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TOWARDS A THREE-FACTOR MOTIVATION-LEARNING FRAMEWORK IN NORMAL AGING

W. Todd Maddox, Marissa A. Gorlick, and Darrell A. Worthy

Introduction

Most behavior stems from *motivation*. As we maneuver through the environment we choose actions from a large repertoire of behaviors. These behaviors are strongly affected by our learning history, but also by our current motivational state to approach positive outcomes or avoid negative outcomes. For example, one could be motivated to be on time for a meeting or to avoid being late for a meeting. Similarly, one could be motivated to achieve a particular score on an exam or avoid falling below a particular score. The goal is the same, but the motivational frame through which one views the goal is different. The approach-avoidance dichotomy is well established in the traditional psychology of motivation (Aarts, Gollwitzer, & Hassin, 2004; Ferguson & Bargh, 2004; Fishbach, Friedman, & Kruglanski, 2003; Gray, 1970, 1985; Higgins, 2000; Hull, 1943; Lewin, 1935; Mowrer, 1960; Murty, LaBar, Hamilton, & Adcock, 2011). Perhaps surprisingly, most cognitive research focuses on information processing and its effects on learning and behavior, with little attention paid to the factors that drive or motivate one to act.

Interestingly, this artificial separation of motivation research from learning research was not present in the 1950s and 1960s (Miller, 1957, 1959; Young, 1959). However, as psychology became more divided and area-driven, learning research became the domain of cognitive and animal psychologists, whereas motivation was primarily studied by social and educational psychologists. In many ways, the cognitive neuroscience revolution that began in the 1980s and 1990s provided the necessary spark for bringing research on learning and research on motivation back together. Cognitive neuroscience research makes clear that the brain does not distinguish between "motivational" brain systems and "learning" brain systems. In fact, some of the most important brain regions for learning, such as the prefrontal cortex, the anterior cingulate, and the caudate nucleus, are known to be involved in motivation, affect, and personality (Baldo & Kelley, 2007; Belin, Jonkman, Dickinson, Robbins, & Everitt, 2009; Berridge, 2003, 2007). In addition, detailed neurobiological theories are beginning to take hold that postulate specific interdependencies between "cognitive" and "motivational" brain regions (Ashby, Isen, & Turken, 1999; Bechara, Damasio, & Damasio, 2000; Bechara et al., 2001; Chiew & Braver, 2011; Jimura, Locke, & Braver, 2010; Murty, Labar, & Adcock, 2012; Pickering, 2004; Spielberg et al., 2011, 2012). Thus, it is clear that motivation and learning are intimately related and advances in one field should be associated with advances in the other.

Organization of the Chapter

The overriding aim of this chapter is to explore the motivation-learning interface broadly, but also with applications in healthy aging. First, we begin by asking the fundamental question, "What is motivation and how is it defined?" We conclude that the layman's definition, and often the implicit scientific definition, is limited in scope. After reviewing common definitions of motivation, we explore more rigorous definitions and conclude that motivation can operate at a *global* or at a *local* level, with each having an approach and an avoidance state. The interaction between the two states is proposed to directly affect the availability of cognitive resources and subsequent behavior. Global motivation, or the big-picture intent of behavior, can involve approaching positive outcomes, such as a promotion or a bonus, or involve avoiding negative outcomes, such as a demotion or pay cut. Local motivation, or the immediate intent of behavior, can involve maximizing performance indices, such as the number of trials performed correctly or the number of points earned, or involve avoiding losses, such as the number of errors or the number of points lost. Global and local motivators are often present at the same time, and understanding how this influences processing biases is critical in predicting learning outcomes.

Next, we explore the learning side of the motivation-learning interface and argue that task demands interact with processing strategies as a form of *task-directed motivation*. Contemporary cognitive psychology acknowledges dissociable-learning systems that influence task-directed motivation (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby, Paul, & Maddox, 2011; Blanco, Otto, Maddox, Beevers, & Love, 2013; Daw, Gershman, Seymour, Dayan, & Dolan, 2011; Glascher, Daw, Dayan, & O'Doherty, 2010; Hayes & Broadbent, 1988; Kendler & Kendler, 1970; Sloman, 1996; Worthy, Otto, & Maddox, 2012). Sometimes the task is such that effortful cognitive control processes and goal-directed behavior optimize performance. At other times, the task is such that automatic, habitual, and procedurally driven behavior optimizes performance.

In this section we bridge a dual-learning systems framework with motivation while exploring the underlying neural systems. We provide strong evidence suggesting a complex three-way interaction between the global motivation (approach or avoidance goals), the local motivation (valence of trial-by-trial feedback: gains or losses), and the learning system (goal-directed or reward-directed). Here the interaction of global and local motivation influences which task-directed system is dominant (Figure 15.1). This has very different implications in modulating

