoiding negative outcomes than approaching positive outcomes (Lighthall et al., 2013). Here participants completed a striatally-mediated probabilistic learning task in which they had to learn which symbol, in three symbol pairs, was more likely to yield positive feedback and which predicted negative feedback (Frank, 2004). Feedback presented after each choice was either "correct" in green or "error" in red. Older adults were better at learning to avoid negative feedback than approach positive feedback. These findings support results from other tasks indicating that procedural learning given negative feedback is better preserved in older adults (Marschner et al., 2005; Mell et al., 2005; Pietschmann et al., 2011; Simon et al., 2010). It is possible that these age-related differences in the effectiveness of feedback processing interact with learning processes as well as the cognitive demands of the task to influence learning outcomes.

OLDER ADULTS, EMOTION, AND COGNITION

Despite well-documented learning deficits associated with normal aging, older adults' affective processing is generally well preserved (Leclerc & Kensinger, 2008; M. Mather, 2012). Older adults continue to have strong emotional experiences and report enhanced emotional well-being when compared with younger adults (Carstensen, Pasupathi, Mayr, & Nesselroade, 2000). Interestingly, whether older adults process positive or negative emotional information more effectively can differ as a function of available cognitive control resources. Specifically, when cognitive control resources are available, older adults show enhanced processing of positive emotional information (Knight et al., 2007; M. Mather & Carstensen, 2005; Petrican, Moscovitch, & Schimmack, 2008), an age difference known as the 'positivity effect' (M. Mather & Carstensen, 2005). Although the positivity effect is not always observed (Murphy & Isaacowitz, 2008), it is frequently seen in the domains of choice (M. Mather, Knight, & McCaffrey, 2005), attention (Isaacowitz, Wadlinger, Goren, & Wilson, 2006; M. Mather

& Carstensen, 2003), and memory (Grady, Hongwanishkul, Keightley, Lee, & Hasher, 2007). For instance, when shown positive, negative, and neutral pictures, older adults recall more positive pictures and fewer negative pictures than younger adults (Charles, Mather, & Carstensen, 2003).

Mather and colleagues argue that older adults' positivity bias is the result of goal-directed processes and thus depend on cognitive control and executive function (Isaacowitz, Toner, & Neupert, 2009; Knight et al., 2007; Kryla-Lighthall & Mather, 2009; M. Mather & Carstensen, 2005; Nashiro, Sakaki, Nga, & Mather, 2012; Petrican et al., 2008). Reduced cognitive control resources should attenuate the positivity effect in attention and memory. Mather and Knight (2005) tested this hypothesis by having older adults view pictures under full attention conditions, or with a secondary task that divided attention limiting cognitive control and working memory resources. In the full attention condition, older adults recalled more positive than negative pictures, whereas younger adults recalled more negative than positive pictures. This is consistent with a positivity effect. However, in the divided attention condition there was a significant reversal of this effect where both groups recalled more negative pictures than positive pictures.

Chapter 1 & Chapter 2: Emotional Biases, Feedback, and Category Learning

Much of the research to date has examined emotional biases for stimuli with inherent emotional content. It is unclear whether these biases in processing emotional stimuli would generalize to learning outcomes when the stimuli of interest are devoid of emotion and emotional *feedback* is provided to guide learning. Further, age-related changes in the efficacy of reward and punishment feedback within rule-based and procedural learning systems suggest that the valence of emotional feedback may play an even larger role during learning.

Mather and colleagues suggest that emotional biases depend on cognitive control resources, however it is also possible that the increased difficulty, represented by overall accuracy, of the task is driving these effects. If cognitive control resources are responsible for effortful emotional biases in older adults, we expect the cognitive control demands of the task to interact with valenced emotional feedback processing biases to influence learning outcomes. During a simple rule-based task that places low load on cognitive control, we expect to see a positivity bias where positive emotional feedback improves performance relative to negative emotional feedback. However, we predict a significant reversal of these effects during a complex rule-based task that places high load on cognitive control resources. However, this does not inform how effortful emotion regulation influences automatic feedback processing during learning.

Procedural learning is an ideal paradigm to test whether an effortful focus on emotional feedback can improve automatic learning. Since cognitive control is available during procedural learning, we may predict that older adults may perform better with positive emotional feedback relative to negative emotional feedback. However, previous research exploring ways to attenuate cognitive deficits have demonstrated that interventions are most effective when they are aligned with the processes that underlie learning (Cooper & Gorlick, Under Review). Thus, if an automatic learning deficit is not responsive to changes in effortful feedback processing, we predict that older adults will maintain a deficit in the procedural task regardless of the social component of the feedback. To test these effects, Chapter 1 and Chapter 2 examine how the valence of emotional and logical feedback interact with task-related limitations on cognitive control and task-related difficulty within rule-based and procedural learning systems.

Learning Perceptual Representations Across the Lifespan

Though age-related deficits are seen across automatic tasks with feedback, this deficit reverses to become an *age-related advantage in perceptual representation learning in the absence of feedback*. For example, Maddox and colleagues recently examined rule-based and perceptual representation learning in older adults and found an age-related deficit in rule-based learning when prototype distortions form two categories which are learned using verbalizable hypotheses and corrective feedback, but an age-related advantage in a perceptual version of the task where familiarity-based learning occurs without feedback through passive training on a single category distortion (Glass et al., 2012). As feedback is not involved, one possibility is that age-related changes in memory processes are driving these effects (Ashby & Maddox, 1993; Reber et al., 1998; J. D. Smith & Minda, 1998; 2002). In line with this idea, it has been demonstrated that category learning is facilitated by dissociable memory processes where rule-based tasks are supported by declarative working memory (i.e. recollection) and perceptual tasks are supported by a non-declarative familiarity (Ashby & O'Brien, 2005).

AGE-RELATED CHANGES IN MEMORY PROCESSES: RECALL AND FAMILIARITY

Numerous researchers have argued that memory is rooted in two dissociable processes - recall and familiarity (Mandler, 1980; Rolls, 2000; Yonelinas, 1997; Yonelinas & Jacoby, 2012). Recall is distinct from familiarity as individuals experience vivid, detailed retrospective information about events that occurred. Such strong evidence that an event has occurred is endorsed with high certainty and prior research has shown that developing such memories depends on working memory which is mediated by the prefrontal cortex and recollection which depends on the integrity of the hippocampus (Fortin, Wright, & Eichenbaum, 2004; Rolls, 2000; Yonelinas et al., 2002). Familiarity, on the other hand, is experienced as enhanced perceptual fluency with events that have occurred often without the presence of specific details. These processes do not seem to depend on the prefrontal cortex and hippocampal integrity and instead are mediated by other medial temporal lobe structures, the striatum, and the visual cortex (Fortin et al., 2004; Rolls, 2000; Vilberg & Rugg, 2007; Yonelinas et al., 2002). Recall and familiarity often work in parallel to support memory however our ability to utilize these two processes changes with age.

Older adults demonstrate neural declines that have been linked with differences in the way memories are retrieved including degradation of the hippocampus and prefrontal cortex (Raz, 2005; Raz et al., 2000; Rosenzweig & Barnes, 2003). Research indicates that these declines may not uniformly affect the processes that support memory. Older adults tend to demonstrate impairments in recall while familiarity-based processing is left relatively intact (Kahana, Howard, Zaromb, & Wingfield, 2002; Light, Patterson, Chung,

& Healy, 2004; Naveh-Benjamin, 2000). In one such study, participants were presented with pairs of words during study (Light et al., 2004). During test, words were presented with either intact pairs or rearranged pairs. Here older adults demonstrate increased hits when pairs were intact and increased false alarms when pairs were rearranged. However younger adults' false alarms remained constant across intact and rearranged pairs suggesting that strong vivid recollections of what occurred at study support performance. Thus, when memory depends on familiarity, older adults can perform as well as younger adults. However, when recognition depends on vivid recollections, older adults are impaired.

A memory framework that incorporates both recall and familiarity might provide insights into the age-related differences seen during category learning under different training conditions (Glass et al., 2012). In prototype distortion learning paradigms, the nature of the training can be manipulated such that learning under one training regimen is best supported by recall and learning under another training regimen is best supported by familiarity (Ashby et al., 1998; Bozoki et al., 2006; Gorlick & Maddox, 2013; Zeithamova et al., 2008). During prototype learning, participants are asked to categorize exemplars that have been distorted from one or two distinct prototypes. A critical distinction lies between perceptual representation-based A-not A (AN) prototype training, where participants become passively familiar with exemplars distorted from a single (A) prototype without corrective feedback, and rule-based A-B (AB) prototype training, where participants are trained on exemplars distorted from two distinct prototypes (A and B) with corrective feedback. Neuroimaging in younger adults indicates that AN learning is supported by a largely automatic visual network that uses perceptual fluency to drive familiarity judgments (Ashby & O'Brien, 2005; Reber et al., 1998). AB learning, on the other hand, is largely supported by a prefrontal network that recalls and compares features in working memory to establish verbal rules for category membership (Zeithamova et al., 2008).

Though familiarity-based judgments support learning in the AN task, there is evidence that younger adults utilize both recall and familiarity during AN learning as hippocampal activity is present during correct trials in both the AB and AN tasks in younger adults (Zeithamova et al., 2008). This suggests that younger adults use recollective processes to some extent in both tasks. As familiarity and recall are differentially affected by aging, it is unclear how older adults are utilizing recall and familiarity during AB and AN learning and how these processes contribute to performance, but previous research can provide some hints (Glass et al., 2012).

In prior work, we examined prototype distortion category learning in older adults and found an age-related deficit in AB learning, but an age-related advantage in AN learning (Glass et al., 2012). Computational prototype models indicate that these learning differences are due to age-related changes in attention and discrimination during test. Older adults broaden attention to the stimulus as a whole which has been shown to best support learning in the AN task (Gorlick & Maddox, 2013). In Chapter 3 we examine whether age-related changes in the contributions of recollection and familiarity may provide a mechanism for this interaction. Here computational models and receiver operating characteristic curves are used to examine the dissociable contributions of memory on performance. We predict that older adults will demonstrate greater familiarity than younger adults during the perceptual AN task enhancing performance and older adults will demonstrate reduced recall during the rule-based AB task relative to younger adults impairing performance.

YOUNGER ADULTS, EMOTION AND ATTENTION IN DISSOCIABLE LEARNING SYSTEMS

The results from Glass et al 2012 are intriguing and draw attention to perceptual learning deficits that can be seen in younger adults. Though younger adult learning is generally better than that of older adults, there is room for improvement. As discussed above, younger adults tend to show unbiased enhancements of emotional information processing relative to neutral information that may be leveraged to improve learning outcomes. For example, during a simple slideshow of emotional images, younger adults remember emotional images more than neutral images with no significant differences between positive and negatively valenced items (Charles et al., 2003). Interestingly, in complex environments the effects of emotional arousal are less consistent with emotional arousal sometimes accentuating and sometimes attenuating cognitive and perceptual processing (Anderson, 2005; Kensinger, 2009; M. Mather, Gorlick, & Nesmith, 2009; Steblay, 1992). This could be due to differences in perceived priority maps when there are multiple features in the environment (Ikkai & Curtis, 2011; T. Lee, Itti, & Mather, 2012). Biased competition theory suggests that bottom-up features such as automatically prioritized contrast differences and top-down goal-relevant information held in working memory are used together to enhance attention for priority targets amid distractors (Beck

& Kastner, 2009; T. Lee et al., 2012). For example, when searching for a friend's face in a crowd, a region of the brain known as the fusiform face area automatically detects the contrast differences that make up each face giving them high priority against the background (Kanwisher, McDermott, & Chun, 1997). In addition the friend's facial features are stored in working memory and reciprocal projections to the visual cortex enhance similar features perceived in the environment (Ranganath & D'Esposito, 2005).

PRIORITY MAPS, EMOTION AND ATTENTION

Mather and colleagues expand upon biased-competition priority maps under *Arousal-Biased Competition* theory (ABC) where arousal enhances ongoing competitive attentional processes between stimuli (T. Lee et al., 2012; M. Mather & Sutherland, 2011). In general, high priority stimuli receive more attentional resources at the expense of low priority stimuli and arousal further exaggerates this attentional polarity. Under this view, attentional priority is not limited to the source of arousal and influences concurrent bottom-up and top-down processes. For example, arousing sounds played before high and low contrast letters led to enhanced perception of high priority high contrast letters and decreased perception of low priority low contrast letters compared to controls (M. Mather & Sutherland, 2011). Another study presented participants with instructions to a) "remember the location of words" or b) "remember the order of words" presented in a list (A. P. Smith, 1982). Arousing sounds played before word presentation selectively enhanced memory for goal-relevant word features compared to controls. Those asked to remember the order demonstrated better memory for the order and worse memory for the location than controls. This pattern reversed in the word location condition. Together this demonstrates how arousal exaggerates arousal-irrelevant attentional competition for both bottom-up perceptual biases and top-down goal-directed biases.

VALENCE EFFECTS ON ATTENTIONAL SCOPE

Mather and colleagues acknowledge that ABC may require modification to account for other factors such as valence (M. Mather & Sutherland, 2011). While emotional arousal in general has been shown to exaggerate priority maps, other research has shown that positive and negative valence influence the scope of attention in different ways. Research has demonstrated that positive arousal broadened the scope of attention, cognition, and action while negative arousal narrowed these aspects (Fredrickson, 2004; Fredrickson & Branigan, 2005; however see Gable & Harmon-Jones, 2008; 2008). Supporting this idea, the *Weapon Focus Effect* has demonstrated that those involved in an altercation remember the weapon but struggle to identify the face of the perpetrator (Steblay, 1992). On the other hand, Isen and colleagues demonstrated that those in a good mood applied a broad definition to sort words into groups compared to controls (e.g., sorting the word “camel” into the group “vehicle”) (Isen & Daubman, 1984). Thus, while attention for high-priority items is enhanced, it is possible that the scope of this attention is valence-dependent.

The scope of attention likely has different effects on performance within rule-based and perceptual representation learning systems. The perceptual system is supported by automatic fluency and depends on broad attentional scope to develop a global representation. In contrast, the rule-based system is supported by hypotheses and feedback, which depends on narrow attentional scope to target concrete feature dimensions while generating verbal rules. Thus, we predict that if negative arousal narrows attentional scope performance would improve in a rule-based task and if positive arousal broadens attentional scope performance would improve in a perceptual representation task. In Chapter 4 we test these effects by including task-irrelevant positive, negative, or neutral emotional primes before stimulus presentation within rule-based and perceptual representation category learning tasks. Computational models are used to examine the effects of emotional arousal on attentional scope and subsequent performance.

Summary of Current Work

Arousal affects a wide array of cognitive processes, yet most cognitive research is conducted with low-arousal paradigms leaving a critical gap in our understanding of learning. In addition, though emotional experience is well preserved across the lifespan it is clear that the effects of these emotions on cognition change. It is still an open question whether the cognitive changes that result from affective processing can be harnessed to develop learning interventions within dissociable systems and how these processes are influenced by age. My dissertation research aims to bridge the dissociable system literature and arousal literature improving our understanding of best practices to optimize performance across the lifespan.

Chapter 1: Attenuating Age-Related Rule-Based Learning Deficits (Gorlick, Giguère, Glass, Nix, Mather, and Maddox, 2013, *Emotion*)

Older adults demonstrate robust deficits in rule-based tasks that depend on feedback processing to facilitate learning, however emotional processing is left relatively intact. Interestingly, older adults often demonstrate enhanced processing of positive emotional information relative to negative emotional information (M. Mather & Carstensen, 2005). However, this "positivity bias" reverses to become a negativity bias as cognitive control demands increase (Kryla-Lighthall & Mather, 2009). It is possible that these emotional biases can be leveraged to improve learning outcomes across the lifespan with attention to task demands.

In this chapter we examine whether intact emotional processing in older adults can be used to attenuate well-established age-related learning deficits in rule-based processing. Because of the prevalence of rule-based learning and set shifting in everyday life, it would be highly advantageous to develop task-specific feedback training protocols that enhance these forms of learning in older adults. To test this question, we use emotional feedback (Experiment 1) in the form of happy or angry faces as feedback or logical feedback (Experiment 2) in the form of gains in points or losses in points as feedback during learning. We also examine how the task demands on cognitive control interact with feedback to influence learning outcomes.

During learning participants complete rule-based set shifting task that was modeled after the classic Wisconsin Card Sort Task (WCST; Heaton, 1993; 1993). The

WCST is ideal to test our hypothesis as older adults demonstrate reliable deficits in set shifting (Rhodes, 2004). In the WCST participants are asked to categorize exemplars into one of four categories that differ on three dimensions. At first participants are naive to the categorization rule (sort by one of the three dimensions) and learn the category structure through corrective feedback over time. Importantly, after 10 consecutive correct responses the rule changes to another dimension without informing the participant. Thus, cognitive control resources are needed to disengage from the old rule and switch to the new rule. This paradigm provided information about initial concept formation as well as the ability to shift set to a new rule. In addition, the task allowed us to examine age and emotional feedback effects separately for initial rule learning and following a rule switch (i.e., set shifting).

In our version of the task, we manipulated the cognitive-control demands associated with the learning task directly by manipulating the number of stimulus dimensions and the number of categories, thus creating a low and a high cognitive control load version of the task (see Method for details). We predicted an interaction between the valence of the face feedback (happy vs. angry) and the cognitive-control demands of the task (low vs. high) on age-based differences in performance. In the low-load version of the task, we predicted that older adults would have enough cognitive-control resources available to enhance positive emotional feedback processing in the happy-face-feedback condition, thus attenuating age-related learning deficits, whereas age-related deficits would be observed in the angry-face-feedback condition. On the other hand, in the high load version of the task, we predicted that older adults would not have enough cognitive control resources available to enhance positive emotional feedback processing. Instead, they would show enhanced negative emotional feedback processing, thus attenuating age-related learning deficits in the angry-face-feedback condition, whereas age-related deficits would be observed in the happy-face-feedback condition. We expect age-related deficits across conditions in the logical feedback condition as seen in prior work examining rule-based tasks (Experiment 2).

EXPERIMENT 1

Experiment 1 examined age-related changes in rule learning and set shifting as a function of the valence of emotional face feedback (happy vs. angry), as well as that of the cognitive load demands of the task (low vs. high).

