CHAPTER

4

Towards a Mechanistic Understanding of Age-Related Changes in Learning and Decision Making: A Neuro-Computational Approach

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Many of our decisions involve uncertainty about the potential outcomes of choices. In some of these situations the probabilities of outcomes are known (or approximated), such as in medical decisions about treatment options (e.g., cancer therapy). In other situations outcome probabilities are unknown and we have to learn about the likelihood with which a certain action leads to a desired outcome. Such situations may involve high-level financial decisions such as investments in stocks or bonds, but they also apply to decisions during grocery shopping when having to choose between different varieties of apples.

Stereotypes about older adults suggest that they might be more risk avoidant and conservative decision makers than younger adults (for a review see Mather, 2006; Mather et al., 2012). Such behavior might be adaptive in situations in which the decision context favors risk-avoidant choices, but may lead to suboptimal decisions in situations that favor risky choice. Recent theoretical ideas suggest that decision making deficits may become obvious once age-related decline in fluid cognitive functions (e.g., processing speed or reasoning abilities) offsets relative increase or stability in more crystalized abilities (learned or acculturated knowledge) (Agarwal, Driscoll, Gabaix, & Laibson, 2009; Samanez-Larkin, 2013).

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Results from empirical studies on age differences in decision making under uncertainty show mixed results regarding age-related changes in risky-choice behavior. Some studies report age-related deficits in decision making, whereas others found no significant differences between younger and older adults (Mata, Josef, Samanez-Larkin, & Hertwig, 2011; Mather et al., 2012). Current meta-analytic data point to a dissociation between studies that focus on explicitly stated probabilities and studies in which the outcome of an option has to be learned (Mata et al., 2011). That is, the current literature suggests that age-related deficits in decision making under uncertainty are primarily due to impairments in learning probabilistic reward structures.

Building on this dissociation, in the current chapter we will concentrate on the psychological and neurophysiological underpinnings of age-related deficits in decision making tasks in which the expected value of choice options has to be learned. We will outline the relationship between age-related changes in the dopamine (DA) system as well as functional changes in subcortical and prefrontal networks involved in making decisions from experience. Furthermore, we will focus on potential links between neuro-computational theories of reinforcement learning and age-related deficits in experience-driven decision making. Finally, we will conclude with a summary of the current research, identify gaps that need to be filled in the future, and provide evidence for potential targets for interventions that aim at improving learning and decision making abilities in old age.

AGE-RELATED DECLINE IN THE DOPAMINE SYSTEM

We start the chapter with a brief review of age-related changes in the dopamine system and their impact on learning and decision making functions in older adults. Age-related changes in the dopamine system have been observed across various areas in the brain. For example, positron emission tomography (PET) and single-photon emission computed tomography studies suggest that aging is associated with a decline in pre- and postsynaptic markers of DA D1, and D2 receptor density is reduced in older compared to younger adults. Age-related reductions in D1 receptor density (about 7% per decade) have been reported in the basal ganglia (caudate nucleus and putamen) (Bäckman et al., 2009; MacDonald, Karlsson, Rieckmann, Nyberg, & Bäckmann, 2012; Wang et al., 1998). Similar findings have been reported for D2 receptor density in the striatum (Volkow et al., 2000; Volkow, Wang, et al., 1998) and the prefrontal cortex (Volkow et al., 2000). Moreover, there is evidence for an association between age-related decline in D2 receptors in the prefrontal cortex and metabolism in the prefrontal and cingulate cortex as well as correlations between D2 receptor decline and performance deficits in the measures of executive control (the Wisconsin Card Sort Test) (Volkow, Gur, et al., 1998; Volkow et al., 2000). Presynaptic markers of DA

function also show substantial decline with age. The binding potential for the DA transporter in the striatum is significantly lower in older than younger adults (Erixon-Lindroth et al., 2005; Troiano et al., 2010; Wong, Müller, Kuwabara, Studenski, & Bohnen, 2012). Although these results point to a substantial negative relationship between age and DA function, it should be noted that so far, there are no longitudinal assessments of age-related changes in DA neurotransmission. Therefore, we lack precise estimates and a detailed understanding of age-related change in pre- and postsynaptic measures of the DA system as well as the relation between baseline DA levels, age-related change, and individual differences in cognitive performance. Furthermore, so far it has not been established whether different aspects of the DA system are differentially affected by age.