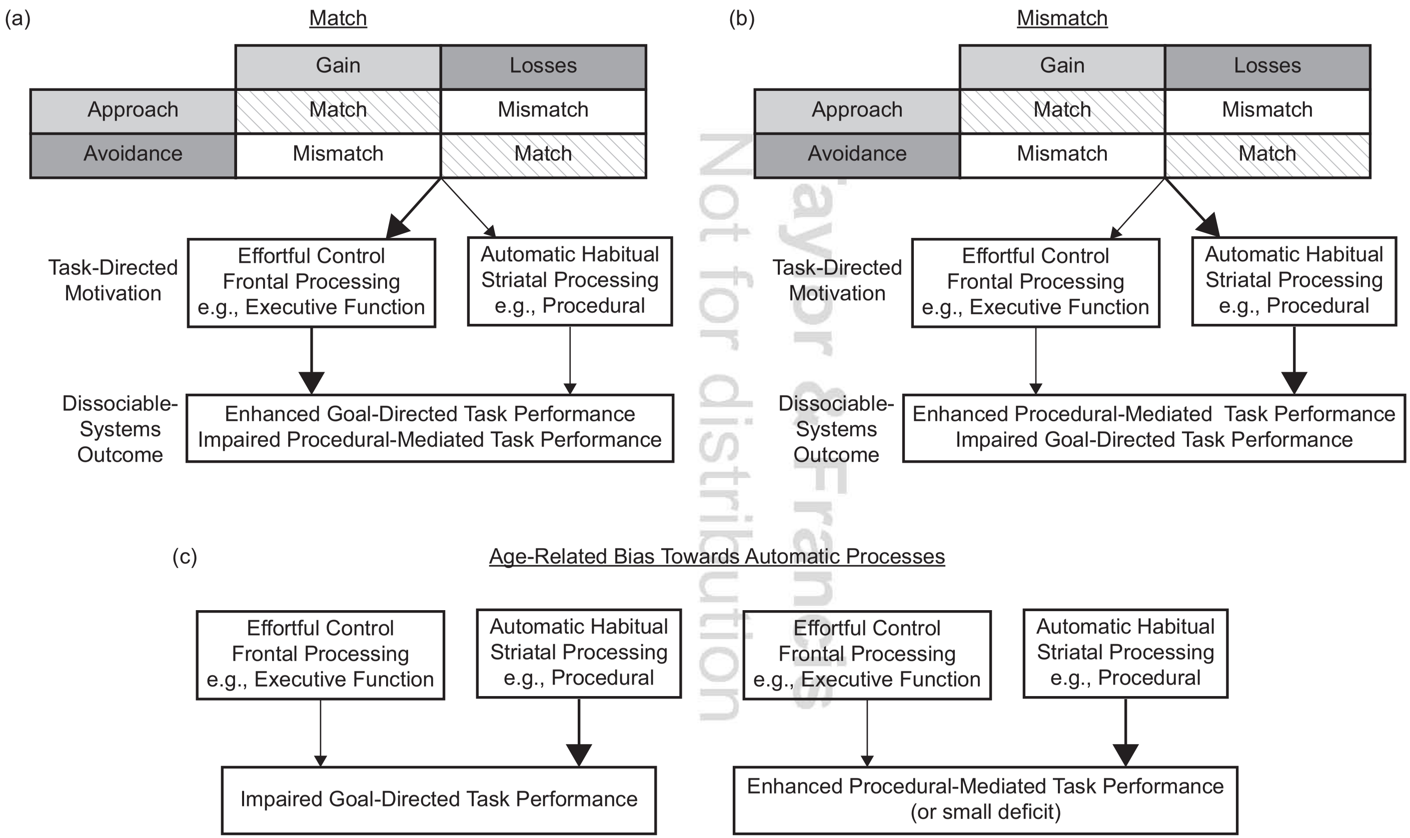

FIGURE 15.1 Regulatory match framework.

goal-directed behavior and reward-directed behavior. Although we describe the three aspects of motivation separately, it is important to emphasize that we espouse highly *interactive systems* whose effects on behavior are not independent.

Finally, we extend these concepts to healthy aging and briefly review two studies from our lab that explore the motivation-learning interface in older adults. Healthy older adults demonstrate differences in baseline levels of task-directed motivation where executive function is diminished, limiting their ability to carry out complex goal-directed behavior and exaggerating their dependence on automatic processes (Figure 15.2). These applications explore age-related changes in the way global motivation influences task-directed motivation during decision making. Critically, we use behavioral tasks that are identical in all respects except

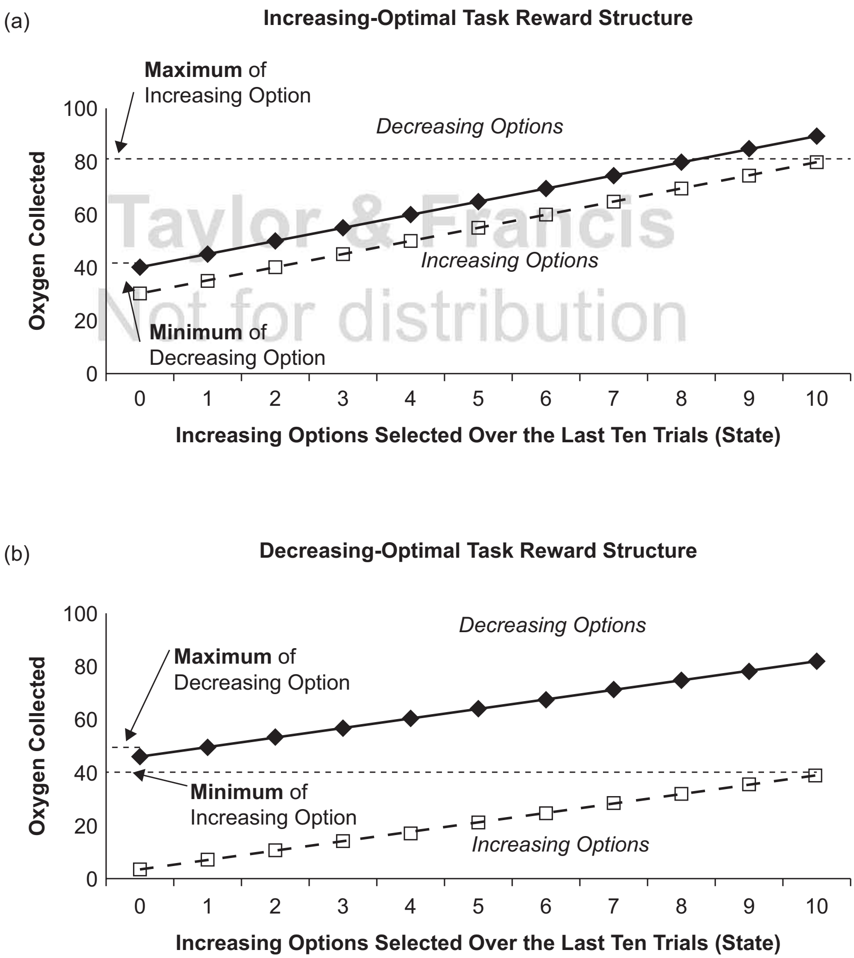

FIGURE 15.2 Task reward structures.

the nature of the optimal learning system. We take advantage of a novel computational modeling approach that allows us to quantify the effects of motivation on dual-processes strategies. Finally, we summarize the complex interaction of global, local, and task-directed motivation, offer some conclusions, and suggest a number of lines of future research.