METHOD

Participants

Thirty older adults (Age: M_{OldLow}= 66.87; $Range_{OldLow}$= 60-79) and 37 younger adults (Age: $M_{YoungLow}$= 21.74; $Range_{YoungLow}$= 18-35) participated in the low-cognitive-load condition, and 36 older adults (Age: $M_{OldHigh}$= 66.67; $Range_{OldHigh}$= 60-82) and 40 younger adults (Age: $M_{YoungHigh}$= 20.08; $Range_{YoungHigh}$= 18-26) participated in the high-cognitive-load condition for monetary compensation. Older adults were given a large battery of neuropsychological tests during a prescreening session including the Wechsler Adult Intelligence Scale-Fourth (Wechsler, 1997), Stroop test (Stroop, 1935), Wisconsin Card Sorting Test (Heaton, 1993), Trail-making test (Corrigan, 1987), and Wechsler

Memory Scale (WMS-IV). All results were normalized for age using standardized procedures and converted to Z-scores. Participants that scored more than 2 standard deviations below the mean for memory, executive function, and attention were excluded from the study. No age differences emerged on the WAIS vocabulary sub-test. Subjective ratings of stress and health were also taken before completing the task, and no age differences emerged. Age, years of education, and scaled WAIS Vocabulary scores are displayed in Table 1.

Table 1: Chapter 1 Experiment 1 participant demographic information.

			Mean Age	Vocabulary Z	Education
Face	Low Cognitive Load	Younger	21.74	0.50	13.74
		Older	66.87	1.41	17.70
	High Cognitive Load	Younger	20.08	0.69	13.74
		Older	66.67	1.17	17.33

**Vocabulary Z is the average Z score on the WAIS Vocabulary measure of intelligence. Education is years of education where a bachelors degree = 16 years.*

Materials and Procedure

Participants in the low-cognitive-load condition completed a simple rule-learning task, with four stimuli constructed from a factorial combination of two binary-valued dimensions. On each of the 64 trials, participants were presented with one of the four stimuli and asked to categorize it into one of two categories. Unbeknownst to the participant, only one of the two stimulus dimensions was relevant to the categorization rule; along that dimension, each binary value was associated with one of the two categories. Participants were asked to pretend that they were ecologists, and that their task was to protect the environment by sorting cattails, frogs, ducks, or dragonflies into native and foreign species using trial-by-trial feedback (see upper panel of Figure 2). Different surface features were used for the happy-face-feedback and angry-face-feedback conditions, and were selected randomly from the four possible stimuli sets (cattails, frogs, ducks, or dragonflies). Once participants correctly categorized ten consecutive stimuli, the rule changed without their knowledge and the irrelevant dimension became relevant. Following the 64th trial, an exit screen provided information about whether the participant had reached their goal or not (defined below).

Participants in the high-cognitive-load condition completed a complex rule-learning task with 64 stimuli constructed from the factorial combination of three stimulus dimensions, with four possible values for each dimension. On each of 128 trials, participants were presented with one of the 64 stimuli and asked to categorize it into one of four categories. Unbeknownst to the participant, only one of the three stimulus dimensions was relevant; along that dimension, each of the four possible values was associated with one of the four categories. Participants were either told that they had to sort dogs by breed or outfits by designer (see lower panel of Figure 2). Each participant was randomly assigned to a cover story (breed or designer) and a feedback condition (happy or angry). Once participants correctly categorized ten consecutive stimuli the rule changed (without their knowledge) and one of the two irrelevant dimensions was now relevant. Following the 128th trial, an exit screen provided information about whether the participant reached their goal or not (defined below).

Emotional face feedback was used in all conditions of Experiment 1. Participants in the low and high load conditions completed the task under happy-face-feedback conditions and under angry-face-feedback conditions. Task order (happy face vs. angry-face-feedback condition) was counterbalanced. On each trial in the happy-face-feedback condition, a correct response was followed by the presentation of a face with a large smile and an incorrect response was followed by a face with a small smile (see Figure 2 for examples). In the angry-face-feedback condition, a correct response was followed by the presentation of a face with a small frown and an incorrect response was followed by a face with a large frown (see Figure 2 for examples). In addition to trial by trial feedback, each condition had a global goal. This goal consisted of a face displayed on the right side of the screen that morphed from a neutral face to an emotional face. In the happy-face-feedback condition, the goal was to make the girl very happy. In the angry-face-feedback condition, the goal was to avoid making the girl very angry. The goal was attained if 80% of the responses were correct. The experiment was performed on PC computers using Flash software.

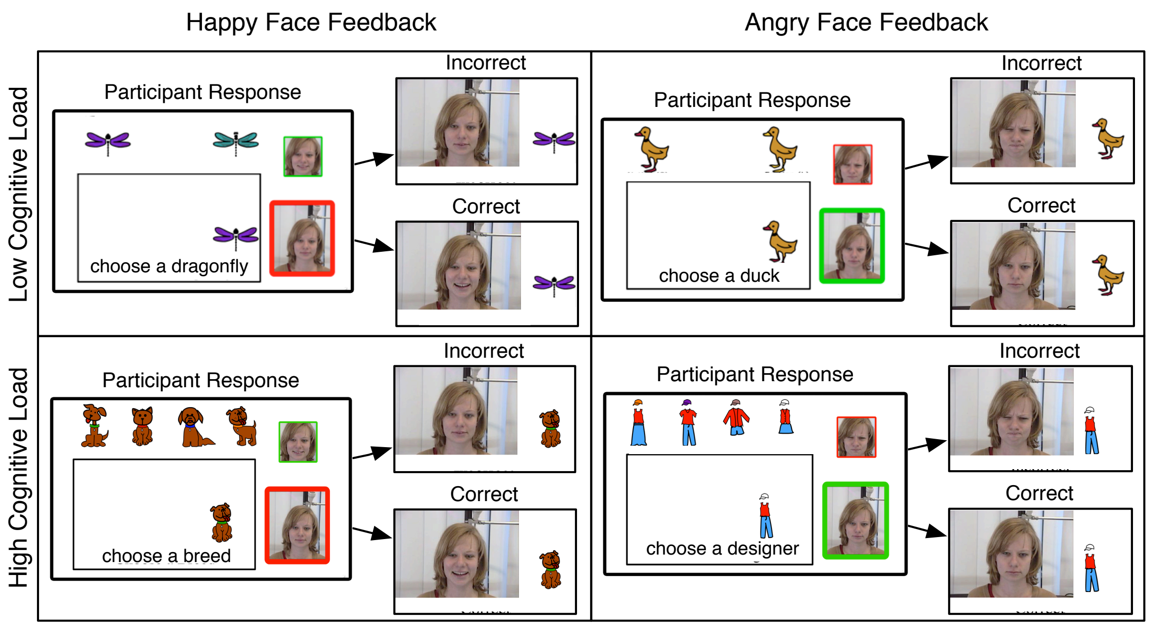

Figure 2. Chapter 1 Experiment 1: Procedure

Screen shots from the happy and angry-face-feedback conditions from the low cognitive load and the high-cognitive-load conditions.

RESULTS

We examined three learning measures: overall accuracy, the number of trials needed to obtain 10 consecutive correct responses when learning the first rule (trials to first rule), and the number of trials needed to obtain 10 consecutive correct responses when learning the second rule (trials to second rule). Each measure taps into a different aspect of learning. Accuracy provides a global measure of learning, the number of trials to learn the first rule provides a measure of initial rule learning, and the number of trials to learn the second rule provides a measure of set shifting. Table 2 includes the means and standard errors for all conditions.

Accuracy

Overall accuracy was calculated for each participant and a 2 (age) X 2 (valence) X 2 (cognitive load) mixed ANOVA was conducted (Figure 3.1). There was a main effect of age, $F(1,139)= 8.61$, $p=.004$, $\eta^2=0.06$, with younger adults performing more accurately than older adults ($M_{Older}=.79$, $M_{Younger}=.83$), and a main effect of task load, $F(1,139)= 12.37$, $p=.001$, $\eta^2=0.08$, with superior performance in the low cognitive load task relative to the high cognitive load task ($M_{Low}=.83$, $M_{High}=.79$). These effects were qualified by a significant three-way age X valence X cognitive load interaction, $F(1,139)= 8.23$, $p=.004$, $\eta^2=0.06$, and no other significant effects.

To decompose the three-way interaction, we conducted age x valence ANOVAs separately for the low- and high-cognitive-load conditions. In the low-cognitive-load condition, the only significant effect was a main effect of age, $F(1,65)= 7.91$, $p=.007$, $\eta^2=0.11$, with younger adults performing more accurately than older adults ($M_{Older}=.81$, $M_{Younger}=.86$). Although the interaction was not significant, we did predict *a priori* that the age-related learning deficit should be attenuated in the happy-face-feedback condition relative to the angry-face-feedback condition. The effect of age was significant for both happy $t(65)= 2.34$, $p=0.02$, and angry face feedback, $t(65)= 2.23$, $p=0.03$.

In the high-cognitive-load condition, there were no main effects of age or valence, but there was an age x valence interaction, $F(1,74)= 11.93$, $p=.001$, $\eta^2=0.14$. Older adults performed as well as younger adults in the angry-face-feedback condition, $t(74)= 0.89$, $p=0.38$, *ns,* ($M_{Older}=0.80$, $M_{Younger}=0.78$), but older adults performed significantly worse than younger adults in the happy-face-feedback condition, $t(74)= 3.44$, $p=.001$, ($M_{Older}=0.74$, $M_{Younger}=.83$). In addition, older adults were significantly more accurate with angry face feedback than with happy face feedback, *t(*35)= 2.77, *p*=.009, whereas younger adults were significantly less accurate with angry face feedback compared to happy face feedback, *t(*39)= 2.14, *p*=.04.

Trials to First Rule

The number of trials needed to learn the first rule was calculated for each participant and a 2 (age) X 2 (valence) X 2 (cognitive load) mixed ANOVA was conducted (Figure 3.2). There was a significant main effect of cognitive load, $F(1,139)= 8.57$, $p=.004$, $\eta^2=0.06$, with participants taking longer to learn the first rule in the high-cognitive-load condition ($M_{Low}=15.6$; $M_{High}=20.6$). There were no main effects of age or valence and no two-way interactions, however, there was a significant age x valence x cognitive load interaction, $F(1,139)= 5.84$, $p=.02$, $\eta^2=0.04$.

To decompose the three-way interaction we conducted age x valence ANOVAs separately for the low- and high-cognitive-load conditions. In the low-cognitive-load condition there were no main effects and no interaction. Again we examined age effects separately in the happy- and angry-face-feedback conditions because of our *a priori* predictions. Older adults performed as well as younger adults in the happy-face-feedback condition, $t(65)= 0.18$, $p=.86$, *ns,* ($M_{Older}=15.67$, $M_{Younger}=15.30$), but took marginally more trials than younger adults in the angry-face-feedback condition, $t(65)= 1.79$, $p=.08$, *ns*, ($M_{Older}=17.07$, $M_{Younger}=14.22$).

In the high-cognitive-load condition, there was no main effect of age or valence. However, there was a significant age x valence interaction, $F(1,74)= 5.25$, $p=.03$, $\eta^2=0.07$. Older adults performed as well as younger adults in the angry-face-feedback condition, $t(74)= 0.30$, $p=.76$, *ns,* ($M_{Older}= 20.9$; $M_{Younger}=22.3$) but older adults took significantly longer to learn the first rule than younger adults in the happy-face-feedback condition, $t(74)= 3.39$, $p=.001$, ($M_{Older}=24.8$; $M_{Younger}=14.5$). In addition, older adults showed no significant difference between the number of trials needed to learn the first rule given angry face feedback compared to happy face feedback, whereas younger adults took significantly more trials to learn the first rule given angry face feedback compared to happy face feedback, $t(39)= -2.11$, $p=.04$.

Trials to Second Rule

The number of trials needed to learn the second rule was calculated for each participant and a 2 (age) X 2 (valence) X 2 (cognitive load) mixed ANOVA was conducted (Figure 3.3). There was a significant main effect of age, $F(1,139)= 6.54$, $p=.01$, $\eta^2=0.05$, with older adults taking more trials to learn the second rule than younger adults ($M_{Older}=22.57$; $M_{Younger}=18.06$). A valence X cognitive load interaction, $F(1,139)= 5.71$, $p=.02$, $\eta^2=0.04$ also emerged suggesting fewer trials are needed for second rule learning with happy face feedback in the low-cognitive-load condition, but fewer trials are needed for second rule learning with angry face feedback in the high-cognitive-load condition.

Although the three-way interaction was not significant, we decided to explore the pattern of age effects to provide some insights onto the nature of set shifting performance. Although potentially informative, these results should be interpreted with caution. In the low-cognitive-load condition, a significant age-deficit emerged in the happy-face-feedback condition, *t(*65)= 3.55, *p*=.001, (M_{Older}=23.40; $M_{Younger}$=15.43), and in the angry-face-feedback condition, *t(*65)= 2.09, *p*=.04, (M_{Older}=24.27; $M_{Younger}$=18.60).

On the other hand, a different pattern emerged in the high-cognitive-load condition. Older adults took marginally more trials than younger adults to learn the second rule in the happy-face-feedback condition, *t(*74)= 1.60, *p*=.11, *ns,* (M_{Older}=26.58; $M_{Younger}$=19.53), and were as fast as younger adults to learn the second rule in the angry-face-feedback condition, *t(*74)= .80, *p*=.42, *ns*, (M_{Older}=16.03; $M_{Younger}$=18.70).

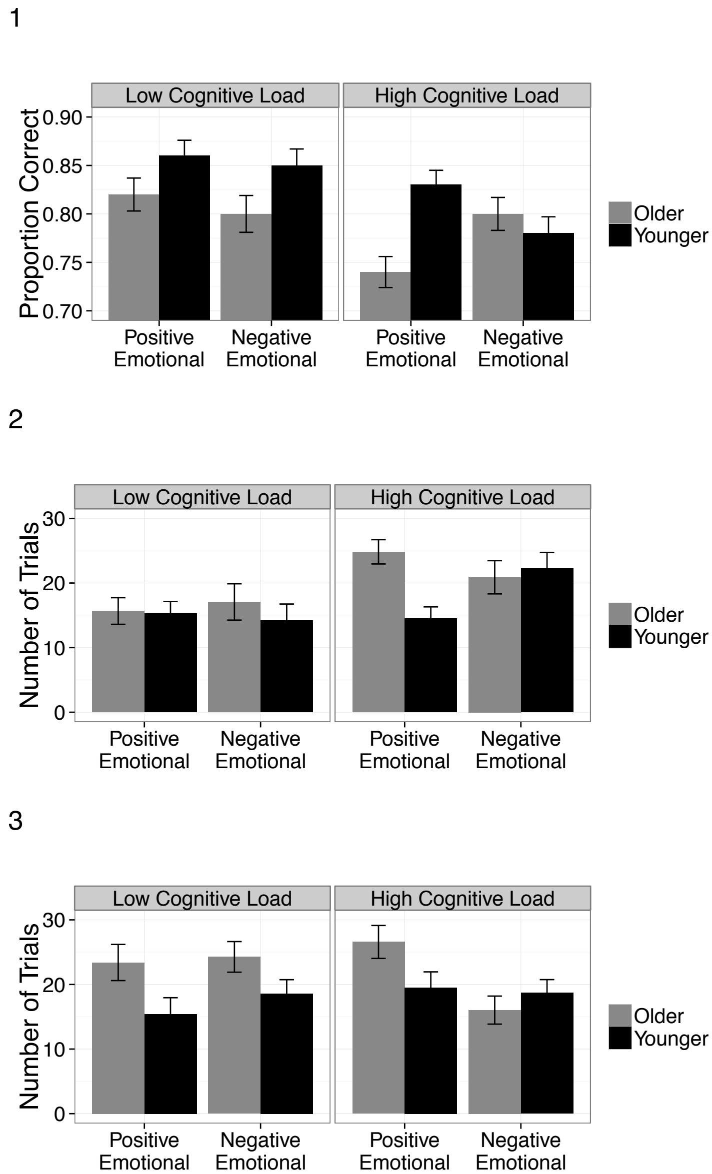

Figure 3. Chapter 1 Experiment 1: Results

Experiment 1: 1) Proportion correct for older and younger adults for the happy- and angry-face-feedback conditions under low cognitive load and high cognitive load, 2) Number of trials to learn the first rule for older and younger adults for the happy- and angry-face-feedback conditions under low cognitive load and high cognitive load, 3) Number of trials to learn the second rule for older and younger adults for the happy- and angry-face-feedback conditions under low cognitive load and high cognitive load. Standard error bars are included.

Experiment 1 Discussion

This study examined age-related changes in rule learning and set shifting as a function of the valence of emotional face feedback (happy vs. angry) in low and high cognitive load learning tasks. Previous research suggests that older adults use cognitive control resources to process positive emotional information more deeply than negative emotional information (Knight et al., 2007; M. Mather et al., 2005; Petrican et al., 2008). However, when cognitive control resources are limited these effects can disappear or, at times, reverse. These biases likely influence the salience of feedback during learning. Thus, we predicted a systematic interaction between age, valence of the feedback and task cognitive load where happy face feedback attenuates age-related learning deficits under low-cognitive-load conditions, and angry face feedback attenuates age-related learning deficits under high-cognitive-load conditions.

For the measures of initial and overall rule learning we found support for the predicted three-way interaction. Under low load conditions we predicted that happy face feedback would attenuate age-related deficits relative to angry face feedback. We found some support for this prediction in initial learning with no significant difference between younger adults and older adults in the number of trials needed to learn the first rule in the happy-face-feedback condition, and an age-deficit where older adults took 2.85 more trials than younger adults in the angry-face-feedback condition. For overall learning, the age-related deficit was 4% in the happy-face-feedback condition and 5% in the angry-face-feedback condition yielding only a 1% difference across feedback conditions. Under high load conditions we predicted that angry face feedback would attenuate age-related deficits relative to happy face feedback. This prediction was supported. For initial learning we found no significant difference between younger adults and older adults in the number of trials needed to learn the first rule in the angry-face-feedback condition, however we found an age-related deficit where older adults took 10.30 more trials than younger adults in the happy-face-feedback condition. Analogously, for overall learning, older adults were as accurate as younger adults in the angry-face-feedback condition and the age-related deficit was 9% in the happy-face-feedback condition. Thus, age-related deficits in initial and overall rule learning were attenuated when the cognitive load was high and angry face feedback was used.

Interestingly, the initial learning benefit observed for older adults in the low-cognitive-load condition with happy face feedback was attenuated significantly once the second rule was introduced and set shifting was required. In fact, the age-related set-shifting deficit was larger in the happy-face-feedback condition (7.97 trials) than in the angry-face-feedback condition (5.67 trials). Thus, it appears that the modest initial learning for older adults with happy face feedback came at the cost of reduced flexibility in processing making it more difficult to shift set.

However, in the high-cognitive-load condition older adults were as fast to shift set as younger adults in the angry-face-feedback condition (yielding a 2.67 trial set shifting advantage) whereas older adults were marginally slower to shift set than younger adults in the happy-face-feedback condition (yielding a 7.05 trial set shifting deficit). Thus, the age-related performance advantage under high-cognitive-load conditions with angry face feedback was large and robust across all three measures of learning.