Effects of Age-Related Dopamine Decline on Cognitive Function

Age-related decline in DA function has been associated with deficits in various cognitive abilities (Braver & Barch, 2002; Bäckman, Lindenberger, Li, & Nyberg, 2010; Li, Lindenberger, & Sikström, 2001). In particular, studies point to an association between decline in D1 receptor density in the striatum and working memory (WM) (Braskie et al., 2008; Bäckman et al., 2009). This finding is consistent with theoretical ideas that suggest that deficits in the updating of WM representations in older adults are due to reduced phasic DA responses that are projected to the prefrontal cortex (Braver & Barch, 2002; Braver et al., 2001). The so-called gating theory suggests that midbrain DA signals regulate the access of new information to WM (Braver & Cohen, 2000). More specifically, the theory holds that DA prediction error (Pe) signals are used to learn when the WM gate should be opened in order to allow new information to access WM and to guide behavior. Consistent with the theory, results of a behavioral study point to specific deficits in older adults when they have to update WM context representations (Braver et al., 2001). These deficits may result from reduced dopaminergic Pe signaling during WM gating in the dorsolateral prefrontal cortex. Results from a PET study on WM training in younger adults show that WM updating training induces transient DA release in the striatum, which seems in line with the predictions of the gating theory (Bäckman et al., 2011). To summarize, based on these findings it is tempting to assume that reductions in DA phasic signaling with age lead to a deficient updating of WM representations and by this affect multiple cognitive operations in older adults that rely on short-term storage and updating of information.

Effects of Age-Related Dopamine Decline on Learning and Decision Making from Experience

Compared to associations between DA and cognitive measures, relationships between age differences in motivational functions such as

reward-based learning and decision making and DA are less well established. This is somewhat surprising, given the rapid progress of research on the involvement of the DA system in reward processing, reinforcement learning, and decision making in younger adults. Moreover, in contrast to cognitive functions, there are relatively detailed mechanistic models of the role of DA (and other neurotransmitters such as norepinephrine) in reinforcement learning and decision making (Aston-Jones & Cohen, 2005; Montague, Hyman, & Cohen, 2004). One advantage of these neurocomputational theories is that they allow us to be more specific regarding age-related changes in the underlying neural mechanisms. For example, reductions in phasic dopaminergic learning signals from the ventral tegmental area should lead to deficits in the updating of reward value representations and to behavioral impairments in reinforcement learning (Eppinger, Haemmerer, & Li, 2011; Nieuwenhuis et al., 2002). Empirical findings support these results, showing age-related behavioral deficits in reinforcement learning, reduced learning effects in reward-related evoked potential (ERP) components in older adults, reduced prediction error signals in the ventral striatum in the elderly as well as alterations in the structural integrity of the midbrain (Chowdhury, Guitart-Masip, Lambert, Dolan, & Düzel, 2013; Chowdury et al., 2013; Eppinger, Kray, Mock, & Mecklinger, 2008; Eppinger, Schuck, Nystrom, & Cohen, 2013; Samanez-Larkin, Levens, Perry, Dougherty, & Knutson, 2012; Schott et al., 2007). Moreover, a combined PET and neuroimaging (fMRI) study in younger and older adults showed age-related changes in the relationship between midbrain DA synthesis and reward-related fMRI activity (Dreher, Meyer-Lindenberg, Kohn, & Berman, 2008).