What Is Motivation and How Is It Defined?

It is commonly thought that motivating someone involves getting them to "try harder." Although this definition captures some important aspects of motivation, it is too simplistic and is lacking in at least two important ways. First, defining motivation as "trying harder" implies an effortful, controlled task-directed motivation that is frontally mediated. As we will see in the next section, the effects of motivation are more complex, with some motivational states enhancing frontal function and others attenuating frontal function. Second, this definition implies that "trying harder" enhances performance, but this is not always the case. In fact, at times decreasing available effortful cognitive control resources through the introduction of a dual task has no effect on performance or even *enhances* performance (Filoteo, Lauritzen, & Maddox, 2010; Maddox, Ashby, Ing, & Pickering, 2004; Waldron & Ashby, 2001; Worthy et al., 2012; Zeithamova & Maddox, 2006, 2007). Thus, trying harder helps in some cases, but hinders in others.

Global and Local Aspects of Motivation

The motivation literature makes a distinction between global approach and global avoidance goals (Carver & Scheier, 1998; Fishbach et al., 2003; Lewin, 1935; Maddox & Markman, 2010; Maddox, Markman, & Baldwin, 2006; Markman & Brendl, 2000; Miller, 1957; Murty et al., 2011). Goals with positive states that one wishes to achieve are called *approach* goals (e.g., a raise), whereas goals with negative states that one wishes to avoid are called *avoidance* goals (e.g., a demotion). Local motivation can involve maximizing performance indices, such as the number of trials performed correctly or the number of points earned, but can also involve avoiding losses, such as the number of errors or the number of points lost. Global and local motivational states can be manipulated independently and vary broadly in the real world and in the laboratory.

One method that we have used for manipulating global approach and global avoidance states is through the use of a raffle ticket procedure (Grimm, Markman, Maddox, & Baldwin, 2007; Maddox, Baldwin, & Markman, 2006; Worthy, Brez, Markman, & Maddox, 2010). In the global approach condition, participants are informed that they will earn a raffle ticket in a drawing to win $50 if their performance exceeds a criterion. In the global avoidance condition, participants are given a raffle ticket for a drawing to win $50 upon entering the laboratory, but are informed that they will lose the ticket if their performance does not exceed a criterion. The bonus criterion and odds of winning the drawing are the same in both conditions. Thus, from an economic standpoint the situation is identical in both conditions; however, the framing of the global motivation incentive is manipulated to create approach or avoidance scenarios.

Local motivators, on the other hand, make up the immediate (trial-by-trial) information that helps individuals maximize gains or minimize losses. To manipulate local motivational states, tasks are framed as gain maximization tasks (local approach) or loss minimization tasks (local avoidance). In the local approach condition, participants gain points on every trial in the task and attempt to maximize gains. In the local avoidance condition, participants lose points on every trial in the task and attempt to minimize losses. Critically, points gained and points lost are equated in such a way that the same overall level of performance is associated with the global motivational performance criterion needed to earn or retain the raffle ticket. Thus, at the level of the task a participant in any of the four possible experimental conditions is in an identical situation economically (earn raffle ticket by maximizing gains, earn raffle ticket by minimizing losses, avoid losing raffle ticket by maximizing gains, avoid losing raffle ticket by minimizing losses).

Figure 15.1 presents a schematic representation of the global and local motivational framework that we propose. The two rows denote the global approach and avoidance motivational states, and the two columns denote the local gains and losses motivational states. Our lab and others have argued that the influence of global and local motivation on task performance is interactive (Avnet & Higgins, 2003; Grimm, Markman, & Maddox, 2012; Grimm et al., 2007; Higgins, 2000; Higgins, Chen Idson, Freitas, Spiegel, & Molden, 2003; Lee & Aaker, 2004; Maddox & Markman, 2010; Maddox, Markman, et al., 2006; Markman, Baldwin, & Maddox, 2005; Shah, Higgins, & Friedman, 1998). We argue that a motivational match serves to up-regulate effortful goal-directed processing, whereas a motivational mismatch serves to down-regulate effortful goal-directed processing, which, given the interactive nature of the systems, serves to enhance automatic habitual processing. Thus, we believe that the locus of these effects is broadly defined as prefrontal (Maddox, Markman, et al., 2006). We hypothesize and find support for the prediction that a match between the global motivation and the local motivation leads to enhanced effortful task-directed cognitive control processing (see Figure 15.1A), whereas a mismatch leads to reduced effortful task-directed cognitive processing (and thus enhanced task-directed habitual processing; Figure 15.1B). It is important to note that in most cognitive research there are uncontrolled or poorly controlled global and local motivational states. At best a mild global approach motivational state is engaged by telling participants to "do their best" or by offering a small monetary bonus for good performance, and a mild local "gains" motivational state is engaged by telling participants to maximize accuracy or maximize points (Maddox & Bohil, 1998).

Dissociable-Learning Systems and Task-Directed Motivation

The theory that humans have multiple memory systems became widely accepted within the field of cognitive neuroscience during the 1980s and 1990s (Eichenbaum, 1997a, 1997b; Schacter, 1987; Squire, 1992; Squire, Knowlton, & Musen, 1993; Tulving, 2002). Since learning is a process of laying down memory traces, it is reasonable to argue that multiple learning systems exist that are capable of utilizing different types of memory traces associated with solving various tasks. Although dissociable-learning systems approaches have been explored in a number of domains, including reasoning (Sloman, 1996), motor learning (Willingham, Nissen, & Bullemer, 1989), discrimination learning (Kendler & Kendler, 1970), and function learning (Hayes & Broadbent, 1988), the focus of the present chapter is on decision making. Critically, we have demonstrated that one cannot develop a complete understanding of motivation and learning without acknowledging the existence of multiple learning systems and exploring system comparisons. Thus, in this chapter we examine goal-directed, cognitive control processes, which are the theme of this edited volume, in direct comparison with habitual, procedural processes to develop a complete view of the motivation-learning interface.