Although we predicted that the highly emotional nature of the face feedback is what led to the complex pattern of age-related deficits and performance advantages, it is possible that these effects also hold with less emotional feedback in the form of points gained and points lost. Experiment 2 addresses this possibility directly.

EXPERIMENT 2

Experiment 1 revealed a systematic interaction between age, valence of the emotional face feedback, and cognitive load associated with solving the task. When task demands on cognitive control are low, happy face feedback attenuates deficits in overall learning, initial rule learning and, to a lesser extent, set shifting. However, during a complex task that places high demands on cognitive control, angry face feedback attenuates these age-related learning deficits. It is still unclear whether this complex three-way interaction generalizes to all valenced feedback or only applies to emotional face feedback.

One study comparing brain activation in younger adults receiving social face feedback vs. monetary feedback found that monetary feedback recruits a wide range of brain regions including the medial orbitofrontal cortex (OFC), striatum, superior frontal gyrus, medial temporal lobe, and insula and social feedback activated a smaller neural network mostly consisting of the medial orbitofrontal cortex (Lin, Adolphs, & Rangel, 2012). In addition to feedback processing, the OFC has been implicated in neural functions that are important for set shifting such as reversal learning (Fellows, 2003). Furthermore, recent research indicates that the OFC is more involved in updating emotional associations than non-emotional associations (Nashiro et al., 2012; Sakaki, Niki, & Mather, 2011b). This suggests that social and monetary feedback act through overlapping but separate neural networks, however it is unclear whether these differences affect set-shifting learning outcomes.

One study suggests that monetary feedback shows similar processing biases as those seen with face feedback in a rule-based task in older adults. Samanez-Larkin and colleagues found that older and younger adults show similar patterns of brain activation while anticipating monetary gain, however older adults show less brain activation while anticipating monetary loss (Samanez-Larkin et al., 2007). While this study suggests that older adults are processing positive monetary feedback differently than negative monetary feedback, it is unclear if the anticipatory biases affect learning outcomes in older adults. Experiment 2 examines whether the performance interaction observed in Experiment 1 holds when highly emotional face feedback is replaced with less emotional point feedback.

To determine whether the emotional aspect of the face feedback was critical, Experiment 2 serves as a replication of Experiment 1, but with the emotional face feedback replaced with less emotional point feedback.

METHODS

Participants

Thirty-one older adults (Age: M_{OldLow}= 67.35; $Range_{OldLow}$= 61-78) and 34 younger adults (Age: $M_{YoungLow}$= 21.88; $Range_{YoungLow}$= 18-35) participated in the low cognitive load task and 31 older adults (Age: $M_{OldHigh}$= 66.74; $Range_{OldHigh}$= 60-79) and 30 younger adults (Age: $M_{YoungHigh}$= 20.55; $Range_{YoungHigh}$= 18-26) participated in the high cognitive load task for monetary compensation (Table 2). Older adults were given the same battery of neuropsychological tests described in Experiment 1 and the same exclusion criteria were applied. In addition, younger and older adults were administered the WAIS vocabulary sub-test (Wechsler, 1997) and no age group differences emerged. Subjective ratings of stress and health were also taken before completing the task, and no age differences emerged.

Table 2: Chapter 1 Experiment 2 participant demographic information.

			Mean Age	Vocabulary Z	Education
Point	Low Cognitive Load	Younger	21.88	0.43	13.84
		Older	67.35	1.34	17.97
	High Cognitive Load	Younger	20.55	0.99	13.83
		Older	66.74	1.33	18.48

**Vocabulary Z is the average Z score on the WAIS Vocabulary measure of intelligence. Education is years of education where a bachelors degree = 16 years.*

Materials and Procedure

The materials and procedures were identical to Experiment 1, except that highly emotionally face feedback was replaced with less emotional point feedback (Figure 4). In the “point gain” feedback condition, a correct response was followed by a display of +3 points and an incorrect response was followed by a display of +1 point. In the point-loss-feedback condition, a correct response was followed by a display of -1 point and an incorrect response was followed by a display of -3 points. In the point-gain-feedback condition, the goal was to fill the point meter to the top, whereas in the point-loss-feedback condition, the goal was to avoid letting the point meter drop to the bottom. Their goal was attained if participants achieved 80% accuracy. As in Experiment 1, task order was counterbalanced and surface features were randomly assigned. The experiment was performed on PC computers using Flash software.

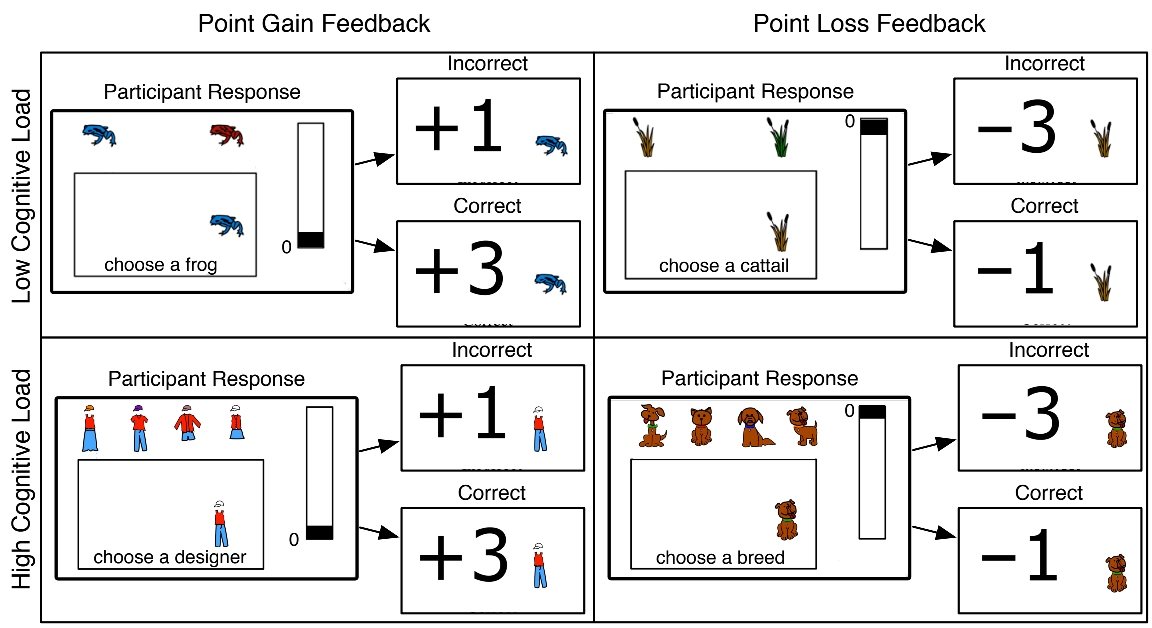

Figure 4. Chapter 1 Experiment 2: Procedure

Screen shots from the point-gain- and point-loss-feedback conditions from the low-cognitive-load and high-cognitive-load conditions.

RESULTS

Following the procedures outlined in Experiment 1, we examined overall accuracy, trials to learn the first rule, and trials to learn the second rule.

Accuracy

Overall accuracy was calculated for each participant and a 2 (age) X 2 (valence) X 2 (cognitive load) mixed ANOVA was conducted (see Figure 5.1). There was a significant main effect of age, $F(1,122)= 15.71$, $p<.001$, $\eta^2=0.11$, with older adults performing worse than younger adults ($M_{Older}=.80$; $M_{Younger}=.85$), and a significant main effect of cognitive load, $F(1,122)= 4.35$, $p=.04$, $\eta^2=0.03$, with participants being more accurate in the low-cognitive-load condition than in the high-cognitive-load condition ($M_{Low}=.84$; $M_{High}=.81$). No other effects reached significance.

Trials to First Rule

The number of trials needed to learn the first rule was calculated for each participant and a 2 (age) X 2 (valence) X 2 (cognitive load) mixed ANOVA was conducted (see Figure 4.2). There was a significant main effect of age, $F(1,122)= 17.74$, $p<.001$, $\eta^2=0.13$,with older adults taking more trials to learn the first rule than younger adults ($M_{Older}=19.1$; $M_{Younger}=14.2$). No other effects reached significance.

Trials to Second Rule

The number of trials needed to learn the second rule was calculated for each participant and a 2 (age) X 2 (valence) X 2 (cognitive load) mixed ANOVA was conducted (see Figure 4.3). There was a significant main effect of age, $F(1,122)= 12.98$, $p<.001$, $\eta^2=0.1$, with older adults taking more trials to learn the second rule than younger adults ($M_{Older}=20.2$; $M_{Younger}=15.7$), and a significant main effect of cognitive load, $F(1,122)= 5.87$, $p=.02$, $\eta^2=0.05$, with participants taking more trials to learn the second rule in the high-cognitive-load condition than in the low-cognitive-load condition (M_{low}=19.5; M_{high}=16.4). No other effects reached significance.

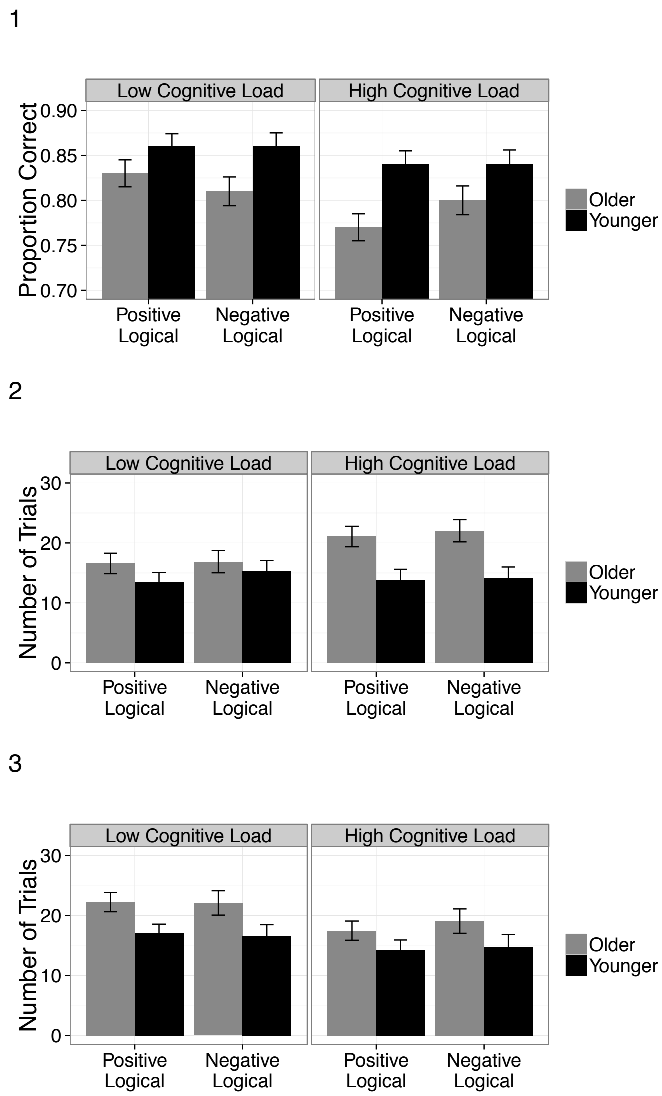

Figure 5. Chapter 1; Experiment 2: Results

1) Proportion correct for older and younger adults for the gain- and loss-point-feedback conditions under low cognitive load and high cognitive load, 2) Number of trials to learn the first rule for older and younger adults for the gain- and loss-point-feedback conditions under low cognitive load and high cognitive load, 3) Number of trials to learn the second rule for older and younger adults for the gain- and loss-point-feedback conditions under low cognitive load and high cognitive load. Standard error bars are included.

Experiment 2 Discussion

This study repeated the format of Experiment 1, but replaced emotional face feedback with logical point feedback. Older adults showed the learning deficits classically seen in set shifting paradigms. Older adults were less accurate, needed more trials to learn the initial rule, and needed more trials to learn the second rule relative to younger adults. This pattern contrasts with the three-way age x valence x cognitive load interaction observed in Experiment 1 where highly emotional stimuli attenuated learning deficits. The results from Experiment 2 are important because they demonstrate that the valence manipulation (positive feedback vs. negative feedback) in isolation was not sufficient to attenuate age-related deficits in a rule-based task. Successful learning depended on the emotional content of the feedback (happy faces vs. angry faces) and age-related deficits are still seen with less emotional feedback (point gain vs. point loss).

Discussion

The overriding aim of this chapter was to see if well-established rule learning and set-shifting deficits observed in normal aging could be attenuated by incorporating emotional faces as feedback. Previous research suggests that older adults enhance emotional information using effortful cognitive-control-based processing, but that the valence of these enhancements changes as a function of the cognitive control resources available (Kryla-Lighthall & Mather, 2009). When cognitive control resources are readily available, positive emotional information is processed more deeply, whereas when cognitive control resources are less readily available, negative emotional information is processed more deeply (Knight et al., 2007). We hypothesized that if highly emotional information in the form of happy faces or angry faces was used as feedback, enhanced processing of emotional information might be exploited to bootstrap learning in older adults. We predicted that happy face feedback would attenuate age-related learning deficits when the task placed minimal load on cognitive control resources, whereas angry face feedback would attenuate age-related learning deficits when the task placed a high load on cognitive-control resources.

The results from Experiment 1 supported our predictions. Under low-cognitive-load conditions older adults performed as well as younger adults in the happy-face-feedback condition and showed a large initial rule learning deficit in the angry-face-feedback condition. This pattern showed a significant reversal under high-cognitive-load conditions where older adults performed as well as younger adults in the angry-face-feedback condition, but showed a large initial rule-learning deficit in the happy-face-feedback condition. Unfortunately, any benefit in initial rule learning that older adults enjoyed with happy face feedback under low-cognitive-load conditions came at a cost in reduced flexibility once the rule switched. Specifically, under low-cognitive-load conditions older adults showed a set-shifting deficit relative to younger adults in both the happy-face and angry-face-feedback conditions. On the other hand, the benefit in initial rule learning that older adults enjoyed with angry face feedback under high-cognitive-load conditions was also present once the rule switched. Specifically, under high-cognitive-load conditions older adults performed as well as younger adults in the angry-face-feedback condition, despite the presence of a modest set-shifting deficit in the happy-face-feedback condition.

Experiment 2 repeated Experiment 1's procedure examining rule-based learning, however, the emotional face feedback was replaced by less emotional point feedback. We predicted that point feedback would not be processed more deeply by older adults than younger adults and thus would yield across-the-board age-related deficits that are classically seen in rule-based tasks. As predicted, age-related deficits emerged for the low and high-cognitive-load conditions when the feedback came in the form of points gained or points lost.

Taken together, these data suggest that age-related rule learning deficits are more flexible then once thought. These deficits can be attenuated if the appropriate feedback is paired with the task demands on cognitive load to optimize the speed of initial learning and the flexibility needed to efficiently shift set. The current study suggests that angry face feedback optimizes rule learning when the task is complex and places a strong demand on cognitive control resources, whereas happy face feedback optimizes rule learning when the task is simpler and places less demand on cognitive control resources.

Nashiro and colleagues examined the differential effects of happy and angry face feedback on older and younger adults' learning in a task with low cognitive load that required initial rule learning and rule switching (Nashiro, Mather, & Gorlick, 2011). As predicted, older adults made more errors in the angry-face-feedback condition than younger adults, but this deficit was attenuated with happy face feedback. Importantly, Nashiro et al. only examined an overall measure of performance, the number of errors made across the task, which obscures differential learning effects across phases of learning. The present study helps fill this critical gap in our understanding of the effects of age and feedback on initial learning and set shifting. Data from the current study suggests that the attenuated age deficit for happy face feedback in Nashiro et al. is most likely due to effects on initial learning and not on set shifting. Future work should explore this more fully.

Rule Learning and Set Shifting

In the current study we found an interesting dissociation between initial rule learning and set shifting for older and younger adults under low and high-cognitive-load conditions. Under low-cognitive-load conditions, we found that the age-related initial rule-learning deficit tended to be attenuated with happy face feedback, but that this came at a cost of even larger set-shifting deficits. On the other hand, under high-cognitive-load conditions, we found that the age-related initial rule-learning and set-shifting deficits were attenuated with angry face feedback.

The nature of the feedback may be partially responsible for the dissociation between initial rule learning and set shifting. Error feedback is critical when determining if a strategy is not working and a rule shift is needed. In the happy face condition, errors are presented as a small smile and in the angry face condition errors are presented as a large frown. This may make angry face errors easier to interpret because the change in emotion is larger and the emotional component of the feedback (negative) aligns with the feedback (error). This asymmetry in the emotional component with feedback would not affect initial rule learning as drastically, because both correct and error feedback can be used to maintain rules.

In the low-cognitive-load condition, older adults process happy face feedback more deeply than angry face feedback. This helps initial rule learning where large smiles are used to guide selection of the first rule; however, small smiles indicating errors are not salient enough to elicit a rule shift. Angry face feedback is ineffective in both initial rule learning and set shifting because it is processed shallowly. In the high-cognitive-load condition, negative feedback is processed more deeply than positive feedback. Happy face feedback is ineffective in both initial rule learning and set shifting because it is processed more shallowly. Angry face feedback is processed more deeply, which allows older adults to learn the initial rule and determine when to shift set through errors indicated with large frowns. This explanation is admittedly speculative but deserves further investigation.

Individual Differences

Given the importance of the cognitive load manipulation in the current findings, it is worth exploring the possibility that individual differences in executive functioning across older adults might affect the pattern of results. Previous research suggests that older adults' executive function interacts with emotional processing (Isaacowitz et al., 2009; M. Mather & Carstensen, 2005; Petrican et al., 2008). Because of our relatively small sample sizes and the fact that we did not collect measures of executive function in our younger adult sample, we deem these analyses exploratory. Even so, some interesting patterns emerged. We utilized the popular Stroop interference task as our measure of executive function (Stroop, 1935) and performed a median-split on Stroop interference z-scores and classifying older adults as high or low on executive functioning. Performance means for each condition are displayed in Table 3.

Table 3. Chapter 1 older adult performance grouped by low and high executive function.