Work on the direct relationship between age-related changes in DA neuromodulation and age differences in decision making is scarce. However, findings in younger adults revealed an association between reduced DA D2 autoreceptor availability in the midbrain, increased stimulated DA release in the ventral striatum, and enhanced trait impulsivity (Buckholtz et al., 2010). That is, these findings suggest that in younger adults, enhanced DA release in the ventral striatum (as induced by amphetamine) is associated with greater impulsivity. Based on these findings it could be argued that reduced DA release in the ventral striatum in older adults may result in less impulsive behavior (Eppinger, Nystrom, & Cohen, 2012).

There are many open questions in this emerging field of research. For example, it is unclear how aging affects tonic versus phasic activity modes of DA (and their interaction) and what the implications of these effects are for learning and decision making. Another issue that merits further research is the relationship between age-related changes in variability of DA activity and age-related deficits in learning and decision making (Garrett et al., 2013). For example, findings by Samanez-Larkin and colleagues (2010) indicate that suboptimal financial decision making in

older adults is associated with increases in variability of fMRI activity in the ventral striatum. A more general question that emerges from this work is whether aging may lead to greater decision noise, that is, unstructured variance in choices and preferences in older adults, and whether these effects are reflected in increased intra-individual variability of neurophysiological measures (Li et al., 2001).

Taken together, there is strong evidence for age-related changes in different aspects of the DA system. These age differences in DA neuromodulation seem to have profound effects on many cognitive and motivational functions. The ubiquity of these effects has lead to some degree of frustration among researchers, and to the notion that DA may be involved in almost every cognitive and motivational function. However, it should be noted that many previous approaches lacked a precise theory of the mechanism by which DA affects specific cognitive or motivational processes. Recent progress in computational approaches and combinations of modeling and neuroimaging techniques will allow us to move on and develop mechanistic rather than descriptive theories of age-related changes in cognitive and motivational functions.

AGE DIFFERENCES IN LEARNING FROM EXPERIENCE

As outlined nicely by Mata et al. (2011), age-related impairments in decisions from experience might result from an underlying deficit in learning the expected value of decision options. The purpose of the following paragraphs is to provide a link between age differences in decisions from experience and age-related changes in neurophysiological mechanisms of reinforcement learning. For the purpose of this chapter we will primarily focus on age differences in learning from uncertain (probabilistic) reward information as well as age-related changes in the neural systems involved in learning from experience. We will also visit the field of computational neuroscience to examine mechanistic ideas about age-related changes in learning and decision making from experience.

Findings from electrophysiological ERP studies suggest that older adults are impaired in learning from uncertain (probabilistic) reward, whereas age-related learning impairments are less pronounced when reward is deterministic (reward information is always reliable) (Eppinger et al., 2008; Pietschmann, Endrass, Czerwon, & Kathmann, 2011). Learning impairments in older adults are associated with deficits in error detection, as indicated by a reduced error-related negativity, an ERP component that is elicited by erroneous responses (Eppinger & Kray, 2011; Eppinger et al., 2008; Herbert, Eppinger, & Kray, 2011; Pietschmann et al., 2011). Furthermore, older adults show less differentiated ERP responses to positive and negative feedback during learning, indicating that they have difficulties

in representing valence information (Eppinger et al., 2008; Herbert et al., 2011). Taken together, these findings suggest that older adults may have deficits in learning the expected value of reward if contingencies between states, actions, and rewards are probabilistic (Eppinger et al., 2011; Hämmerer & Eppinger, 2012).

Recent findings from fMRI studies show that these learning impairments might be due to age differences in dopaminergic teaching signals that are projected from the midbrain (ventral tegmental area and substantia nigra) to the ventral striatum and ventromedial prefrontal cortex (vmPFC) (Chowdury et al., 2013; Eppinger, Schuck, et al., 2013; Samanez-Larkin, Worthy, Mata, McClure, & Knutson, 2014). These learning signals reflect discrepancies between actual and expected outcomes (prediction errors) and can be captured using reinforcement learning models (Niv & Schoenbaum, 2008). In environments that involve a continuous updating of predictions about the expected value of a stimulus or action, these models use the temporal difference (TD) learning algorithm to formalize learning (Sutton & Barto, 1998).