Decision Making

Recently, there has been a surge of interest in examining the distinction between model-based versus model-free decision-making systems and strategies (Blanco et al., 2013; Daw et al., 2011; Glascher et al., 2010; Worthy et al., 2012). Motivation plays a prominent role in distinguishing these two approaches to decision-making situations. Model-based decision making is goal-directed, relies heavily on cognitive control and higher-level processing, and involves developing and utilizing a model of the environment that considers how each action can affect both immediate and future outcomes. Model-based decision making is *state-based* because individuals are primarily motivated to perform actions that improve their future state (Glascher et al., 2010). Model-free decision making does not rely on cognitive control but instead on habitual, procedural-based processing, and the motivational focus is centered on performing actions that lead to immediate reward or punishment. Actions that lead to immediate reward are reinforced, and actions that lead to either immediate punishment or no reward are not. Model-free decision making is *reward-based* because individuals are primarily motivated to perform actions that are followed directly by reward (Glascher et al., 2010).

Model-based and model-free decision-making processes, though somewhat overlapping and interactive, are thought to critically depend on separate neural systems, with the weight given to each system varying across individuals and under different circumstances (Eppinger, Walter, Heekeren, & Li, 2013; Worthy, Cooper, Byrne, Gorlick, & Maddox, 2014). Areas of the ventral striatum are thought to be critical when generating reward prediction errors that are representative of immediate model-free rewards (Hare, O'Doherty, Camerer, Schultz, & Rangel, 2008; O'Doherty, 2004). In addition to ventral striatal regions that focus on available rewards, the intraparietal sulcus and lateral regions of the PFC, particularly the dorsolateral PFC (DLPFC), are critical in developing global model-based reward representations that map out the holistic structure of the reward space (Daw et al., 2011; Glascher et al., 2010; Smittenaar, FitzGerald, Romei, Wright, & Dolan, 2013).

Given the critical regions underlying model-based and model-free processing, it should come as no surprise that recent studies have found an association between state-based and reward-based decision making and working memory processes that are mediated by the DLPFC. Here the presence of a dual task adversely affects state-based decision making but not reward-based decision making (Blanco et al., 2013; Daw et al., 2011; Worthy et al., 2012).

Empirical Tests of the Motivation-Learning Interface in Decision Making

Enhanced cognitive control processing, or "trying harder," is not always advantageous for efficient learning. When considering the interaction of global and local motivators on available cognitive resources, we predict a three-way interaction between global motivation, local motivation, and learning system. Specifically, we predict that a motivational match (global and local approach or global and local avoidance) enhances task-directed cognitive control processes at the expense of task-directed procedural learning processes, and thus should enhance goal-directed learning, such as model-based decision making, at the expense of procedural learning, such as model-free decision making (Figure 15.1A). Analogously, we predict that a motivational mismatch (global approach and local loss minimization or global avoidance and local gain maximization) enhances task-directed procedural learning processes at the expense of task-directed cognitive control processes and thus should enhance procedural learning, such as model-free decision making, at the expense of goal-directed learning, such as model-based decision making (Figure 15.1B). We have found strong support for these predictions using a raffle ticket global motivation (seeking a ticket or saving a ticket) and local point motivation (gains vs. losses) in model-based and model-free decision making and category learning (Maddox & Markman, 2010; Maddox, Markman, et al., 2006; Markman et al., 2005; Worthy, Maddox, & Markman, 2007). Other forms of global motivation have been examined (e.g., performance pressure, stereotype threat) as well as other goal-directed and procedural tasks (e.g., the Wisconsin Card Sorting Task, stimulus identification, math problems), and the predictions from the motivation-learning framework were supported (Glass, Maddox, & Markman, 2011; Maddox, Filoteo, Glass, & Markman, 2010; Markman, Maddox, & Worthy, 2006; Worthy, Markman, & Maddox, 2009).

Motivation-Learning Interface in Normal Aging

One thing that is noticeably lacking in the normal aging literature is research focused on the influence of global and local motivational manipulations, their influence on task-directed motivational effects, and how this interacts with both goal-directed and habitually mediated tasks. To our knowledge this three-factor motivational match framework (global motivation, local motivation, and task-directed motivation) has not been fully explored in normal aging, although one study examined the interactive effects of global and local motivators (Barber & Mather, 2013a) and a number of other studies have explored a global or a local motivational manipulation in isolation (Barber & Mather, 2013b; Braver, 2012; Braver & Barch, 2002; Braver et al., 2001; Castel et al., 2011; Ennis, Hess, & Smith, 2013; Frank & Kong, 2008; Freund, 2006; Hess, Auman, Colcombe, & Rahhal, 2003; Hess & Ennis, 2013; Hess, Leclerc, Swaim, & Weatherbee, 2009; Hess, Osowski, & Leclerc, 2005; Hess, Popham, Dennis, & Emery, 2013; Hess, Popham, Emery, & Elliott, 2013; Jimura & Braver, 2010; Jimura et al., 2011; McGillivray & Castel, 2011; Peters, Hess, Vastfjall, & Auman, 2007; Popham & Hess, 2013; Samanez-Larkin et al., 2007; Westbrook, Kester, & Braver, 2013; Westbrook, Martins, Yarkoni, & Braver, 2012). However, few studies have explored task-directed motivation using behavioral tasks, such as decision-making tasks, that are identical in all respects except the nature of the optimal learning system and for which computational modeling approaches can be applied that provide direct insights onto the locus of motivational effects (however, see Maddox, Filoteo, & Huntington, 1998; Maddox, Pacheco, Reeves, Zhu, & Schnyer, 2010).

To examine this important issue we first explore how the well-documented structural brain changes associated with normal aging affect task-directed processing in these dissociable-learning systems (goal-directed and habitual) and associated tasks. We then briefly summarize the results from two recent studies conducted in our lab that examine the motivation-cognition interface in aging.