	Task Load	Feedback	Older Good EF	Older Poor EF
Accuracy Rate	High	Happy Face	0.78 (0.02)	0.69 (0.02)
		Angry Face	0.82 (0.02)	0.79 (0.03)
		Point Gain	0.8 (0.02)	0.76 (0.02)
		Point Loss	0.8 (0.02)	0.79 (0.02)
	Low	Happy Face	0.84 (0.02)	0.8 (0.03)
		Angry Face	0.81 (0.03)	0.79 (0.03)
		Point Gain	0.83 (0.02)	0.83 (0.02)
		Point Loss	0.82 (0.02)	0.79 (0.02)
Initial Rule Learning	High	Happy Face	24.3 (2.53)	25.5 (2.83)
		Angry Face	21.3 (3.47)	20.38 (3.88)
		Point Gain	22.92 (2.66)	19.72 (2.26)
		Point Loss	22.23 (2.87)	21.89 (2.44)
	Low	Happy Face	14.5 (2.83)	17 (3.03)
		Angry Face	16.81 (3.88)	17.36 (4.15)
		Point Gain	16.31 (2.39)	16.87 (2.47)
		Point Loss	18.81 (2.59)	14.8 (2.67)
Set Shifting	High	Happy Face	19.15 (3.28)	35.88 (3.67)
		Angry Face	13.95 (2.90)	18.63 (3.25)
		Point Gain	15 (2.46)	19.28 (2.09)
		Point Loss	16 (3.13)	21.28 (2.66)
	Low	Happy Face	19.25 (3.67)	28.14 (3.92)
		Angry Face	22 (3.25)	26.86 (3.47)
		Point Gain	20.56 (2.22)	24 (2.29)
		Point Loss	20.5 (2.83)	23.8 (2.92)

Summary statistics for older adults grouped by poor or good executive function (EF) measured using the Stroop task. Standard errors in parentheses.

Experiment 1 utilized emotional face feedback to attenuate learning differences. An examination of Table 3 suggests that when executive function is good and the cognitive load is low, happy face feedback may attenuate the age-related initial rule-learning deficit. However, under high-cognitive-load conditions, good executive function had little effect on initial rule learning. With respect to set shifting, high functioning older adults showed faster set shifting than low functioning older adults in all four conditions. Experiment 2 utilized less emotional point feedback and the results were more straightforward. As suggested by an examination of Table 3, in general high functioning older adults showed faster initial rule learning and set shifting than low functioning older adults, but high functioning older adults never performed at an equivalent or better level than younger adults.

Taken together these data suggest that good executive function plays a different role in positive versus negative emotional information processing biases. In the low-load condition, those with good executive function show emotional biases where happy face feedback leads to age-related advantages in initial rule formation, as well as an attenuation of the set-shifting deficit. However, older adults with poor executive function are worse than younger adults in initial rule formation and set shifting across valence. We do not see this interaction in the high-cognitive-load condition where negative emotional information is more salient. Here, older adults show performance advantages given angry face feedback regardless of their level of executive function. This lends support to the idea that emotional biases for positive emotional feedback were driven by executive processes however negative emotional feedback biases were not.

Although the results presented in this study are compelling, there are a number of limitations that are worth noting. First, given the importance of cognitive-control demands and resources in the present work, a more detailed examination of individual differences in cognitive control processing and resources is in order. The preliminary analyses presented above are suggestive, but a larger sample size is needed before definitive conclusions can be drawn. In addition, though the Stroop task taps executive function it also relies on attentional resources. It would be informative for future work to look for convergent evidence across several measures of executive function. Second, measures of affect and mood should be included in future work. We collected subjective ratings of stress and health and found no age differences. Even so, affect and mood may have differed across age groups and conditions. Although it is difficult to imagine how these might account for the systematic interaction observed in the present study, these measures might still be informative. In fact, it would be interesting to see how the different feedback conditions change affect and mood throughout the course of learning. These ratings could provide insights as to whether these effects are due to age differences in emotion regulation strategies or differences in the processing of emotional information.

Conclusions

This chapter reports the results from two experiments that examined the effects of highly emotional face feedback on in initial rule learning and set shifting using tasks that involve a low or a high cognitive load. When the task placed minimal load on cognitive control resources, we found that happy face feedback tended to attenuate age-related initial rule learning deficit, but that this advantage came with a cost once the rule switched. Under the same cognitive load conditions, we also found that angry face feedback led to large age-related initial rule learning and set shifting deficits. However, when the task placed a heavy load on cognitive control resources, we found that angry face feedback attenuated an age-related deficits in initial rule learning and set shifting, whereas happy face feedback led to age-related initial rule-learning and set-shifting deficits. When the highly emotional face feedback was replaced with less emotional point feedback, we found age-related performance deficits across the board.

Chapter 2: Age-Related Biases in Emotional Processing and Dissociable Feedback-Driven Learning Systems (In Preparation)

Chapter 1 provides important insights into how emotionally-valenced feedback can reduce age-related deficits in rule learning, however it provides no insights into how emotional feedback could reduce age-related deficits in procedural learning. Chapter 2 aims to bridge this gap in our understanding by examining how the valence of socially salient feedback (happy, angry) affects procedural learning in older adults. Older adults demonstrate general deficits when learning is supported by procedurally processes that learn nonverbal mathematical relationships through corrective feedback. This type of task is commonly referred to as an information integration category structure (Ashby & Maddox, 2010). Here accuracy is maximized if information from two or more stimuli dimensions is integrated at an automatic predecisional stage.

In Chapter 1 we put forward the hypothesis that cognitive control resources are used to effortfully enhance positive emotional information processing. During procedural information integration tasks learning is difficult and incremental, however it done automatically through striatal processes placing few demands on effortful cognitive control. Thus, the processes that govern emotion regulation are available to deeply process happy feedback. Though it is possible that this effortful positivity bias will improve procedural learning outcomes, learning critically depends on *automatic* feedback processing. In fact, effortful feedback processing has can impair automatic procedural category learning. For example, when cognitive control resources are limited during feedback processing through experimental manipulations we see improved information integration learning and impaired rule-based learning in younger adults (Filoteo et al., 2010).

Thus, we had two competing predictions about the way emotional feedback would influence procedural learning. On the one hand, cognitive control is available during procedural learning and we might predict that happy feedback improves performance. However another possibility is that older adults' *effortful* bias towards positive emotional stimuli will not help during a task supported by *automatic* feedback processing. To examine this question we asked participants to categorize complex 4 dimensional items that vary on 2 features. In this task the rule determining category membership can be manipulated to assess either the effortful rule-based or automatic procedural learning systems. This provides an ideal paradigm to compare age-related benefits from effortful emotional feedback processing broadly in dissociable automatic and effortful learning systems.

If emotional biases broadly affect effortful and automatic feedback processing, we expect to see an age-related advantage in the information integration task given positive emotional feedback and an age-related impairment with negative emotional feedback. This would be in line with other work that has demonstrated a positivity bias when cognitive control resources are available (Knight et al., 2007; Kryla-Lighthall & Mather, 2009). However, if effortful emotional biases are not helpful in a task supported by automatic feedback processing, we expect to see no effect of social feedback in attenuating age-related learning deficits during procedural learning. In the rule-based task we expect to replicate findings from Chapter 1 where older adults have better performance with negative emotional feedback in a task that places high demands on cognitive control.

In addition to our primary research question, we also were interested in how important the social salience of the feedback was in driving any effects. To test this question we ran a logical points condition on a small sample of individuals. We predict a main effect of age across tasks where older adults are less successful at learning than younger adults.

METHOD

Participants

Younger adults 18-35 and older adults age 60-90 were recruited to participate in this study and given monetary compensation or course credit (Table 4; N=29 older adult demographic information not currently available in the logical condition). Within each social (emotional, logical) x strategy (rule-based, procedural) condition valence conditions were compared (positive, negative) between age group and no significant differences in age, years of education, or verbal intelligence as measured by the WAIS vocabulary emerged. Older adults were given a large battery of neuropsychological tests during a prescreening session including the Wechsler Adult Intelligence Scale-Fourth (Wechsler, 1997), Stroop test (Stroop, 1935), Wisconsin Card Sorting Test (Heaton, 1993), Trail-making test (Corrigan, 1987), and Wechsler Memory Scale (WMS-IV). All results were normalized for age using standardized procedures and converted to Z-scores.

Participants that scored more than 2 standard deviations below the mean for memory, executive function, and attention were excluded from the study.

Table 4. Chapter 2 participant demographic information.

Sample size (N), Age in years, years of education (Bachelor's = 16), and WAIS Vocabulary Z-Scores for A) the emotional-face-feedback conditions and B) the logical-point-feedback conditions.

A

				N	Age	Education	Vocabulary
Emotional	Information Integration	Positive	Younger	42	21.1 (3.36)	14.1 (1.64)	0.93 (0.97)
			Older	48	69.36 (5.61)	16.94 (2.94)	0.93 (0.88)
		Negative	Younger	48	21.4 (3.64)	14.12 (1.77)	0.89 (0.8)
			Older	45	69.41 (6.85)	16.91 (2.37)	0.95 (0.82)
	Rule-Based	Positive	Younger	28	22.29 (4.09)	14.86 (1.88)	0.57 (0.98)
			Older	27	66.74 (5.89)	17.26 (2.25)	1.18 (0.74)
		Negative	Younger	28	22.07 (3.91)	14.75 (1.73)	0.54 (0.99)
			Older	27	66.93 (5.75)	17.52 (2.24)	1.17 (0.74)

B

				N	Age	Education	Vocabulary
Logical	Information Integration	Positive	Younger	14	24.43 (4.5)	15.36 (2.02)	0.92 (0.94)
			Older	20	69.08 (7.02)	16.77 (1.59)	1 (0.84)
		Negative	Younger	14	23.86 (4.8)	15.14 (2.21)	1.07 (0.88)
			Older	26	68.41 (6.98)	16.59 (3.14)	0.77 (0.99)
	Rule-Based	Positive	Younger	12	21.92 (3.37)	14.83 (1.85)	0.72 (0.78)
			Older	15	71.5 (8.4)	17 (1.51)	0.58 (0.85)
		Negative	Younger	8	22.12 (3.72)	14.75 (1.83)	0.79 (0.85)
			Older	19	69 (7.6)	15.62 (2.57)	0.59 (0.85)

**Standard deviations in parentheses.*

Materials

In this task participants categorized binary four dimensional stimuli into two categories either using a verbal rule-based structure or a mathematical information integration structure (Grimm, Markman, Maddox, & Baldwin, 2008). The information integration category structure is determined using a mathematical formula that makes it difficult to verbalize the category structure. First, one stimulus dimension was made irrelevant. Then for each remaining stimulus dimension, the possible properties of each stimulus were given a value of 1 or -1. Each category structure was created by the following mathematical formula (where the three relevant stimulus dimensions are randomly selected and assigned to X, Y, and Z): If $X+Y+Z > 0$; then Category A; else Category B. A unidimensional rule-based category structure was also included to replicate findings from Chapter 1 in a novel task with high cognitive load. Here category members were determined by randomly choosing one of the four binary dimensions as the verbalizable rule.

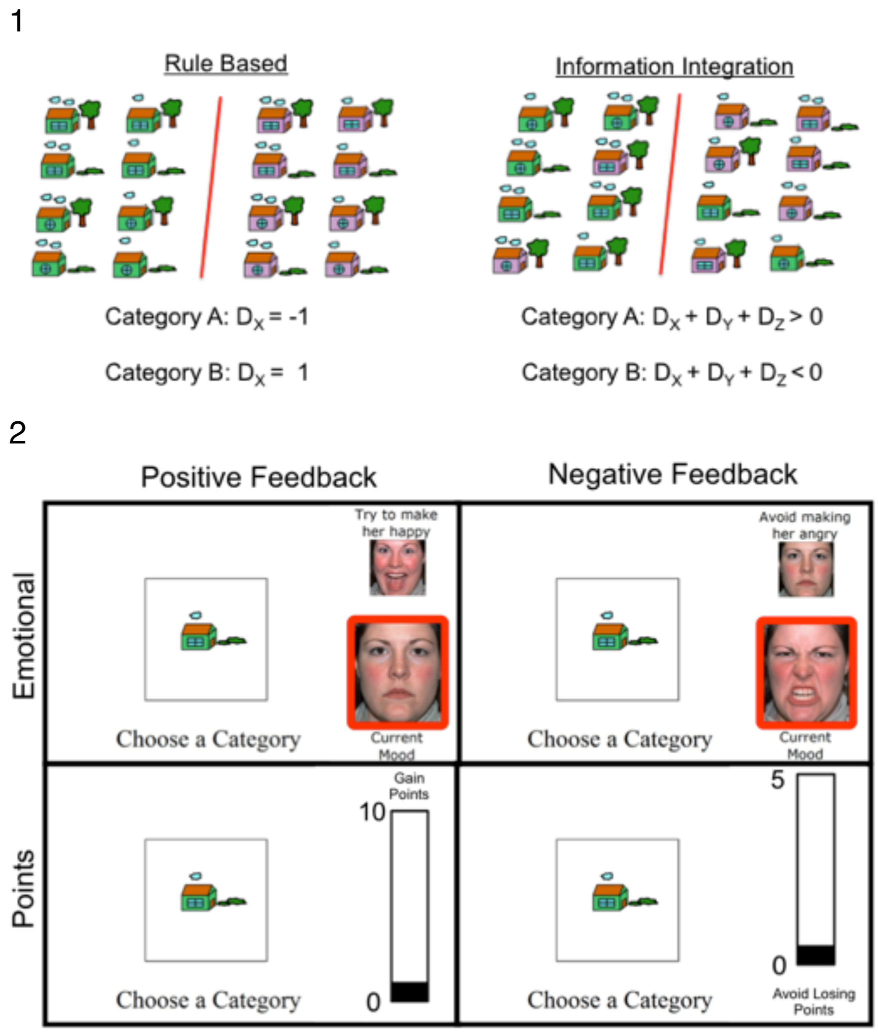

Figure 6. Chapter 2 Stimuli and Procedure

1) Example stimuli with their category membership for the complex rule-based (left) and information integration (right) tasks. 2) Screen captures for the emotional (top) and logical (bottom) categorization tasks. Within each of these condition the valence of the feedback was either positive (left; happy face or point gains) or negative (right; angry face or point losses).

Procedure

Emotional Feedback Task

Feedback valence (positive, negative) and supporting strategy (information integration, rule-based) was manipulated between subjects (Figure 6.1, upper panel). In the positive emotional feedback condition, participants are trying to make a face as happy as possible. Each correct response increases happiness and each incorrect response returns the faces' mood to neutral. After 10 consecutive correct responses the face reaches it's goal level of happiness and the task is complete. In the negative emotional feedback condition, participants must avoid making a face angry. Each correct response reduces anger and each incorrect response returns the faces' mood to the maximum amount of anger. After 10 consecutive correct responses the face is as neutral as it's goal and the task is complete. This measure is akin to the "Trials to First Rule" measure seen in Chapter 1. We selected colored photographs a model expressing happy and angry emotions from a validated set{Tottenham:2009ec}. The same female Caucasian model was used for both the happy- and angry-face-feedback conditions. A spectrum of emotional intensity was creating using Yale's MorphAge software, which has been created specifically for the purpose of morphing one face image into another. This allows us to create a controlled spectrum of emotion from highly arousing faces to neutral faces in steps of 10.

Logical Feedback Task

The logical points condition was similar to the emotion condition described above, however here feedback is devoid of social content (Figure 6.2, lower panel). Feedback valence (positive, negative) and supporting strategy (information integration, rule-based) was manipulated between subjects. In the positive-point-feedback condition participants' goal was to earn 10 points to achieve their goal. Each correct response increased their points by 1 and each incorrect answer dropped their total points back to 0. After 10 consecutive correct responses the point meter is full and the task is complete. In the negative-point-feedback condition participants' initial goal is to earn 5 points to each their goal. Each correct response increased their points by 1 and each, however incorrect answer dropped their total points back to 0 and their goal increases by 1. Thus, in the negative point feedback condition participants avoid extending their goal. They reach their dynamic goal the point meter is full and the task is complete in both tasks. While this manipulation is a good way to examine losses in this task, it makes it harder to compare trials to criteria across valence conditions. Thus, for comparative purposes we adjusted the "trials to reach the goal" in the losses condition to the number of trials needed for 10 consecutive correct responses or trials until the goal was reached, which ever comes first.

RESULTS

Information Integration with Emotional Feedback

Trials to Criterion

Within the emotion condition, the number of trials needed to achieve 10 consecutive correct responses was calculated for each participant and a 2 age X 2 valence mixed ANOVA was conducted (Figure 7.1). There was a significant main effect of age, $F(1,106)= 10.54$, $p<.001$, $\eta^2=0.06$, with older adults taking more trials to learn the rule than younger adults (M_{Older}= 97.47 (43.38); $M_{Younger}$= 72.24 (37.51)). There were no other significant effects.

Trials to Criterion: Influence of Strategy Use within the Information Integration Task

Though we instantiated a mathematical rule to assign category membership in the information integration task, it is possible to successfully reach 10 consecutive correct responses with a rule-based strategy. To look at more fine-grained measures of performance with strategy use in mind, we grouped individuals by those that could have reached the goal by using a unidimensional rule (any of 8 possible unidimensional rules as seen in the rule-based condition) and those that needed to use an information integration strategy for success during the last 10 trials (Figure 7.2). When participants used the information integration strategy, older adults show global deficits in both the happy-face-feedback, $t(47)=3.66$, $p<0.001$, condition and the angry-face-feedback condition, $t(40)=2.36$, $p=0.02$. However, when participants used the rule-based strategy, older adults show marginal deficits in the happy-face-feedback condition, $t(39)=1.85$, $p=0.07$, but not the angry-face-feedback condition, $t(49)=0.42$, $p=0.68$, ns. Rule-based findings replicate those seen in the high-cognitive-load condition of Chapter 1 where negative emotional feedback improves learning outcomes in older adults.

Rule Based with Emotional Feedback

Trials to Criterion

The number of trials needed to learn the rule was calculated for each participant and a 2 age X 2 valence mixed ANOVA was conducted (see Figure 4.2). There was a significant main effect of age, $F(1,106)= 4.10$, $p<.05$, $\eta^2=0.04$, with older adults taking more trials to learn the rule than younger adults ($M_{Older}=34.71$ (25.02); $M_{Younger}=25.89$ (25.61)). This was qualified by a significant age x valence interaction, $F(1,106)= 8.22$, $p<.01$, $\eta^2=0.07$, where older adults demonstrated a deficit with positive emotional feedback ($M_{Older}=46.11$ (43.94); $M_{Younger}=19.89$ (12.67)), $t(88)=3.09$, $p<0.001$, and learned as quickly as younger adults given negative emotional feedback ($M_{Older}=23.62$ (17.36); $M_{Younger}=28.14$ (28.11)), $t(91)=1.57$, $p=0.12$. These findings replicate those seen in the high-cognitive-load condition of Chapter 1 where negative emotional feedback improves learning outcomes in older adults.

Information Integration with Logical Feedback

Trials to Criterion

Within the logical condition, the number of trials needed to achieve 10 consecutive correct responses (adjusted for the losses condition) was calculated for each participant and a 2 age X 2 valence mixed ANOVA was conducted (Figure 7.3). There was a significant main effect of age, $F(1,69)= 8.36$, $p=.01$, $\eta^2=0.11$, with older adults taking more trials to learn the first rule than younger adults ($M_{Older}= 97.47$ (50.41); $M_{Younger}= 49.75$ (34.15)). There were no other significant effects.