Temporal Difference Learning

The core idea of TD learning is that, during learning, the expected value of a stimulus or state is continuously updated as a function of the difference between the sum of the current reward and the future value prediction minus the current value prediction (see Figure 1 and Eqn (1)). For example during grocery shopping one might encounter a new product (for example, a new variety of apples). Before eating the apple, the prediction regarding the taste might be neutral or slightly positive (otherwise one would not have bought it). Assume that the apple tastes extraordinarily good. That is, the taste is better than predicted. This should be reflected in a strong positive Pe (see Figure 1). However, one moment later you might realize that the apple is not an

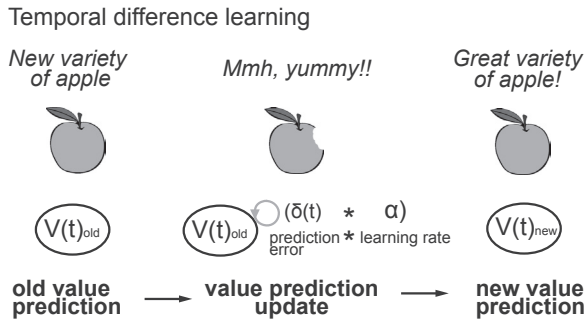

FIGURE 1 Illustration and schematic picture of the temporal difference reinforcement learning algorithm.

organic product (as you might have preferred). This would induce a negative Pe and reduce the expected value of the apple. According to reinforcement learning theory, the prediction error is used to continuously update value predictions. After repeated experience with the same variety of apples (that is, with learning), the value prediction gets more and more accurate.

More formally, according to the TD algorithm the prediction error $\delta(t)$ is defined as the immediate reward $R(t)$ plus the predicted future value $V(t+1)$ minus the current value prediction $V(t)$ (Eqn (1)):

$$\delta(t) = R(t) + \gamma \cdot V(t+1) - V(t)$$

The Pe $\delta(t)$ is used to update the old value prediction (Eqn (2)):

$$V(t)\,\text{new} = Vt\,(\text{old}) + \alpha \cdot \delta(t)$$

The (exponential) discount factor $0<\gamma<1$ in Eqn (1) accounts for the fact that humans (and other animals) tend to discount the value of future reward. That is, more distant reward is perceived as less valuable (high discount rate) than more immediate reward. In the apples example above, assume that you would have to buy an apple today but can consume it only 2 days from now. The expected value of this apple (apart from being less fresh than today) is presumably lower than the value of an apple that could be consumed right away.

The learning rate $0<\alpha<1$ in Eqn (2) determines how much a specific event affects future value predictions. A learning rate close to 1 would suggest that the most recent outcome has a strong effect on the value prediction, whereas a small learning rate indicates that much experience has to accumulate to affect value predictions. In the apple example, a low learning rate in subject A would mean that new information (such as where the apple comes from or where it was bought) does not have much impact on the value prediction (e.g., because subject A does not care about this information). In contrast, a high learning rate in subject B would mean that this information has a strong impact on value predictions (e.g., because subject B does care about the origin of the apple).

To summarize, a core feature of reinforcement learning theory is that reward prediction errors are used to learn (update) the expected future value associated with stimuli (states) and/or actions. Deficits in DA phasic Pe signaling may lead to less differentiated reward representation in the vmPFC and therefore to impairments in reinforcement learning (Eppinger et al., 2011). In a recent study we used reinforcement learning modeling in combination with fMRI to investigate the effects of aging on approach and avoidance learning (Eppinger, Schuck, et al., 2013). Behavioral findings showed that older adults are impaired in learning from reward (when they have to choose actions that lead to reward), but not in avoidance learning (when they have to learn to avoid stimuli

that lead to negative outcomes) (see Eppinger, Schuck, et al., 2013). To examine whether we can explain age-related deficits in learning from reward based on the association between model parameters and neural activity, we examined correlations between Pe estimates and the blood oxygenation level-dependent (BOLD) signal. Results of this analysis showed that impairments in learning from reward in older adults were associated with reduced Pe signaling in two areas that receive strong projections from the dopamine system, the ventral striatum and the vmPFC. In contrast, as in the behavioral results, we found no evidence for age differences in the correlations between prediction errors and BOLD activity during learning from negative feedback.