Learning Systems and Task-Directed Motivation in Normal Aging

A number of structural brain changes are well documented in normal aging. For example, anatomical studies suggest that dramatic dopaminergic and volumetric declines across several brain regions are associated with normal aging, with the prefrontal cortices showing the largest volumetric declines in white and gray matter (Backman et al., 2000; Gunning-Dixon & Raz, 2003; Raz et al., 2005; Raz, Williamson, Gunning-Dixon, Head, & Acker, 2000). These structural and functional brain changes are associated with impairments in working memory and executive function, both of which are critical for goal-direct learning, such as model-based decision making (Bopp & Verhaeghen, 2005; Braver, 2012; Braver & Barch, 2002; Denburg, Tranel, & Bechara, 2005; Denburg et al., 2009; Filoteo & Maddox, 2004; Gunning-Dixon & Raz, 2003; Jimura et al., 2011; MacPherson, Phillips, & Della Sala, 2002; Maddox, Chandrasekaran, Smayda, & Yi, 2013; Park et al., 2002; Racine, Barch, Braver, & Noelle, 2006; Samanez-Larkin, Kuhnen, Yoo, & Knutson, 2010; Schnyer et al., 2009; Titz & Verhaeghen, 2010; Wasylyshyn, Verhaeghen, & Sliwinski, 2011; Westbrook et al., 2012, 2013). For example, older adults show persistent robust deficits in tasks that critically rely on executive processes, such as set-shifting during the Wisconsin Card Sort Task (Head, Kennedy, Rodrigue, & Raz, 2009).

Structural and functional declines in the striatum are also well documented (Backman et al., 2000; Gabrieli, 1995; Li, Lindenberger, & Sikstrom, 2001). These brain changes are likely associated with age-related deficits in procedural-based learning (McArdle, Ferrer-Caja, Hamagami, & Woodcock, 2002; Park et al., 2002; Salthouse, 1991, 1994; Salthouse, Atkinson, & Berish, 2003). However, in some domains, including model-free decision making and category learning, age-based procedural deficits are less robust, sometimes being present and at other times not (Filoteo & Maddox, 2004; D. Howard & Howard, 2001; J. Howard & Howard, 1997, 2001; Maddox, Pacheco, et al., 2010; Maddox et al., 2013; Raz, 2000; Raz et al., 2003; Samanez-Larkin et al., 2007; Simon, Howard, & Howard, 2010; Worthy, Gorlick, Pacheco, Schnyer, & Maddox, 2011; Worthy, Otto, Doll, Byrne, & Maddox, in press). For example, older adults show intact early learning relative to younger adults during an implicit task where explicit processing of associations does not contribute to performance (D. Howard et al., 2004).

Model-based and model-free strategies are highly interactive, and the robust cognitive declines associated with effortful controlled (model-based) processing along with less severe declines associated with automatic habitual (model-free) processing likely bias older adults towards the automatic habitual system. Importantly, the proposed bias towards automatic habitual processing, presented schematically in Figure 15.1C, should lead to age-related deficits in goal-directed tasks, such as model-based decision making, but should lead to smaller deficits or possibly age-related advantages in habitual, procedural-mediated tasks, such as model-free decision making. When applied to decision making, we formalize this framework in a computational model that includes a weighting parameter that quantifies the bias towards the model-based system. An additional advantage of this computational modeling approach is that multiple strategies can be formalized mathematically, applied to the behavioral data, and compared.

It is important to be clear that we are not arguing that this framework broadly characterizes older adult cognition. Clearly the issue is much more complex. For example, in several domains normal aging does not lead to deficits in performance, and in some cases it actually leads to *enhanced* performance that may or may not be due to a shift in bias away from model-based processing (for excellent examples of this perspective, see Hess, 2014; Peters et al., 2007). These include some aspects of value-driven episodic memory (Castel et al., 2011; McGillivray & Castel, 2011), familiarity-based memory (Light, Patterson, Chung, & Healy, 2004), cognition in socioemotional context (Blanchard-Fields, 2009; Blanchard-Fields, Jahnke, & Camp, 1995), and some aspects of category-learning and decision-making tasks (Glass, Chotibut, Pacheco, Schnyer, & Maddox, 2011; Worthy et al., 2011). Even so, this is a useful framework that seems to be applicable in many broad domains, such as decision making.

Application 1: Task-Directed Motivation and Decision Making in Normal Aging

The effects of normal aging on decision making are mixed. Some studies find deficits (Denburg et al., 2005; Eppinger et al., 2013; Kuhnen & Knutson, 2005; Mell et al., 2005, 2009; Samanez-Larkin et al., 2011), whereas others find advantages (Blanchard-Fields, 2009; Blanchard-Fields et al., 1995; Cooper, Worthy, Gorlick, & Maddox, 2013; Grossmann et al., 2010; Worthy et al., 2011; Worthy & Maddox, 2012). One way to address this apparent discrepancy in the literature is to determine the processing locus associated with optimal performance in each task and to examine whether older adults show deficits in some types of tasks but not others. The ideal approach is to use tasks that are identical in local and global motivation as well as surface features but for which the processing system that supports optimal decision making is manipulated. We focus on state-based and reward-based decision-making strategies that are optimally supported by effortful cognitive control and automatic habitual processing systems, respectively, and test the hypothesis that normal aging is associated with a shift in balance away from model-based processing towards model-free processing (see Figure 15.1C). This empirical approach should be complemented with the application of computational models.

In a recent study from our lab (Worthy et al., 2014) we examined the degree to which older and younger adults utilize model-free versus model-based reinforcement learning strategies, using two tasks that are identical in all respects, except in one task model-based processing was optimal (state-based decision making) and in the other model-free processing was optimal (reward-based decision making). In both tasks a mild global approach motivation was instantiated by informing participants that their goal was to maximize points gained and to exceed a performance goal (identical in all conditions), and a local approach motivation was instantiated by including only points gained for each option selection. Thus, as we were holding local and global motivation constant in this study we were most interested in investigating the inherent task-directed motivational states of older and younger adults.