Rule-Based with Logical Feedback

Trials to Criterion

Within the logical condition, the number of trials needed to achieve 10 consecutive correct responses (adjusted for the losses condition) was calculated for each participant and a 2 age X 2 valence mixed ANOVA was conducted (Figure 7.3). There was a significant main effect of age, $F(1,50)= 9.32$, $p<.001$, $\eta^2=0.16$, with older adults taking more trials to learn the first rule than younger adults ($M_{Older}= 54.94$ (54.94); $M_{Younger}= 22.93$ (13.48)). There were no other significant effects.

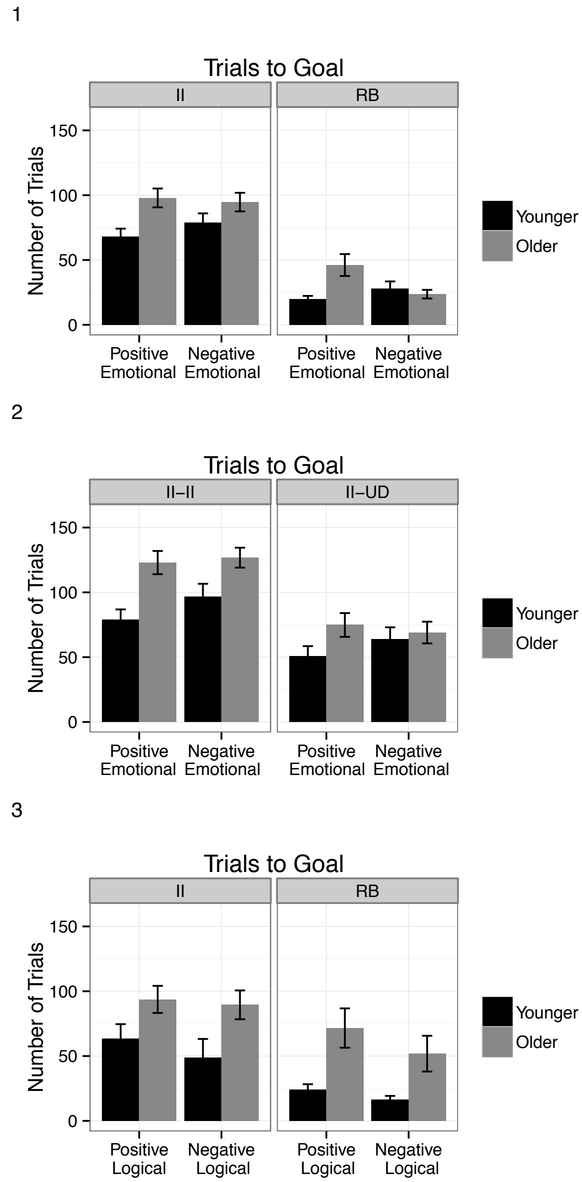

Figure 7. Chapter 2: Results

The number of trials needed to learn the rule for older and younger adults in 1) the rule-based and information integration tasks in the happy- and angry-face-feedback conditions strategy (II = information integration structure and RB = unidimensional structure) 2) within the information integration condition by strategy (II-II = information integration strategy and II-UD = unidimensional strategy) and 3) the rule-based and information integration tasks in the happy- and angry-face-feedback conditions (II = information integration structure and RB = unidimensional structure). Standard error bars are included.

Discussion

This chapter examined whether age-related deficits in automatic procedural learning could be attenuated using emotional faces as feedback, an intervention that has been successful in effortful rule-based tasks (Gorlick et al., 2013). Previous research has demonstrated that older adults use cognitive-control to effortfully attend to positive emotional information more than negative emotional information, however this positivity bias depends on whether cognitive control resources available and reverses to become a negativity bias in the absence of these resources (Kryla-Lighthall & Mather, 2009). We had two predictions on the applications of effortful emotional biases in an automatic procedural task where cognitive control resources are available. One prediction is that available cognitive control resources would attend to happy-face-feedback attenuating the age-related learning deficit in older adults. However, another possibility is that effortful emotional biases will not be effective in a task that is best supported by automatic feedback processing. In a complex effortful rule-based task, on the other hand, we predicted enhanced performance with negative-face-feedback relative to positive-face feedback as seen in Chapter 1.

The results of this study support the prediction that effortful emotional biases are ineffective at attenuating automatic procedural learning deficits in older adults. These persistent deficits are in stark contrast to age-related enhancements in rule-based learning using negative emotional feedback, which replicate prior findings. Importantly, though we see global deficits in the information integration task, it is clear that strategy use is an important factor in determining learning outcomes. Grouping participants by those using a rule-based strategy versus those that are using an information integration strategy during the procedural task demonstrated important insights. Those older adults that used an information integration strategy in the procedural task maintained deficits, however those that used a rule-based strategy demonstrate the same interaction between valence and age seen in the rule-based task where negative-face-feedback improves complex effortful learning. These findings highlight the robustness of age-related biases for negative-emotional-feedback when learning a complex effortful rule-based task. These results also demonstrate the importance of considering strategy use regardless in addition to task manipulations to develop a complete understanding of the factors driving performance in dissociable learning systems. Future work would be good to incorporate tasks where latent strategic differences can be better revealed using formal computational models (Ashby, 1992; 2014; Ashby & Waldron, 1999; Maddox, Filoteo, & Lauritzen, 2007). This could be achieved using stimuli with continuous feature dimensions where decision-bound models can be applied.

Adding to evidence from Chapter 1, Chapter 2 also finds that the social component of feedback is critical in driving the effects of valenced feedback in attenuating learning deficits.

A sample that completed a logical-point-feedback version of the task with gains and losses demonstrated deficits classically seen in both rule-based and procedural tasks. This provides further support for the importance of socially relevant feedback in reducing learning difficulties in older adults.

Learning Perceptual Representations without Feedback: Age Differences, Memory Processes, and Emotional Influences

Chapters 1 and 2 explored the relationship between emotional feedback processing and performance within rule-based and procedural systems, however learning can occur in the absence of feedback using an automatic occipital system that builds perceptual representations (Ashby & Maddox, 2005; Ashby & O'Brien, 2005). For example, one perceptual representation task trains participants passively on exemplars distorted from a single prototypical exemplar with no corrective feedback. At test, participants state whether they believe novel exemplars are a members of the trained category or not. This kind of learning is supported by automatic perceptual representations of the trained category. Prototype learning is a nice paradigm to compare automatic perceptual representation-based learning to effortful rule-based learning. During rule-based prototype learning, exemplars distorted from two prototypes are presented during training and participants actively sort these exemplars into category A or category B with corrective feedback. In this way, learning rule-based distortions from two prototypes is similar to other rule-based strategies such as set-shifting (Chapter 1) and unidimensional categorization (Chapter 2) which use hypothesis testing processes to guide performance.

Importantly, perceptual representation learning outcomes *improve* across adulthood. Maddox and colleagues have demonstrated that older adults show well established rule-based learning deficits in the prototype learning paradigm, however there is a significant reversal in the perceptual representation task where older adults demonstrate an advantage over younger adults (Glass et al., 2012). In the next two chapters we explore the processes that underlie this age by learning system interaction (Chapter 3) and explore ways to push younger adults towards better learning outcomes using emotional oddballs to prime attention (Chapter 4).

Chapter 3: Age Differences in the Contributions of Recall and Familiarity during Category Learning (Gorlick, Schnyer Abdul-Razzak & Maddox, Under Review)

Age-related deficits in learning are the focus of much research, however it is important to note cases where older adults' performance is enhanced relative to younger adults. One area of enhanced cognition is seen when learning perceptual representations of distorted exemplars. Perceptual representations are developed in the absence of feedback learning without feedback as seen in Chapters 1 and 2. Instead, learning is supported by developing perceptual *familiarity* with representatives from one category over time (Ashby & O'Brien, 2005; Reber et al., 1998). On the other hand, learning distortions of two prototypes with corrective feedback involves *recalling* previously seen exemplars for comparisons while generating hypotheses and is similar to rule-based learning strategies discussed in Chapters 1 and 2. Not surprisingly, older adults demonstrate age-related deficits in rule-based learning, however older adults demonstrate age-related advantages in a perceptual representation learning (Glass et al., 2012). This may be due to age-related changes in the memory processes that underlie learning within these systems; recall and familiarity.

The goal of this chapter is to explore how age-related changes in memory processes such as recall (vivid representations of past events) and familiarity (perceptual fluency with stimuli) contribute to rule-based learning with corrective feedback and perceptual representation learning without feedback and whether they provide insights into age-related performance differences. After training, participants were asked to categorize exemplars and rate how confident they were in their responses. Confidence ratings were used to generate ROC curves where the shape of the curve provides information about the use of recall and familiarity during test.

METHOD

Participants

Participants from the Austin community and students of the University of Texas were recruited from alumni mailings, fliers, and newspaper ads. After excluding those that scored below 50% accuracy during the final test block, 29 older adults (M_{age}=67.7) and 28 younger adults (M_{age}=22.3) were included in the AB task and 31 older adults (M_{age}=68.3) and 31 younger adults (M_{age}=21.5) were included in the AN task for payment or class credit. Older adults were administered a battery of neuropsychological tests (assessing attention, verbal memory, visual memory, speed, and executive function) in order to determine whether they were functioning within the normal range for their age. The neuropsychological battery includes the Wisconsin Card Sorting Test (Heaton, 1993), Wechsler Adult Intelligence Scale-Fourth Edition (Wechsler, 1981) Stroop test (Stroop, 1935),Trail-making test (Corrigan, 1987), and Wechsler Memory Scale (WMS-IV). All results were normalized for age using standardized procedures and converted to Z-scores. Neuropsychological tests were broken down into three subgroups of cognitive function. 1) Attention: Digit Span, Letter Number Sequencing**,** 2) Memory: CVLT, WMS-III Logical Memory**,** and 3) Speed/Executive Function: Stroop, Trails A and B, FAS, WCST. Older adults scoring 2 SD below the mean on one or more tests from each of these subgroups were excluded. Age groups were well matched between conditions on age, years of education, and gender (Table 5).

Table 5. Chapter 3 participant demographic information.

		Age	Years of Education	Gender
AB	Older	66.62 (5.08)	18 (2.14)	F=15; M=14
	Younger	22.71 (5.54)	14.14 (2.06)	F=13; M=15
AN	Older	67.9 (4.97)	17.26 (2.28)	F=15; M=16
	Younger	21.61 (3.63)	14.27 (2.01)	F=19; M=12

** Education is years of education where a bachelors degree = 16 years. Standard Deviations are in parentheses.*

Materials

Cartoon animals constructed from 10 binary features such as head orientation (up or forward), body color (grey or yellow), and tail (thin or thick) served as stimuli from a total of $2^{10} = 1024$ possible stimuli (Figure 8.1). One stimulus was selected at random to represent the A prototype for each participant. The B (N) prototype has the opposite value on each binary dimension. The prototype was distorted on one to four randomly selected features to create the category stimuli. Stimuli that differed from the prototype on five features were ambiguous and not included.

Procedure

We used a 2 training (AB, AN) between-participant design. Training consisted of 20 trials followed by a test phase with 42 novel items including the prototypes, and equal numbers of A and B items. Each participant completed 3 blocks of 20 training and 42 test trials.

On each training trial an exemplar was presented (Figure 8.2). During AB prototype learning, participants were shown 10 A and 10 B stimuli in a random order, and corrective feedback was given after the participant responded category A or category B. This type of training is supported by the frontally-mediated hypothesis testing system. Within each category, 2 learning stimuli differed from the category prototype on 1 feature, 3 differed on 2 features, 3 differed on 3 features and 2 differed on 4 features. Across all 10 stimuli within each category, the category typical features were presented 7 or 8 times and the opposite category typical features were presented 2 or 3 times. During AN prototype learning, participants viewed 20 A stimuli in a random order and a keystroke advanced to the next stimulus with no corrective feedback. This form of training has been shown to be supported by perceptual fluency. Five stimuli differed from the category A prototype on 1, 2, 3, and 4 features.

In both the AB and AN tasks, a 42-trial test phase followed learning that included both prototypes and 5 stimuli that differed from each prototype on 1, 2, 3 and 4 features. On each test trial, the participant was prompted to give an A or B (N) response with no corrective feedback. After each response, the participant was also asked, “How confident are you?” in the accuracy of their response to measure explicit metacognitive awareness. Confidence was measured using a 4-point scale (“Not sure”, “25% sure”, “ 75% sure”, or “100% sure”).

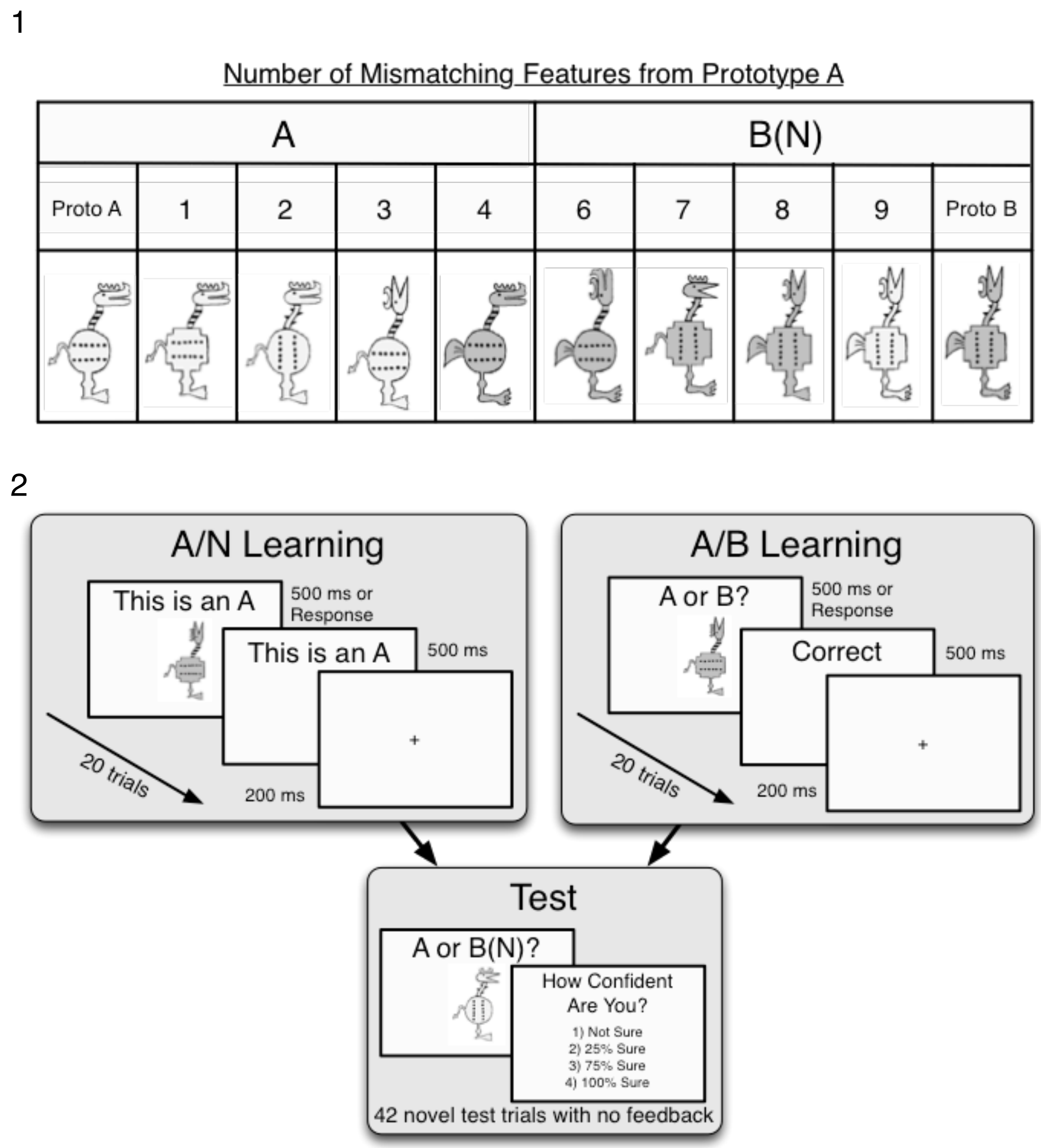

Figure 8. Chapter 3 Stimuli and Procedure

1) Category exemplars and their membership for each distance from prototype A. 2) Participants completed 3 blocks of 20 learning trials and 42 test trials. Training differed for the rule-based AB task with corrective feedback and perceptual representation-based AN tasks without corrective feedback to assess the contribution of recall and familiarity to performance. Test was identical for AB and AN tasks. No corrective feedback was given and participants were asked, "How confident are you?" after each response to assess receiver operating characteristics which represent memory processes.

Results

Because our interest is in post-training category recognition, we focused the following analysis on the final test block.

Performance

Proportion correct was calculated for each participant and a 2 Training (AB, AN) X 2 Age (younger, older) ANOVA was conducted (Figure 2.1). There was no main effect of Age, $F(1,115) = .004$, $p= .94$, however there was a main effect of Training, $F(1,115) = 12.27$, $p < .001$, $\eta^2=.10$, where particiants were more accurate in the AB task ($M = .74$) than the AN task ($M = .68$). This was qualified by a significant Training X Age interaction, $F(1,115) = 8.70$, $p< .004$, $\eta^2=.07$. To decompose the effects of Age on AB and AN accuracy, we conducted independent sample t-tests within each training conidtion. In the AB task, older adults demonstrated significantly impaired performance relative to younger adults, ($M_{younger}=.77$, $M_{older}=.72$), $t(55)= 2.28$, $p=.03$. In the AN task older adults demonstrated maringally enhanced performance relative to younger adults ($M_{younger}=.65$, $M_{older}=.71$), $t(60)= 1.91$, $p=.067$. Thus, our results replicate prior work examining performance in this prototype learning task (Glass et al., 2012) and indicates that performance depends on age. Older adults outperform younger adults when training is based on repeated passive exposure to members of one category (AN) and younger adults outperform older adults when training is based on active participant categorization of both members of category A and category B with corrective feedback (AB).

Dissociable Recognition Systems

When examining recognition performance, accuracy rates alone do not do a good job of representing what is known about category membership. For example, if a participant always responds that exemplars are members of category A, they will have perfect accuracy for members of category A, but no ability to distinguish category A from category B. The relationship between the hit rate and false alarm rate contains information about the *sensitivity* of the system, or the ability to determine what was seen and what was not accounting for this kind of response bias (Table 6).

Table 6. Chapter 3 hits, false alarms and sensitivity.