A study by Chowdury et al. (2013) revealed very similar results during probabilistic reinforcement learning. Moreover, using a pharmacological intervention with the dopamine precursor L-DOPA, these authors could show that the Pe signals in the ventral striatum in the elderly could be partially restored by enhancing DA levels. That is, the results by Chowdury et al. (2013) point to a potential pharmacological intervention to improve learning and decision making abilities in old age. Taken together, these findings are nicely consistent with the idea that reduced dopaminergic signaling from the midbrain may lead to less differentiated reward representations in the vmPFC and to behavioral impairments in learning.

However, although these interpretations are consistent with several previous theoretical accounts and empirical findings (Eppinger et al., 2011; Hämmerer & Eppinger, 2012; Nieuwenhuis et al., 2002), it should be noted that the interactions between the midbrain DA system and the prefrontal cortex might be more complex than currently suggested. For example, electrophysiological data in monkeys indicate that the ventral striatum prediction error signal critically depends on intact projections from the vmPFC (Takahashi et al., 2011). That is, it could be that reduced Pe signals in the ventral striatum in older adults are not due to diminished DA projections, but rather due to deficits in vmPFC representations in the elderly. Support for this view comes from a study by Samanez-Larkin et al. (2012), which indicates that the diminished integrity of white matter pathways from the medial prefrontal cortex to the ventral striatum partially mediates the association between age and reduced learning performance in older adults.

Age Differences in Different Types of Reinforcement Learning

As stated above, our definition of decisions from experience refers to decision making tasks in which participants have to learn about the probability of outcomes in order to make optimal decisions that incorporate risk. It should be noted that this definition is agnostic with respect to

learning mechanisms involved. So far we have mostly addressed situations in which younger and older adults learn to choose actions based on past experience. This type of reinforcement learning is sometimes referred to as model-free learning, because it is purely experience driven and does not rely on a forward model of the environment. Model-free learning is powerful and computationally robust. However, it also has its limitations, because it relies on multiple repetitions of associations and tends to be inflexible and slow (Doll, Simon, & Daw, 2012; Gershman, Markman, & Otto, 2013). Thus, model-free learning and decision making mechanisms may fail in more complex situations in which contingencies in the world change and we have to rapidly adjust behavior.

For these situations we need adaptive decision mechanisms that allow us to anticipate the consequences of future actions and to choose the sequence of future actions that has the highest probability to lead to the desired goal (Doll et al., 2012). Current decision making theories refer to these mechanisms as model-based learning and decision making (Balleine & O'Doherty, 2010; Daw, Niv, & Dayan, 2005). The advantage of model-based mechanisms is that they allow us to rapidly and flexibly adjust behavior to changes in the environment (such as changes in outcome probabilities). The downside is that they are computationally expensive because they involve a complete representation of the decision space (all possible combinations of states, actions, and rewards in a given situation). In a recent behavioral study we investigated the interplay of model-based and model-free decision making mechanisms in younger and older adults using a two-stage Markov decision task (see Figure 2(A)). In the first stage of this task, participants have to choose between two options (the two airplanes in Figure 2(A)). Depending on their choice, they transition to either the second-stage options with light gray background (see Figure 2(A), right-hand side), or the second-stage options with dark gray background (see Figure 2(A), left-hand side). In the second stage, they have to make another decision between two options (the figures in the second stage). Subsequently, they receive feedback for their choice (either a reward of 10 Eurocents or no reward). Feedback for the second-stage options is probabilistic and changes over time (see Figure 2(A)). The idea of this task is that in order to reach a preferred (rewarded) state in the second stage, participants have to engage in a strategic decision in the first stage. That is, they have to integrate model-free information about the reward probabilities in the second stage of the task with a model-based representation of the transition structure in the first stage of the task (see Figure 2(A) and (B)). Intuitively this means that in the second stage of the task, participants have to continuously learn which is the currently best option (model-free learning). However, in order to get the currently preferred stimulus in the first stage, they have to make a model-based decision, that is, they have to incorporate the transition probabilities into their decision. Thus, in order to get to the lower-right figure with light gray background in Figure 2(A) (second stage) one has to choose the