The reward structure associated with the state-based task is shown in Figure 15.2A. The decreasing option consistently provided larger rewards on each trial, but selecting the increasing option led to improvements in the participant's state on future trials (i.e., the spot along the x-axis), while selecting the decreasing option led to declines in the participant's state on future trials. The optimal strategy was to consistently select the increasing option, which allowed participants to reach the highest state, despite always providing smaller immediate rewards on each trial compared to the decreasing option.

The reward structure associated with the reward-based task is shown in Figure 15.2B. Here, the optimal strategy was to consistently select the decreasing option, even though selecting the increasing option led to improvements in state. The maximum value that could be obtained from repeatedly selecting the increasing option and reaching the highest state (55 units of oxygen) is smaller than the minimum value that could be obtained from simply selecting the decreasing option task on each trial (65 units of oxygen). Participants performed a four-choice variant in which two increasing and two decreasing options were included. On each trial, participants selected one of the four options and received the oxygen that was extracted, which was added to a tank labeled "Cumulative."

A model-based strategy should lead to better performance in the state-based task compared to a model-free strategy because participants should be more likely to select the increasing option, which improves their state on future trials. A model-free strategy should lead to better performance in the reward-based tasks compared to a model-based strategy because participants should be more likely to select the decreasing option, which improves their current (and, by extension, future) state. If older adults are more likely to utilize a model-free strategy compared to younger adults, then they should perform better on the reward-based tasks, but worse on the state-based tasks.

We tested this hypothesis behaviorally by examining the total points earned in the task as well as by applying a recently developed HYBRID reinforcement learning model (HYBRID RL) (Worthy et al., 2014). The HYBRID RL model provides unique insights into model-based and model-free strategies during learning as both of these systems are assessed together and the weight placed on the model-based system (w) is estimated (details can be found in Worthy et al., 2014). Figure 15.3A displays the point total data, and Figure 15.3B displays the w parameter estimates. As predicted, we found an age-related performance deficit in the four-option state-based task, but an age-related performance advantage in the four-option reward-based task. Also as predicted, we found that younger adults placed greater weight on the output from the model-based system than older adults. We also examined the correlation between estimated w parameter values and the proportion of trials participants selected the increasing option over the course of the task. There was a strong positive association in both the state-based task (r=.63, p<.001), where these selections are advantageous, and the reward-based task (r=.55, p<.001), where these selections are disadvantageous, suggesting that model-based processing drives the selection of the increasing option regardless of its utility during the task. This study demonstrates the usefulness of rigorously defined tasks and computational models as tools for exploring age-based strategic changes that underlie performance.

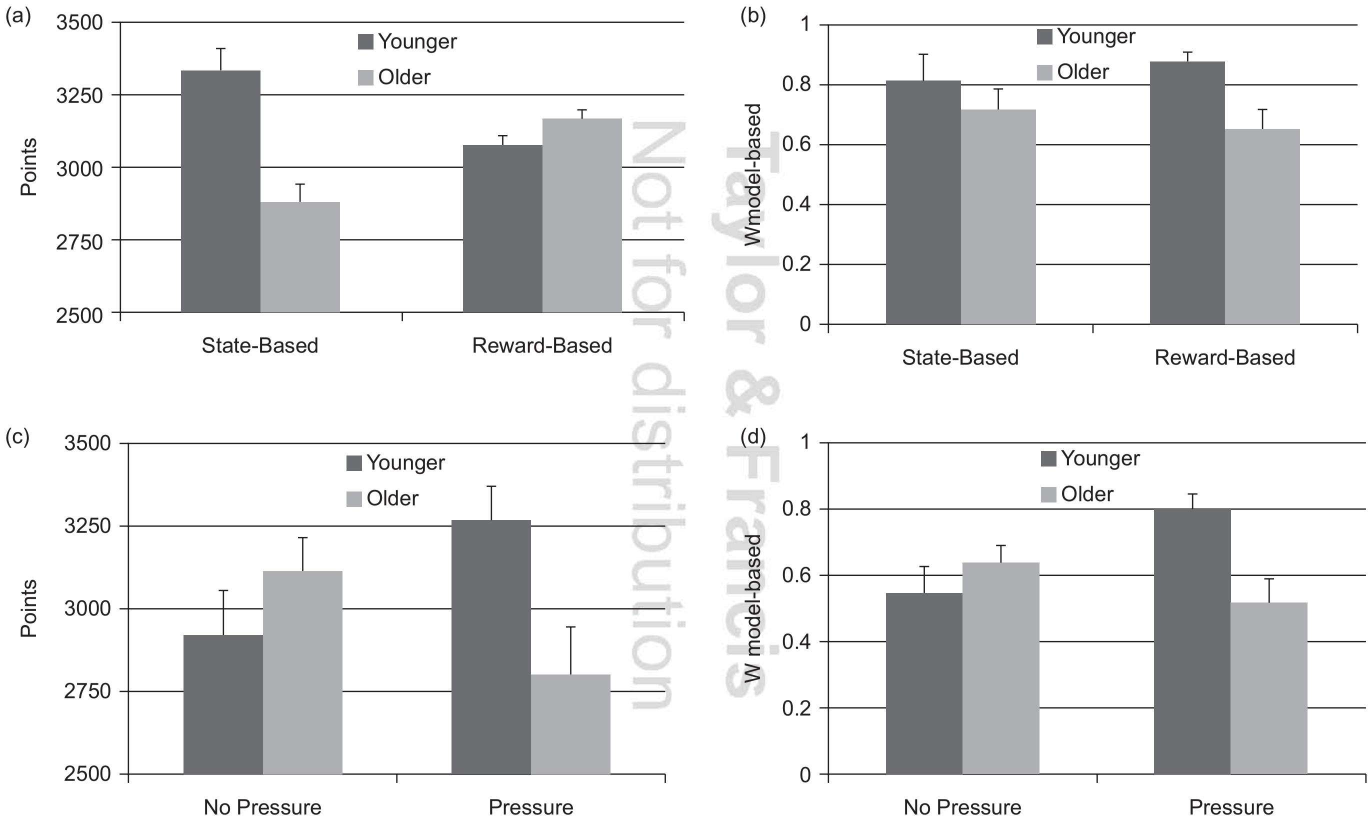

FIGURE 15.3 Behavioral and modeling results.