Hits, false alarms and sensitivity (behavioral d') for the AB task (trained with feedback; mean category A and category B (AB)) and the AN task (separate category A (trained without feedback; AN-A) and category N (untrained; AN-N)) for older and younger adults at each confidence threshold.

			Thresholds		
			c2 (Liberal)	c3	c4 (Conservative)
AB	Sensitivity	Older	0.49 (1.49)	0.51 (1.5)	*0.33 (1.21)*
		Younger	-0.14 (1.65)	0.82 (1.44)	*1 (1.36)*
	False Alarms	Older	0.78 (0.3)	**0.36 (0.35)**	0.14 (0.24)
		Younger	0.88 (0.21)	**0.57 (0.4)**	0.19 (0.33)
	Hits	Older	0.86 (0.28)	**0.47 (0.38)**	**0.19 (0.27)**
		Younger	0.95 (0.08)	**0.75 (0.29)**	**0.36 (0.36)**
AN-A	Sensitivity	Older	0.4 (1.32)	1.26 (1.92)	1.05 (1.74)
		Younger	0.1 (2.05)	0.6 (2.09)	0.73 (1.86)
	False Alarms	Older	0.78 (0.36)	0.39 (0.43)	0.12 (0.31)
		Younger	0.76 (0.35)	0.43 (0.39)	0.12 (0.24)
	Hits	Older	0.87 (0.3)	0.63 (0.39)	0.26 (0.36)
		Younger	0.87 (0.25)	0.62 (0.33)	0.21 (0.29)
AN-N	Sensitivity	Older	-0.28 (1.29)	-0.07 (1.65)	-0.4 (1.53)
		Younger	0.15 (1.71)	0.71 (2.08)	0.14 (1.85)
	False Alarms	Older	0.85 (0.31)	0.5 (0.43)	0.17 (0.33)
		Younger	0.8 (0.28)	0.46 (0.4)	0.19 (0.32)
	Hits	Older	0.81 (0.33)	0.46 (0.44)	0.12 (0.27)
		Younger	0.84 (0.28)	0.5 (0.38)	0.21 (0.31)

**bold items are significant at p<.05, italicized are marginal at p<.1; standard deviations are in parentheses.*

When examining performance, accuracy rates alone do not do a good job of representing what is known about category membership. For example, if a participant always responds that exemplars are members of category A, they will have perfect accuracy for members of category A, but no ability to distinguish category A from category B. The relationship between the hit rate and false alarm rate contains information about the *sensitivity* of the system, or the ability to determine what was seen and what was not accounting for this kind of response bias (Table 5). Measuring hits and false alarms at different confidence intervals can be used to generate receiver operating characteristic (ROC) curves that provide insights onto the relevant memory processes underlying category learning (Figure 9.2). Signal detection theory makes a distinction between recall (linear with an intercept greater than 0) from familiarity (symmetrical curvilinear) using ROC curves. These curves represent the combined contributions of these processes when remembering category membership. Generally younger adults use a combination of recall and familiarity processes during recognition tests which generates asymmetrical curves with larger sensitivity (behavioral d') as confidence increases (Davachi & Wagner, 2002; Fortin et al., 2004).

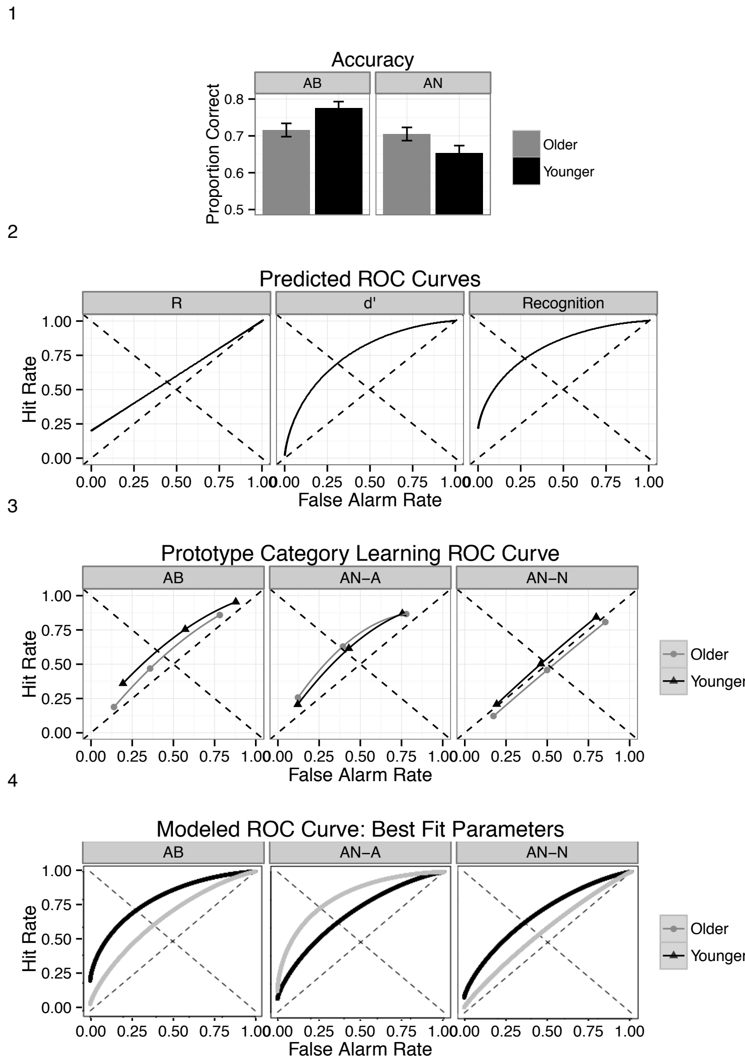

Figure 9. Chapter 3: Behavioral Results and Model Predictions

1) Proportion correct for younger and older adults for the rule-based AB task with corrective feedback and perceptual representation-based AN task without corrective feedback. Standard error bars included. 2) Predicted ROC curves for linear recall (left; R), quadratic familiarity (center; d'), and recognition which incorporates both recall and familiarity (right). 3) Observed ROC curves for the AB (corrective feedback comparing both categories during training; left), for AN-A (passively viewed without feedback during training; center), and AN-N (untrained; right) across three confidence thresholds. 4) ROC curves for the mean best fit model parameters for the AB (corrective feedback comparing both categories during training; left), for AN-A (passively viewed without feedback during training; center), and AN-N (untrained; right).

To examine whether older and younger adults use different underlying psychological processes when reflecting on category membership at test, ROC curves were generated and sensitivity (behavioral d') was examined (Figure 9.3; Table 2). In the AN task, members of category "N", or the untrained category, behave like "new" items that lack familiarity as described in signal detection theory. Thus, we do not expect as much familiarity with the untrained "N" category that wasn't explicitly trained. However, in the AB task both category A and category B were trained and prototypes were randomly assigned to features. Thus, here we examine sensitivity (behavioral d') at each certainly threshold (c_2, c_3, c_4) for each age group (Younger, Older) and training condition (AB, AN-A, AN-N). Here the certainty thresholds are determined using confidence ratings. At the most liberal confidence threshold (c_2) hit rates are calculated by counting any correct response with confidence of 25% sure or higher as a hit (25% sure, 75% sure, 100% sure) and any correct response with confidence of "Not Sure" as a miss. At the most conservative threshold (c_4) hit rates are calculated by counting any correct response with confidence of 100% sure as a hit and any correct response with confidence of 75% sure or lower as a miss (Not Sure, 25% sure, 75% sure). The c_3, confidence threshold was intermediate to c_2 and c_4.

A visual inspection of the data indicates age differences in the psychological processes involved in the AB task, but not the AN task. In the AB task, older adults' ROC curves tend to be shifted to the left and younger adult to the right. There is a similar level of response bias in both curves as the range is about the same for older adults and younger adults. This indicates that older adults are more conservative and younger adults are more liberal with their response bias.

In the AN task, ROC curves appear roughly symmetrical for category A with the largest d' at an intermediate threshold whereas the ROC curves are flat for category N. In the AB task, on the other hand, curves have different shapes in older and younger adult groups where younger adult curves appear asymmetrical and older adult curves appear symmetrical. Younger adults demonstrate greater discriminability for more conservative response bias than older adults in the AB task (Figure 9.3, AB). This is indicative of strong vivid information about category membership in combination with familiarly as seen in Fortin et al 2004 and as predicted by a dual process model of recognition memory (Fortin et al., 2004; Yonelinas, 1997; Yonelinas & Jacoby, 2012).

Formal Comparisons of ROC Curves

Repeated measures ANOVA can be used to formally test whether behavioral sensitivity scores represent differently shaped curves (M. W. Howard, Bessette-Symons, Zhang, & Hoyer, 2006; Yonelinas, Dobbins, Szymanski, Dhaliwal, & King, 1996). Significant interactions indicate that the ROC curves are different shapes and thus represent different underlying contributions of recall and familiarity. For the following analyses we excluded N=2 older adults that did not have false alarms for category N and sensitivity could not be measured.

There is a significant main effect of threshold (c_2 – liberal threshold, c_3 – moderate threshold, c_4 – conservative threshold), $F(2, 346) = 5.55$, $p=.004$, where sensitivity is larger at c_3 than c_2, $t(178)= 3.19$, $p=.002$, *ns,* and c_4 than c_2 $t(178)= 2.09$, *p*=.03, *ns,* and no difference emerged between c_3 and c_4, $t(178)= 1.15$, $p=.24$, *ns,* (M_{c2} = .13, SD_{c2} = 1.3; M_{c3} = .62, SD_{c3} = 1.32; M_{c4} =.49, SD_{c4} = 1.18). There is also a significant main effect of training, $F(2, 173) = 4.92$, $p=.008$, where sensitivity is higher in the AN-A than the AN-N training condition, t(364) = 3.41, p<.01, and the AB training condition than the AN-N training condition, t(355) = 2.69, p=.007, but there were no significant differences between the AN-A and AB conditions, $t(349) = 1.01$, $p=.31$, *ns,* (M_{AB} = .50 , SD_{AB} = .93; M_A = .68, SD_A = 1.27; M_N =.04, SD_N = 1.25). This main effect is qualified by a Training x Age interaction, $F(2, 173) = 2.19$, $p=.056$ and no other significant effects. To decompose these effects, Age X Threshold mixed effects ANOVAs were conducted within Training conditions for sensitivity.

In the AB training condition, there is no significant effect of Age $F(1, 55) = .21$, $p=.64$, *ns,* a marginal main effect of Threshold, $F(2, 110) = 2.74$, $p=.09$, and a significant interaction between Age and Threshold, $F(2, 110) = 3.53$, $p=.03$. Independent sample t-tests indicate that younger adults have higher sensitivity at the most conservative c_4 threshold than older adults, $t(55) = 1.95$, $p = .056$. No other significant differences emerged (Table 5).

In the trained category for the AN task (AN-A), there is a significant effect of Threshold, $F(2, 116) = 3.17$, $p=.05$, and no other significant effects. Collapsing across Age, paired t-tests indicate that sensitivity is significantly larger for c_3 than c_2, $t(59) = 2.19$, $p=.03$, and c_4 than c_2, t(59) = 2.12, p=.04) However, there are no significant differences in sensitivity between c_3 and c_4, $t(59) = .12$, $p=.90$.

In the untrained category for the AN task (AN-N), there is a marginal main effect of Age, $F(2, 120) = 3.55$, $p=.06$, and no other significant effects. Collapsing across thresholds, younger adults have higher sensitivity than older adults, $t(92) = 2.29$, $p=.02$, $M_{Older} = -.25$, $SD_{Older} = .96$; $M_{Younger} = .33$, $SD_{Younger} = 1.43$. In addition, single sample t-tests indicate that neither younger adults, $t(92) = 1.72$, $p=.09$, nor older adults, $t(92) = 1.63$, $p=.11$, *ns*, were significantly different than 0 (guessing).

Thus, these analyses indicate that the processes underlying category recognition, as represented by the shape of the ROC curves, is different for younger and older adults for the AB task, but not the AN task. In the AB task, there is an interaction between age group and threshold suggesting different underlying processes. In the AN task there is a main effect of Threshold for category A but no interaction in either category. This suggests that younger adults and older adults are using the same psychological processes during AN learning.

Computational Modeling

Though this measure of sensitivity (behavioral d') indicates that older and younger adults are using different strategies to recognize category membership in the AB task, it does not address the dissociable contributions of recall and familiarity that underlie these differences. Yonelinas and colleagues propose a Threshold Dual Process memory model that underlies recognition memory (Yonelinas, 1997; Yonelinas et al., 1996). Here recall and familiarity are both used to guide category recognition, not sensitivity alone as described by signal detection theory. This concept can be seen in Figure 9.2 where familiarity-based judgments have a quadratic curve (d'), recall-based judgments are linear (R), and recognition memory is a combination of these two processes.

$$hits = R + (1 - R)(p(hit) > confidence)$$

$$false\ alarms = p(false\ alarm) > confidence$$

It is possible to model ROC curves within individuals for each training group to determine the dissociable contributions of *R* and *d'* to the path of the curve (M. W. Howard et al., 2006). Here *R* and *d'* are fit as free parameters. For each iteration of *R* and *d'* an ROC curve is generated and confidence thresholds are moved along the ROC curves until the lowest χ^2 between the observed response distribution and the model predictions is found. Thus, there are 5 free parameters in the model; three confidence intervals ($0 < c_2 < c_3 < c_4 < 1$), one recall parameter ($0 < R < 1$), and one familiarity parameter ($0 < d' < 3.2$). ROC curve fits give insights into the unique contributions of recall (*R*) and familiarity (*d'*) to category recognition.

We fit computational models of ROC curves separately for the two categories within the AB and AN task for each individual. The model provided a good fit to the data ($M_{\chi 2} = 1.37$, $SD_{\chi 2} = 3.43$). As the category labels are arbitrary in the AB task (randomly assigned prototypes for A and B for each participant) and both are trained equally, mean parameter estimates for the two categories are taken for each individual. The AB training condition was also examined by modeling both categories together and the pattern of results was consistent with the reported findings. In the AN task category A was trained through repeated exposure to exemplars and category N was not. Thus, we included AN categories (AN-A, AN-N) separately for analysis for each individual (Figure 9.4).

Computational Modeling Results

To examine the contribution of familiarity to category recognition, a 2 Age (younger, older) x 3 Training (AB, AN-A, AN-N) ANOVA was conducted on the *d'* parameter (Figure 10). There was a significant main effect of Training, $F(2, 170) = 4.97$, $p=.008$, which was qualified by a significant Age x Training interaction $F(2, 170) = 6.50$, $p=.002$. Independent sample t-tests were conducted to decompose the effects of the interaction. In the AB training condition, younger adults have significantly higher *d'* than younger adults, $t(54)=2.44$, $p=.02$, ($M_{YoungerAB} = .95$, $SD_{YoungerAB} = .79$, $M_{OlderAB} = .53$ $SD_{OlderAB} = .44$). However, in the AN-A training condition older adults have significantly higher *d'* than younger adults, $t(58) = 2.07$, $p=.04$, ($M_{YoungerAN\text{-}A} = .61$, $SD_{YoungerAN\text{-}A} = .93$, $M_{OlderAN\text{-}A} = 1.61$ $SD_{OlderAN\text{-}A} = 1.31$), and older adults have marginally higher *d'* than younger adults in the AN-N training condition, $t(58) = 1.42$, $p=.06$, ($M_{YoungerAN\text{-}N} = .60$, $SD_{YoungerAN\text{-}N} = .89$, $M_{OlderAN\text{-}N} = .22$ $SD_{OlderAN\text{-}N} = .57$).

To determine whether familiarity was related to better performance, the *d'* parameter was correlated with performance for each training condition. There was a significant relationship between *d'* and performance in the AB training condition, $r^2 = .10$, $p=.02$, the AN-A training condition, $r^2 = .10$, $p=.02$, and the AN-N training condition, $r^2 = .19$, $p<.001$.

To examine the contribution of recall to category recognition, a 2 Age (younger, older) x 3 Training (AB, AN-A, AN-N) ANOVA was conducted on the *R* parameter

(Figure 10). There was a significant interaction between Age and Training, $F(2, 170) = 3.45$, $p=.03$. Independent sample t-tests were conducted to decompose the effects of the interaction. In the AB training condition, younger adults have significantly higher *R* than younger adults, $t(54)=3.21$, $p=.002$, ($M_{YoungerAB} = .22, SD_{YoungerAB} = .27, M_{OlderAB} = .05$ $SD_{OlderAB} = .09$). However, in the AN-A training condition, $t(58) = .77$, $p=.43$, *ns,* ($M_{YoungerAN\text{-}A} = .10, SD_{YoungerAN\text{-}A} = .23, M_{Older} = .15$ $SD_{Older\ AN\text{-}A} = .31$), and the AN-N training condition, $t(58) = 1.27$, $p=.20$, *ns,* ($M_{YoungerAN\text{-}N} = .11, SD_{YoungerAN\text{-}N} = .24, M_{OlderAN\text{-}N} = .04$ $SD_{OlderAN\text{-}N} = .19$), there where no significant age-related differences in *R*.

To determine whether recall was related to better performance, the *R* parameter was correlated with performance for each training condition. There was a significant relationship between *R* and performance in the AB training condition, $r^2 = .13$, $p=.006$, but not the AN-A training condition, $p=.42$, *ns*, nor the AN-N training condition, $p= .09$, *ns*.

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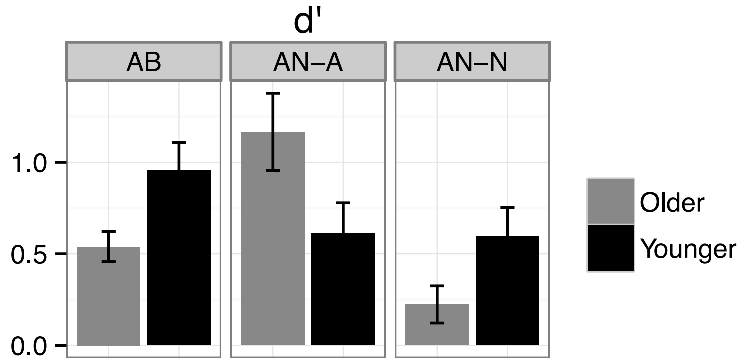

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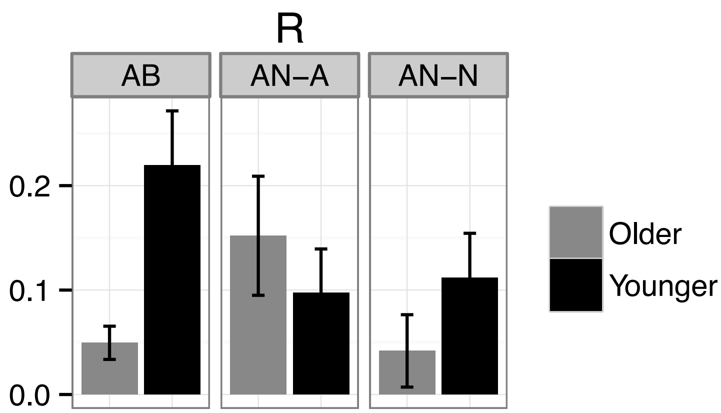

Figure 10. Chapter 3: Computational Modeling Results

Computational modeling results for dissociable memory processes of 1) familiarity as d' and 2) recall as R for each training condition. Results are grouped by the type of category training where AB represents the mean of the model fits for category A and category B which were both trained with corrective feedback. AN-A represents the category presented during training without corrective feedback. AB represents the category not presented during training. Standard error bars included.