Proof

Application 2: Global Avoidance Motivation (Pressure) and State-Based Decision Making in Normal Aging

Application 2 reviews a study by Cooper, Worthy, Gorlick, and Maddox (2013) that examined the effects of age and social pressure on performance in a two-option state-based decision-making task (see Figure 15.2A). Here participants are told to attempt to exceed a performance criterion for a monetary bonus. However, their eligibility is a team effort that depends on their own success as well as that of a fictitious partner. Should one of them fail, neither will receive the bonus. Immediately prior to the start of the task, the participant is informed that his or her partner has succeeded and the fate of both of their monetary bonuses rests with the participant. Thus, performance pressure acts as a global avoidance motivator where the participant's goal is to avoid disappointing his or her partner. Combined with the local motivation to maximize points gained, global and local motivations are mismatched. Thus, we predict that pressure will lead to a performance decrement due to increased reliance on model-free processing. We tested this hypothesis behaviorally by examining the total points earned in the task as well as by applying the HYBRID RL model. Figure 15.3C displays the point total data, and Figure 15.3D displays the *w* parameter estimate, representing processing system bias. As predicted, we found a performance deficit in the pressure condition relative to the no-pressure condition in older adults that was due to a reduced reliance on the model-based system in the pressure condition. Somewhat surprisingly, we found a performance advantage in the pressure condition relative to the no-pressure condition in younger adults that was due to an increased reliance on the model-based system in the pressure condition. It is possible that younger adults viewed the pressure manipulation as a challenge in decision making, and thus as a global approach motivation, whereas older adults viewed the pressure manipulation as a threat, and thus as a global avoidance motivation.

General Discussion

The common belief that motivation involves simply "trying harder" is at best simplistic and at worst inaccurate. In this chapter we offer a three-factor framework for understanding the effects of motivation on cognitive processing and performance. We argue that global motivation and local motivation interact and drive the balance of processing between effortful, frontally mediated cognitive control processes and automatic, striatally mediated habitual procedural processes (Maddox & Markman, 2010). As outlined in Figures 15.1A and 15.1B, we propose that a regulatory match between the global and local motivational states affects the existing balance between cognitive control and habitual procedural processing. A regulatory match (global approach with local gains or global avoidance with local losses) shifts the bias towards cognitive control processing, whereas a regulatory mismatch (global approach with local losses or global avoidance with local gains) shifts the bias towards habitual procedural processing. Critically, the effect of this biasing on task performance depends upon the optimal strategy for solving the task. When the task is goal-directed, relying heavily on cognitive control processes, a regulatory match enhances performance, whereas a regulatory mismatch impairs performance. On the other hand, when the task is reward-based, relying heavily on habitual procedural processes, a regulatory match impairs performance, whereas a regulatory mismatch enhances performance (Figures 15.1A and 15.1B).

In this chapter we began to apply this three-factor framework to normal aging. We conclude that to date the three-factor framework has not been fully explored in normal aging, but the handful of research has been conducted that explores aspects of the framework. Global motivational effects have been explored in normal aging in the realm of global avoidance during stereotype threat. The results are in general agreement with the regulatory match framework outlined in Figure 15.1. Specifically, older adults show poor goal-directed performance under global avoidance (stereotype threat) and local gains conditions, as would be expected from a regulatory mismatch (Barber & Mather, 2013b; Hess et al., 2003; Popham & Hess, 2013).

Local motivational effects have also been explored in normal aging and again, though not well controlled, the results are in general agreement with the regulatory match framework outlined in Figure 15.1. During habitual, procedural-based learning tasks with a mild global approach motivation to maximize performance, older adults are better at avoiding negative outcomes (regulatory mismatch) than approaching positive ones (regulatory match) (Frank & Kong, 2008; Lighthall, Gorlick, Schoeke, Frank, & Mather, 2013; Marschner et al., 2005; Mell et al., 2005; Pietschmann, Endrass, Czerwon, & Kathmann, 2011; Simon et al., 2010). This follows from the three-factor framework as procedural-based learning should be enhanced under a motivational mismatch (i.e., the avoid-negative outcome condition), and attenuated under a motivational match (i.e., the approach-positive outcome condition). Clearly, though, these effects need to be tested more rigorously in a controlled setting.

To date only one study has explored the broad global/local motivation match framework in normal aging by manipulating both levels of motivation, and even in this study the focus was on a goal-directed task, with no examination of habitual procedural-mediated processing (Barber & Mather, 2013a). Even so, this is the first study of its kind and it provided strong support for the regulatory match hypothesis in normal aging. Specifically, Barber and Mather (2013a) showed that stereotype threat (global avoidance) led to better performance for losses relative to gains, whereas no threat led to better performance for gains relative to losses.

Although progress has been made towards understanding the motivation-learning interface in normal aging, it is clear from this review that the literature is lacking in at least two ways. First, more emphasis should be placed on understanding task-directed biases across the life span. We propose that normal aging is associated with a shift in balance away from goal-directed towards reward-based processing (see Figure 15.1C). Unfortunately, the majority of extant research focuses on goal-directed tasks at the expense of an examination of reward-based processing, and the literature is almost completely devoid of research that explores goal-directed *and* reward-based processing within the same experiment, using tasks that are identical in all respects, except for the cognitive processing system that mediates optimal processing (however, see Maddox, Pacheco, et al., 2010; Worthy et al., 2011, 2014; Worthy & Maddox, 2012). Second, the use of computational modeling techniques should be increased, with the aim of better understanding the strategies being utilized to solve specific tasks. Despite the clear age-related structural and functional declines in brain and cognitive functioning with healthy aging, under some conditions older adults are remarkably adept at selecting cognitive strategies to optimize performance using the limited resources available. Although cognitive deficits are well established, in some cases older adults perform as well or better than younger adults (Glass, Chotibut, et al., 2011; Maddox, Pacheco, et al., 2010; Worthy et al., 2011, 2014; Worthy & Maddox, 2012). Of course, under many other conditions older adults appear unable to utilize the optimal strategy for solving a task and instead fall back on a simpler, suboptimal strategy (Filoteo & Maddox, 2004; Maddox et al., 1998, 2013). Without including computational models that provide insights into these age-based changes in strategy selection, these findings are often deemed anomalous or contradictory.