Discussion

Some aspects of learning and memory show declines across adulthood while others are left relatively intact (Glass et al., 2012; M. W. Howard et al., 2006; Light et al., 2004; Maddox et al., 2010; Park et al., 2002; Salthouse, 2004; Verhaeghen et al., 2003; Verhaeghen & Cerella, 2002), however little research has examined how these differences interact within dissociable learning systems. Prior work from our lab found that older adults have poor learning relative to younger adults when training consists of comparing category A to category B with corrective feedback (Chapters 1 and 2), however, this finding does not generalize to an automatic perceptual representation task where older adults demonstrated better learning than younger adults (Glass et al., 2012).

We hypothesize that this age by system interaction may be due to age-related changes in the dissociable processes that underlie memory - recall and familiarity. In prior work, younger adults' memory has been shown to be supported by two dissociable types of retrieval – one that depends on vivid impressions of specific experiences (recall) and another that provides a sense of perceptual fluency (familiarity) (Davachi & Wagner, 2002; Yonelinas et al., 1996). It has been suggested that age related declines in recognition do not affect these processes uniformly with greater declines in recall while familiarity is left relatively intact (Light et al., 2004). These changes in recognition likely affect learning outcomes differently depending on training demands.

In this Chapter we examined how age-related changes in recall and familiarity influence new category learning as a function of different training conditions where rule-based learning depends on declarative memory (recall; AB) and verbal rules and perceptual representation learning without feedback depends on fluency (familiarity; AN). An examination of the behavioral ROC curves indicates that older adults and younger adults are using different psychological processes during the AB task and similar psychological processes during the AN task. Computational models indicate that younger adults have significantly higher recall (*R*) in the AB task than older adults and successfully use this process to correctly recognize category members. This age difference in recall was not seen in either category A or N of the AN task. In addition, older adults revealed greater familiarity (*d'*) for the passively trained category of the AN task than younger adults and successfully use this process to correctly recognize category members. Importantly, in the AB task both *R* and *d'* are significantly correlated with overall performance across groups. However, in the AN task *d'* for both category A and N is correlated with overall performance and *R* is not. Further, a visual inspection of the ROC curves generated by the model's best fitting parameters support highlight these distinctive characteristics of the curve and match the pattern seen in the behavioral data (Figure 9.4).

Glass and colleagues suggested that age-related performance differences in AB and AN learning may be due to differences in strategy selection or due to greater declines in the declarative memory system than the procedural memory system (Glass et al., 2012; Poldrack & Foerde, 2008). In line with several other studies (Filoteo et al., 2010; Maddox et al., 2008), the data reported here suggests that age-related changes in the contributions of dissociable recall and familiarity processes are, to some extent, responsible for age-related changes in category learning performance within these systems. Further, these data contribute to growing evidence against single-system hypotheses where only a single declarative memory process underlies learning. However, it is unclear how the strategic differences mentioned by Glass et al. are related to reported differences in in the contributions of recall and familiarity. Future work should examine whether strategy is interacting with the contributions of memory processes to affect learning outcomes.

These findings are important in a number of ways. These data lend support to findings from prior work that indicate these tasks are driven by two dissociable systems and links these differences to specific components of memory (Bozoki et al., 2006; Gorlick & Maddox, 2013; Maddox et al., 2011; Zeithamova et al., 2008). It is worth noting that both recall and familiarity aid performance during rule-based AB prototype learning and only familiarity aids performance during perceptual representation-based AN learning in the absence of feedback. Thus, though dissociable, these processes work in parallel to aid performance in the AB task. In addition, these results align with multiple studies that suggest that older adults have poor memory accuracy due to impairments in recall and good memory accuracy due to intact familiarity (M. W. Howard et al., 2006; Light et al., 2004). By using multiple types of prototype category training within the same paradigm we were able to demonstrate that the relationship between memory processes and performance is complex where the outcomes depend on training. These results suggest that an older adult bias towards familiarity based processing may help guide best practices for life-long learning. Learning P performance in older adults is best when training is supported by perceptual fluency in the absence of feedback.

Chapter 4: Emotional Priming in Rule-Based and Perceptual Representation-Based Learning (Gorlick & Maddox, 2013, *PLOS ONE*)

Chapter 3 demonstrated how recall, or narrow attention to specific features, and familiarity, or global perceptual representations, influence rule-based category learning and perceptual representation-based category learning. Interestingly, younger adults demonstrated a learning deficit relative to older adults in the perceptual representation-based system. This finding highlights the fact that learning deficits are not limited to older adults. However, we may be able to use a different set of emotional biases seen in younger adults to change attention and thus improve performance.

Attentional scope is likely critical in when considering the effectiveness of recall and familiarity during learning. During rule-based tasks, narrow attention to specific features is needed to test hypotheses based on recollections of prior exemplars. During perceptual representation tasks, broad attention to the stimulus as a whole is needed to create a global perceptual representation of the stimulus thus developing familiarity(Ashby & O'Brien, 2005). Prior work examining younger adults has demonstrated that emotional arousal influences the scope of attention (Fredrickson & Branigan, 2005), however little work has been done to determine how exhilarating or threatening conditions that are independent of learning influence changes in attentional scope and subsequent task performance.

The goal of this research is to investigate how task-irrelevant positively and negatively emotionally-arousing primes affect performance during rule-based learning and perceptual representation-based learning (Ashby & Maddox, 2010; Zeithamova et al., 2008) and focus on younger adults where the influence of emotional primes is best understood. During training we presented either a positively or a negatively arousing emotional prime before each stimulus. During test participants are asked to categorize novel stimuli without primes and accuracy is examined. In addition, computational models provide insights into arousal's effects on attention during test.

Positive emotional primes have been shown to broaden attention, thus we predict that attention will be evenly distributed across features. On the other hand, negative emotional primes have been shown to narrow attention, thus we predict that focus would be limited to a small number of features. Importantly, these predictions apply to both perceptual representation (AN) and rule-based (AB) learning tasks, but are predicted to have very different effects. Specifically, in the rule-based AB task, we predict that negative emotional primes will narrow attention for features from category A and category B, an ideal scope for verbalizable rule development yielding high accuracy. Positive emotional primes will broaden attentional focus for category A and category B making it difficult to develop concrete rules yielding low accuracy. However, in the perceptual representation-based AN task, we predict that positive emotional primes will broaden attention facilitating global perceptual fluency with category A thus yielding high accuracy. Negative emotional primes will narrow attention creating a weak global perceptual-representation of category A yielding low accuracy. Thus, we predict an interaction between task (AB, AN) and valence of primes (positive, negative), where negative arousal enhances performance in the rule-based AB task and positive arousal enhances performance in the perceptual representation-based AN task.

METHOD

Participants

One hundred forty five undergraduates age 18-35 participated in the AB condition (n_{NegArs}= 34, n_{Pos}= 37, $n_{NegCont}$= 37, $n_{PosCont}$= 37) and 145 undergraduates age 18-35 participated in the AN condition (n_{NegArs}= 40, n_{Pos}= 32, $n_{NegCont}$= 35, $n_{PosCont}$= 38) from the University of Texas at Austin community participated for class credit. Participants were excluded if performance was less than 40% or if 90% or more of their responses were of one category type. The University of Texas at Austin Internal Review Board approved the procedures of this study and written consent was obtained for all participants.

Materials

Twenty prime images were presented during training that were taken from 20 yoked images of positive/neutral scenes and 20 yoked images of negative/neutral scenes. Images were a subset of those used in Mather & Nesmith (M. Mather & Nesmith, 2008) and were matched on arousal and similarity. Matched images were taken from the International Affective Picture System (Lang, Bradley, & Cuthbert, 2005) and outside sources on the internet to best match on appearance, complexity, content, and focus of interest while manipulating arousal. Mather and colleagues validated matched images with several raters. Yoked images that were rated as at least 1.5 points apart in arousal on a scale from 1 (low arousal) to 9 (high arousal) and similar to each other with at least a

5.3 rating on a scale of 1 (not at all similar) to 9 (extremely similar).

Cartoon animals constructed from 10 binary features such as head orientation (up or forward), body color (grey or yellow), and tail (thin or thick) served as stimuli from a total of $2^{10} = 1024$ possible stimuli (Figure 11.1). For each participant one stimulus was selected at random to represent the A prototype. The B (or anti) prototype has the opposite value on each feature. Category stimuli were derived by distorting the prototype on one to four randomly selected features. Exemplars that differ from the prototype on five features were not used as they are ambiguous.

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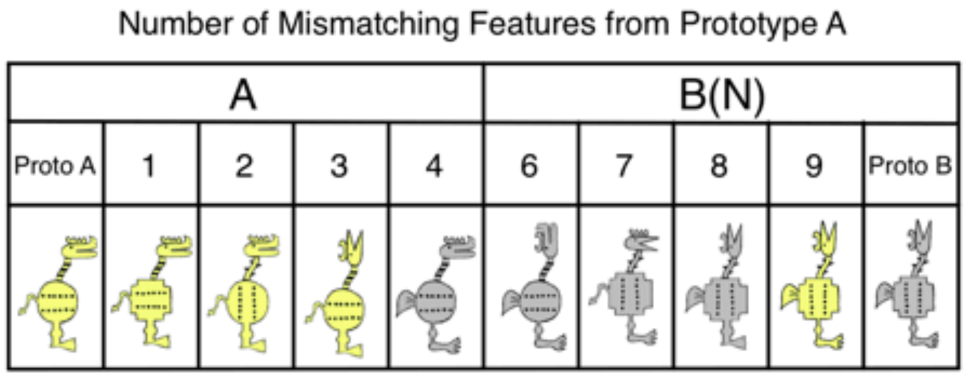

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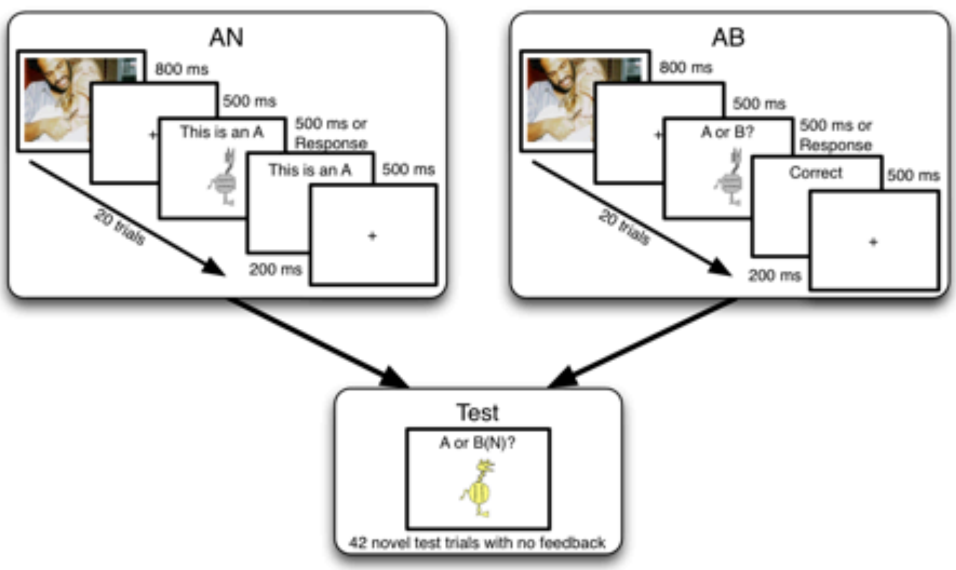


Figure 11. Chapter 4 Stimuli and Procedure

1) Category Structure. 2) Participants completed 2 blocks of 20 training trials and 42 test trials (including prototypes and antiprototypes). In this study we presented emotional/neutral emotional prime images 500 ms before stimuli presentation during training to induce a positive or negative mood.

Procedure

We used a 4 emotional prime (negative-arousing, negative-control, positive-arousing, positive-control) X 2 task (AB, AN) between-participant design. Training was manipulated between tasks and consisted of 20 trials followed by a test phase with 42 novel stimuli including the prototype and the antiprototype, and equal numbers of A and B items. On each training trial, an emotional or neutral prime was presented for 800ms, followed by a fixation cross for 500ms before the stimulus is presented (Figure 11.2). Each participant completed 2 blocks of 20 training and 42 test trials.

During AB prototype training, participants were shown 10 A and 10 B items in a random order, generated a response and were given corrective feedback. Within each category, 2 training stimuli differed from the category prototype on 1 feature, 3 differed on 2 features, 3 differed on 3 features and 2 differed on 4 features. Across all 10 stimuli within each category, the category typical features were presented 7 or 8 times and the opposite category typical features were presented 2 or 3 times. During AN prototype training, participants were shown 20 A items in a random order with a keystroke required to advance to the next item. Five items differed from the category A prototype on 1, 2, 3, and 4 features.

In both the AB and AN tasks, a 42-trial test phase followed training that included each prototype and 5 stimuli that differed from each prototype on 1, 2, 3 and 4 features. On each test trial, 2 seconds after stimulus onset, the participant was prompted to give an A or B (not A) response with no corrective feedback.

RESULTS

We were most interested in the effect of emotional primes on stable performance and focused our analysis on the 42-trial final test block (including 40 novel examples and

2 prototypes). We expected and found no performance differences between the positive- and negative-control conditions for the AB task [$M_{\text{NegControl}}$ = .65, $M_{\text{PosControl}}$ = .67, $t(72)<1.0$, p = .47] and for the AN task [$M_{\text{NegControl}}$ = .64, $M_{\text{PosControl}}$ = .61, $t(71)<1.0$, p = .47]. Therefore, in the following analyses we collapsed across positive and negative control groups within the AB and AN task and refer to them as the "control" group.

Overall Test Accuracy

Proportion correct was calculated for each participant and a 2 task (AB, AN) X 3 emotional prime (negative, control, positive) ANOVA was conducted. There was no main effect of task, F(1, 284) = 2.16, p= .14, η^2 = .008, or emotional prime, F(2, 284) = .274, p = .76, η^2 = .002. However, there was a significant two-way interaction, $F(2, 284)$ = 5.770, p = .003, η^2 = .04 (Figure 12.1).

To decompose the effects of emotional prime valence on AB and AN accuracy, we conducted independent sample t-tests between the negative and positive prime conditions within each task. In the AB task, accuracy was higher in the negative prime condition (M_{Neg}= *.68*) than the positive prime condition (M_{Pos}= *.59*), $t(69) = 2.37$, p = .021, η^2 = .08. However, in the AN task, accuracy was higher in the positive prime condition (M_{Pos}= *.67*) than the negative prime condition (M_{Neg}= *.58*), $t(70) = 2.30$, p = .024, η^2 = .07. This indicates that task performance depends on the valence of emotional primes with negative primes enhancing AB task performance and positive primes enhancing AN task performance. Performance in the control condition fell between the positive and negative conditions for both tasks and there was no statistical difference,

$t(145) = 1.43$, $p = .154$, $\eta^2 = .014$, *ns*, between the control prime conditions in the AB and AN task (M_{AB}=.66, M_{AN}=.62) suggesting that the tasks are of equivalent difficulty.

Prototype Accuracy

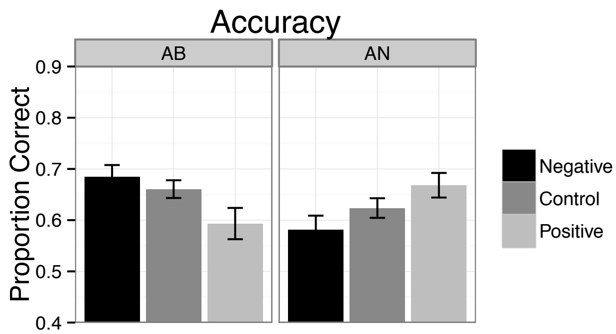
Prototype accuracy was calculated for each participant. In the AB condition the average accuracy for the A and B prototypes was calculated and in the AN condition accuracy for the A prototype was calculated. A 2 task (AB, AN) X 3 emotional prime (negative, control, positive) ANOVA was conducted on prototype accuracy. There was no main effect of task, $F(1, 284) = 2.27$, p=.13, $\eta^2 = .008$, or emotional prime, $F(2, 284) = .84$, $p = .43$, $\eta^2 = .006$. However, there was a significant two-way interaction, $F(2, 284) = 5.503$, $p = .005$, $\eta^2 = .04$ (Figure 12.2). Post-hoc analyses suggested that prototype accuracy was marginally higher in the negative prime condition (M_{Neg}= *.84*) than the positive prime condition (M_{Pos}= *.69*), $t(69) = 1.84$, $p = .07$, for AB learning, but was higher in the positive prime condition (M_{Pos}= *.87*) than the negative prime condition (M_{Neg}= *.62*), $t(70) = 2.46$, $p = .016$, for AN learning. This indicates that prototype accuracy in each task depends on the valence of emotional primes.

Antiprototype Accuracy

Antiprototype accuracy was examined in the AN task only since both prototypes were trained in the AB condition and category labels are arbitrary. We conducted a one-way ANOVA examining priming condition (positive, control, negative) within the AN task (Figure 12.3). There was a main effect of prime, $F(2, 142) = 3.09$, $p = .05$, $\eta^2 = .04$, T-tests between the negative and positive prime conditions indicated that accuracy was higher in the positive prime condition (M_{Pos}= *.75*) than the negative prime condition

(M_{Neg}=.48), $t(70) = 2.43$, $p = .018$, $\eta^2 = .08$. Together, these results indicate that prototypes and antiprototype accuracy depends on the valence of emotional primes and training where negative primes improve accuracy in the AB task and positive primes improve accuracy in the AN task.