Future Directions

There are a number of future directions that we suggest pursuing. First and foremost more work is needed to explore the neurobiological basis and neurobiological mechanisms that drive the motivation-learning effects. We argue that a motivational match serves to up-regulate effortful goal-directed processing, whereas a motivational mismatch serves to down-regulate effortful goal-directed processing, which, given the interactive nature of the systems, serves to enhance automatic habitual processing. Thus, we believe that the locus of these effects is broadly defined as prefrontal.

Research examining the neural mechanisms of appetitive and aversive incentives has not rigorously tested the interaction between global and local motivations. One study by Ashby, Isen, and colleagues (Ashby et al., 1999; Isen, 1993, 1999) showed that positive affect (a global approach motivation) increases dopamine release from the ventral tegmental area (VTA) into the anterior cingulate during tasks that involve local gains motivation (global/local match), thus increasing cognitive flexibility. Though this hypothesis this does not address the mechanism underlying aversive global and local matches, it is likely that the VTA plays a critical role in the motivation-cognition interface. The VTA broadcasts reward and punishment signals across the cortex and subcortical structures through a series of white matter loops. These projections include a link to the medial prefrontal cortex, a region critical in driving state-based processing, and the nucleus accumbens, a region critical in driving reward-based processing. As this dopaminergic network includes aspects of both model-based and model-free processes, it is likely important in determining the behavioral biases seen in the three-factor account of the motivation-learning interface, explored in the current chapter. Although no specific predictions are offered, it is clear that appetitive and aversive incentive processing is not well understood in the context of global and local motivation and their interactions with cognitive processes should be explored as detailed neurobiological theories are developed.

Second, although each of the studies outlined earlier supports one facet of the complex motivation-learning interface, more systematic work is needed that explores the interactive nature of global, local, and task-directed motivational effects on normal aging. We would like to see this work take advantage of computational modeling approaches like those outlined in the two applications, but we also feel strongly that more attention is needed to the nature of the task in all studies. Too often a single task is utilized whose cognitive processing locus is underspecified and poorly understood. In addition, it is rare for studies to include pairs of tasks that are identical in all respects except some critical factor, such as the cognitive processing system or strategy that underlies optimal learning. More studies of this sort are needed, especially in the realm of normal aging.

Third, these domains of research should be bridged through computational cognitive neuroscience. This approach combines direct explorations of the neural systems that underlie behavior with insights from computational models that represent relevant cognitive processes. Much of this work is ongoing in younger adults (Ashby & Crossley, 2011; Crossley, Ashby, & Maddox, 2012; Daw et al., 2011) and should be extended to normal aging (Samanez-Larkin et al., 2011).

Finally, we would like to see this approach extended to other participant populations, such as children (Hartley, Decker, Otto, Daw, & Casey, 2013) and individuals with depressive symptoms, that also demonstrate motivational differences (Beevers et al., 2012; Luking & Barch, 2013; Maddox, Gorlick, Worthy, & Beevers, 2012; Pagliaccio et al., 2013). Prior work in our and others' labs suggests that individual with depressive symptoms are in a chronic global avoidance state and also show deficits in reward processing but enhancements in punishment processing. Thus, depressed individuals are likely in a regulatory mismatch under gains conditions but are in a regulatory match under losses conditions. From our regulatory match framework we predict that depressives will show attenuated effortful goal-directed processing under gains, but accentuated goal-directed processing under losses. In a recent study, we (Maddox et al., 2012) found support for this hypothesis using a gains and losses version of the two-option state-based decision-making task (Figure 15.2A). We recently reanalyzed these data with the HYBRID RL model and found a reduction in optimal model-based processing in individuals with elevated depressive symptoms relative to individuals experiencing fewer depressive symptoms in the gains condition, but the reverse pattern in the losses condition. These data suggest that the chronic global motivational state inherent in individuals with elevated depressive symptoms interacts with the local motivational state to maximize gains or minimize losses. Other applications of this sort should be undertaken in future work.

Conclusions

In this chapter we showed that the layman's belief that motivation involves simply "trying harder" is at best simplistic and at worst inaccurate. We developed a three-factor motivation-learning framework that argues that performance is determined from a three-way interaction between one's global motivation to approach positive outcomes (e.g., raise, bonus) or avoid negative outcomes (e.g., demotion, pay cut), the local task reward structure to maximize trial-by-trial gains or minimize trial-by-trial losses, and the optimal strategy for solving the task (Maddox & Markman, 2010). When there is a match between the global and local motivational states, effortful cognitive control processing is enhanced and habitual procedural processing is impaired, leading to enhanced goal-directed task performance but impaired habitual reward-mediated task performance. However, when there is a mismatch between the global and local motivational states, effortful cognitive control processing is attenuated and habitual procedural processing is enhanced, leading to enhanced habitual reward-mediated task performance but impaired goal-directed task performance.

We examined this motivation-learning framework in normal aging, and though only one study has examined two of these factors within the same experimental context, a number of others have explored the effects of a single factor that support our predictions. One recent study (Worthy et al., 2014) and a reanalysis of a second (Cooper et al., 2013), both conducted in our lab, highlight a task-directed motivational bias towards reward-mediated processing in healthy aging, which is revealed through computational modeling. We concluded that in general these data support the motivation-learning framework, but that much more work is needed. In particular, we argued that more attention must be paid to task-directed motivational differences, and we strongly advocate for the use of computational models in the interest of identifying the cognitive strategies being used by younger and older adults during cognitive tasks.

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