1



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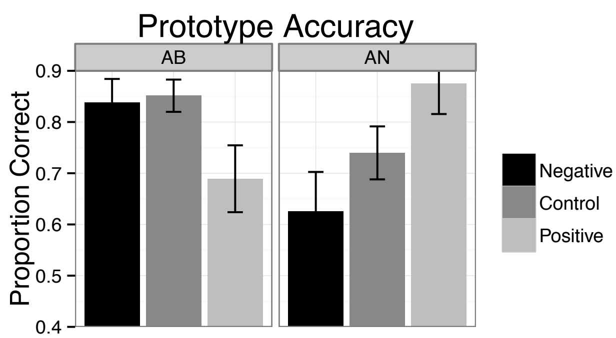

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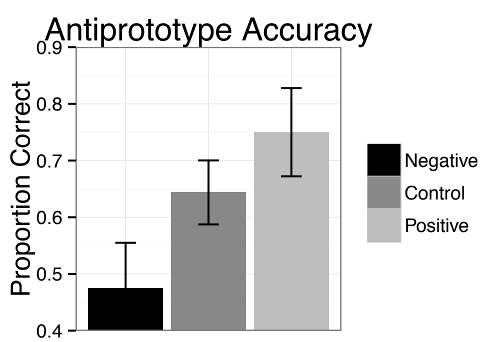

Figure 12. Chapter 4: Behavioral Results

1) Proportion correct for negative, control, and positive emotional prime conditions during test for the AB task and the AN task. 2) Proportion prototypes correct for negative, control, and positive emotional prime conditions during test for the AB task and the AN task. 3) Proportion antiprototypes correct for negative, control, and positive emotional prime conditions during test for the AN task. Standard error bars included.

Computational Models

The accuracy based analyses support our prediction that positive emotionally-valenced arousal will improve perceptual representation-based AN learning, whereas negative emotionally-valenced arousal will improve rule-based AB learning. However, these analyses provide no information regarding our prediction that the locus of these effects is in emotional arousal's influence on attentional scope. Specifically, we hypothesized that AN learning requires broad attentional focus and thus will be enhanced by positive emotional arousal, whereas AB learning requires narrow attentional focus and thus will be enhanced by negative emotional arousal. To test these predictions we turn to computational modeling techniques. We applied simple prototype models to each individual's data (Ashby & Maddox, 1993; Posner & Keele, 1968; J. D. Smith & Minda, 1998).

The model assumes that on each trial, the participant calculates the attention-weighted Euclidean distance between the current stimulus (x) and the prototype for the categories (P_A for category A, and P_B for category B(N)). The attention weights stretch and shrink the perceptual space along each stimulus dimension with larger attention weights stretching the space (increasing dimension-level discriminability). The (city block) distance between x and P_A is calculated as:

$$d_{xP_A} = \sum w_i \left|(x_i - P_{A_i})\right| \quad (1)$$

where w_i represents the attention-weight associated with dimension i. The attention weights are constrained to sum to 1, yielding 9 free w_i parameters. The stimulus' binary value for dimension i is denoted by x_i, and prototype A's binary value for dimension i is denoted by P_{A_i}. P_B is calculated on each trial using the same method. The predicted probability of responding A to a stimulus, $P(A \mid x)$, is calculated as:

$$P(A \mid x) = \frac{\eta_{iA}}{\eta_{iA} + \eta_{iB}} \tag{2}$$

where $\eta_{iA} = e^{-cd}$ (d is calculated in Eq. 1). The c parameter represents the perceptual sensitivity of the system, and is the 10th free parameter. Larger values of c stretch the perceptual space uniformly leading to greater overall discriminability across stimuli. For each participant, we fit the model to 42 test items from the test block using maximum likelihood procedures.

Attentional Focus

We predict that positive emotional primes broaden attention whereas negative emotional primes narrow attention. As a test of this hypothesis we identified the dimension with the maximum attention weight ($w_{\max}$; Figure 13.2). A large $w_{\max}$ implies narrow attention and a small $w_{\max}$ implies broad attention. We conducted a 2 task (AB, AN) X 3 emotional prime (negative, control, positive) ANOVA on the $w_{\max}$ values and found no main effect of task and no interaction. As predicted, there was a main effect of emotional prime, $F(2, 284)= 7.036$, $p = .001$, $\eta^2= .047$, where negative primes were associated with larger $w_{\max}$ ($M_{Neg}= .57$) and positive primes were associated with smaller $w_{\max}$ ($M_{Pos}= .46$) values. This indicates that negative emotional primes narrow attention while positive primes broaden attention.

In addition to looking at maximal attentional weight, we examined attentional scope by calculating the number of dimensions needed to capture ninety-five percent of the attentional weights (w_i). Here smaller values indicate that fewer dimensions are attended to and thus attention is narrow. We conducted a 2 task (AB, AN) X 3 emotional prime (negative, control, positive) ANOVA on the number of dimensions needed to capture 95% of attentional weights and found no main effect of task and no interaction. However, as seen with maximal attentional weights, there was a main effect of emotional prime, $F(2, 284)= 3.93$, $p = .02$, $\eta^2= .03$, where negative primes were associated with smaller w_{95} ($M_{Neg}= 3.3$) and positive primes were associated with larger w_{95} values ($M_{Pos}= 3.7$). This indicates the effects of emotion on attentional scope are robust to multiple measures of attention.

Perceptual Discriminability

We also predict that narrow attention facilitates AB learning whereas broad attention facilitates AN learning thus leads to increased perceptual discriminability. As a test of this hypothesis we conducted a 2 task (AB, AN) X 3 emotional prime (negative, control, positive) ANOVA on the perceptual discriminability (c) values (Figure 13.1) and found a main effect of task, $F(1, 284) = 8.299$, $p=.004$, $\eta^2 = .028$, no main effect of emotional prime, $F(2, 284) = .429$, $p = .65$, $\eta^2 = .003$, and an interaction $F(2, 284) = 6.628$, $p = .002$, $\eta^2 = .05$. In support of our prediction, post hoc analyses revealed that perceptual discriminability was higher in the negative prime condition ($M_{Neg}=9.03$) than the positive prime condition ($M_{Pos}=4.48$), $t(69) = 2.26$, $p = .027$, $\eta^2 = .07$ for the AB task, but was higher in the positive prime condition ($M_{Pos}=2.78$) than the negative prime condition ($M_{Neg}=5.44$), $t(70) = 2.24$, $p = .028$, $\eta^2 = .07$ for the AN task.

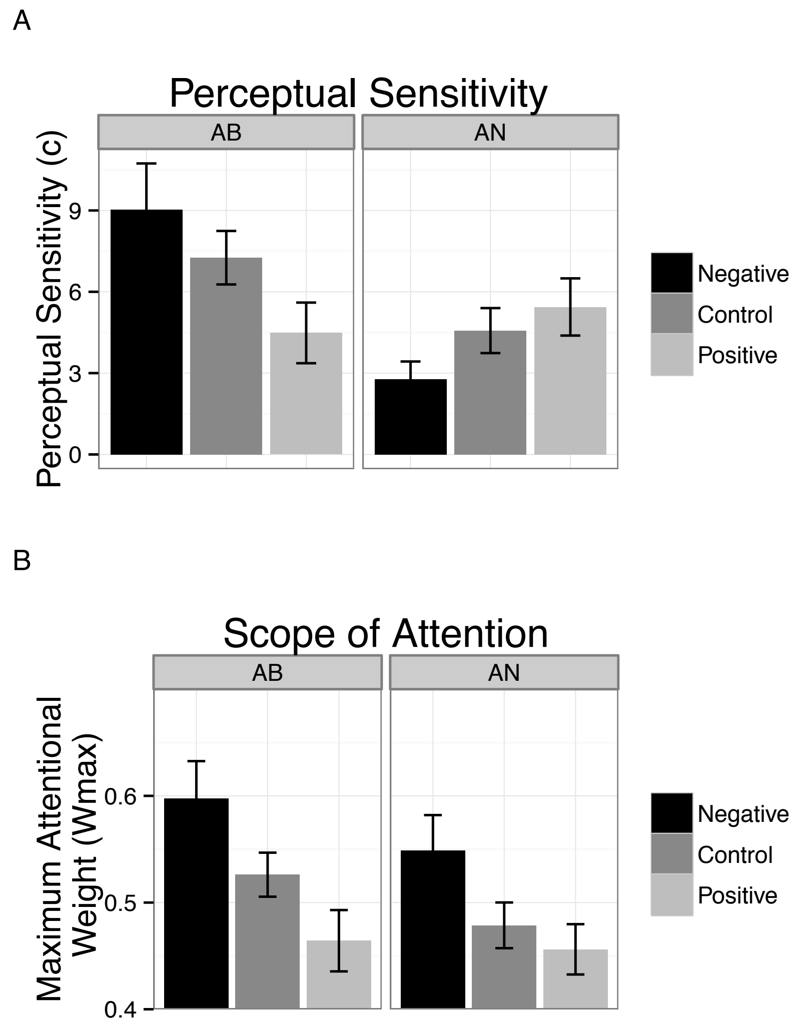

Figure 13. Chapter 4: Computational Modeling Results

1) Perceptual discriminability parameter estimates (c) X emotional primes (negative, positive, neutral) for the AB task and the AN task. 2) Maximum dimension weight parameter (w_{max} *) estimates X emotional primes (negative, positive, neutral) for the AB task and the AN task. Standard error bars included.*

Parameter Estimates and Performance

To further test our assumption that narrow attention facilitates AB learning and broad attention facilitates AN learning, we correlated AB and AN accuracy with the maximum attentional weight (w_{max}) and perceptual discriminability (c) parameter values. A larger maximum attentional weight (w_{max}) was associated with increased performance in the AB task, $r^2 = .23$, $F(1,143) = 8.03$, $p = .005$, but not the AN task, $r^2 = -.06$, $F(1,143) = .045$, $p = .50$, *ns*. In addition, increased perceptual discriminability (c) was associated with increased performance in both the AB task, $r^2 = .63$, $F(1,143) = 95.50$, $p < .001$, and the AN task, $r^2 = .48$, $F(1,143) = 41.92$, $p < .001$. Thus, focused attention was associated with improved accuracy in the AB task only, whereas greater discriminability was associated with improved accuracy both the AB and AN tasks.

DISCUSSION

The current study represents the first to examine arousal's effects on learning in dissociable perceptual representation-based and rule-based prototype learning systems. The *Arousal-Biased Competition* theory (ABC) states that arousal exaggerates ongoing competitive attentional processes between high- and low-priority stimuli (M. Mather & Sutherland, 2009; 2011). High-priority items are given more attentional resources at the expense of low-priority items, but no strong claims are made regarding the effects of valence on attention. Fredrickson and colleagues have demonstrated that positively-valenced arousal broadens the scope of attention whereas negatively-valenced attention narrows the scope of attention (Fredrickson, 2004; Fredrickson & Branigan, 2005). However, Gable and Harmon-Jones argue that high approach-motived positive arousal narrows attention as seen under negative arousal (Gable & Harmon-Jones, 2008;

Harmon-Jones & Gable, 2009). Thus, while attention for high-priority items is enhanced, it is unclear whether scope of this attention is valence-dependent.

The overriding aim of this study was to determine how positive and negative emotionally arousing primes affect attentional resources and performance in dissociable prototype learning systems – one mediated by declarative memory and rule-based processing and another mediated by perceptual fluency. Prior research suggests that negative emotional primes narrow attention, which should facilitate targeting features for verbalizable rules, while positive emotional primes broaden attention, which should facilitate a strong perceptual representation. Though the effects of priming on cognition are subtle, which is often reflected in modest effect sizes (Sakaki, Gorlick, & Mather, 2011a), the predicted interaction between valence and system is an important one. Prototype distortion learning is an ideal paradigm to test this hypothesis because computational models are available that provide estimates of attentional scope.

Performance

We hypothesized that the valence of emotional primes (positive, negative) affects attentional scope during training and therefore interacts with the system that mediates learning in each task (AB, AN). The results supported our predictions. In the AB task, negative emotional primes improved overall and prototype accuracy relative to positive emotional primes, whereas in the AN task positive emotional primes improved overall, prototype, and antiprototype accuracy relative to negative emotional primes.

Attention

Mather and colleagues suggest that priority items seen after high-arousal primes benefit from enhanced attentional resources regardless of valence in their theory of *Arousal Biased Competition* (M. Mather & Sutherland, 2011). Our computational modeling data indicates that this relationship is more complex and the valence of emotional primes affects the scope of enhanced attention. In the negative emotional prime condition, greater attentional weight was placed on one stimulus dimension compared to the positive emotional prime condition regardless of task suggesting that negative emotional primes narrow and positive emotional primes broaden attentional scope for subsequent stimuli.

Perceptual Discriminability

Perceptual discriminability (c) depends on both the valence of the emotional prime (negative, positive) and the task (AB, AN) and tracks performance. In the AB task those in the negative emotional prime condition were more sensitive to differences between exemplars than those in the positive emotional prime condition. There is a significant reversal of this pattern in the AN task. This indicates that global discriminability helps in both the perceptual representations that aid familiarity judgments during the AN task and declarative memory processes that aid in verbalizable rule formation in the AB task. Modeling results fit with results from Chapter 3 indicating that recall is important during rule-based learning but not perceptual representation-based learning and familiarity is important for both tasks.

Stimulus Dimensionality

The present research examined AB and AN prototype category learning using cartoon stimuli composed of 10 binary value features. Previous research examining these learning systems has looked at the categorization of high-dimensional stimuli such as random Posner dot patterns (Posner & Keele, 1968; Reber et al., 1998; J. D. Smith & Minda, 2002) or low-dimensional stimuli such as Gabors (Ell, Cosley, & McCoy, 2011; Maddox, Ashby, & Bohil, 2003; Nadler, Rabi, & Minda, 2010). One question that this raises is whether the current findings would generalize to these other types of stimuli. Much of the work utilizing dot patterns examined AN category learning. Reber et al. (1998) looked at functional activation during test after participants were trained on distortions from one Posner dot pattern prototype. This task is analogous to our AN task as both examine stimuli with high number of features (patterns of 9 dots in the Posner task) that are distorted from one prototype. Both Reber et al (1998) and Zeithamova et al (2008) found changes in activation in the posterior occipital cortex suggesting an overlapping neural network. Thus, we predict that the effects of emotional primes on AN learning would generalize to performance during the Posner dot pattern task.

Predictions for Gabor patch stimuli are less clear. In fact, the results from one study using Gabor patch stimuli appear counter to what we observed. Nadler et al (2012) found that induced positive mood improved learning in a rule-based task where participants categorized Gabor patches by one dimension (Nadler et al., 2010). Improved performance is attributed to increased prefrontal dopamine enhancements to cognitive flexibility, which aids in rule development (Ashby, Isen, & Turken, 1999). Though positive affect helps rule acquisition in this case, it is likely that the relative importance of cognitive flexibility and attentional scope differ as a function of the dimensionality of the stimuli. High dimensional stimuli require narrow attentional scope in order to select salient features during rule development. Gabor patches are simple stimuli that only vary on two dimensions (frequency and orientation) and attentional scope is not as important in determining learning outcomes. Thus, it is possible that stimulus dimensionality is an important factor that interacts with learning system and mood in determining learning outcomes. Future work should better address these conflicting findings by manipulating the number of stimulus feature dimensions and comparing emotionally valenced priming effects directly with mood induction effects.

Conclusions

These data suggest that the valence of task-irrelevant emotional arousal is a critical factor in determining learning outcomes in younger adults. Negative emotional primes narrow attentional scope optimizing rule-based learning that depends on targeting features to test verbalizable rules. Positive emotional primes broaden attentional scope optimizing perceptual-representation learning that depends on fluency with a group of stimuli.

Final Remarks and Future Directions

Together this work highlights how important a dissociable learning systems approach is in understanding the influence of emotion, memory, and feedback processing on learning outcomes across adulthood. I have reviewed evidence demonstrating that emotional biases can attenuate age-related deficits in rule-based set shifting, but only positive emotional feedback for a task with low cognitive load and negative emotional feedback for a task with high cognitive load (Chapter 1). Critically, the social salience of the feedback was important in improving performance outcomes. These effortful emotional feedback biases successfully attenuated effortful learning deficits, however these benefits did not generalize to procedural learning deficits (Chapter 2). This may be due to differences in the way feedback is processed where automatic learning benefits from automatic feedback processing and effortful emotional biases are an ineffective intervention. In addition, I provided evidence that age differences in the contributions of dissociable memory processes are, at least in part, driving an older adult advantage seen in perceptual representation-based learning (Chapter 3). Though younger adults demonstrated deficits in perceptual representation-based learning relative to older adults, emotional stimuli could be leveraged to alter attention attenuating this deficit. Here the valence of task-irrelevant emotional primes determined the scope of enhanced attention. Positive primes broadened attentional scope facilitating perceptual fluency and negative primes narrowed attentional scope facilitating hypothesis testing (Chapter 4).

Future Directions

Emotional factors interact with task demands as well as learning system learning system to influence performance outcomes in Chapters 1, 2, and 4, however it is still unclear how changes in performance are influenced by one's mood. Though the current dissertation focuses on the influence of emotional stimuli on cognitive and performance outcomes it does not consider how this is mediated by altered mood. Other research has found that those in a depressive mood are more sensitive to loss than gain (Maddox, Gorlick, Worthy, & Beevers, 2012). Further, depressive symptoms have been shown to interact with dissociable systems where those with elevated depressive symptoms tend to process automatic decision-making tasks better than effortful decision-making tasks (Beevers et al., 2012). Future work would do well to examine whether these depressive effects on decision-making generalize to dissociable learning across the lifespan. In addition, depressive symptoms often manifest as an increased attention for negative emotional items and additional work could examining valenced emotional feedback processing could uncover ways to attenuate deficits.

Chapters 1 and 2 demonstrate how age-related biases in emotional feedback processing can be used to improve learning. It is well established that older adults report increased well-being relative to younger adults when the resources are available. The SAVI model, or Strength and Vulnerability Integration model, suggests that age-related changes in the effectiveness of emotion regulation may be due to strategic changes (Charles, 2010). Here lifespan experience dealing with negative events leads to enhanced strategies for coping with exposure to negative stimuli. However, this does not account for the greater socio-emotional framework where younger adults that are coming to the end of an era also experience positive emotional biases (Carstensen, 2006). For example, when individuals come to the end of their senior year they experience "senior-itis" or an increased desire to be with friends and a decreased desire to acquire knowledge. Thus, while there is evidence that temporal horizons impact emotional biases, it is possible that superior emotion regulation strategies are also strengthened. Future work should examine whether age differences in emotion regulation influence emotional feedback processing.

Though tasks are designed to be supported by rule-based, procedural, or perceptual representation-based systems, it is possible that some participants are using a different strategy. Chapters 3 and 4 demonstrate the power of computational models in uncovering latent psychological processes. Future studies should incorporate computational models to gain insights into strategy use. Category learning tasks with stimuli that have continuous feature dimensions are ideal for examining strategy use (Ashby, 1992; 2014; Ashby & Waldron, 1999; Maddox, Filoteo, & Lauritzen, 2007). Here decision bound models provide valuable insights into the underlying methods participants are using to solve the task.

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