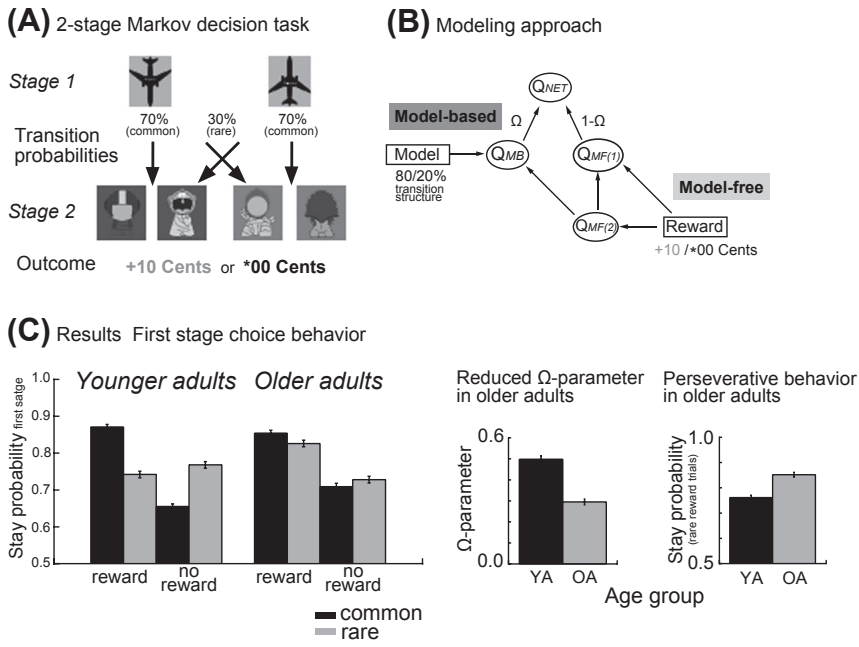

FIGURE 2 (A) Schematic picture of the two-stage Markov decision task. In the first stage of this task participants have to make a goal-directed decision that integrates knowledge of the transition structure with knowledge of the currently best option on the second stage. (B) A hybrid reinforcement learning algorithm is used to model choice behavior in the task. The model provides an estimate of the relative contribution of model-free and model-based decision mechanisms to behavior. (C) The behavioral results show a shift from model-based to model-free choice behavior in older compared to younger adults. *Figure adapted with permission from Eppinger, Walter, et al. (2013).*

upper-right option in the first stage. However, given the probabilistic nature of the transition structure, from time to time one will also end up at the other two states (figures with dark gray background in Figure 2(A)). The critical dependent variable in this task is the choice behavior in the first stage when participants have to integrate their knowledge of the transition structure with model-free information about the currently best option in the second stage. Choice behavior in the first stage of this task was fit using a hybrid reinforcement learning algorithm (Daw, Gershman, Seymour, Dayan, & Dolan, 2011; Eppinger, Walter, Heekeren, & Li, 2013; Wunderlich, Smittenaar, & Dolan, 2012) (for a schematic depiction see Figure 2(B)). This algorithm assumes that choices in the first stage of the task are driven by a weighted combination of model-based reinforcement learning (Q_{MB}), which accounts for the transition structure, and model-free SARSA (λ) TD learning ($Q_{MF(1)}$ and $Q_{MF(2)}$). The weighting of model-based versus model-free decision mechanisms is determined by the free parameter omega (Ω). If Ω approaches 0 behavior is model

free, which is reflected in a main effect of reward. In contrast, an Ω value close to 1 indicates model-based choice behavior, which is reflected in an interaction between transition structure and reward on the previous trial. Results show substantial age-related deficits in model-based behavior in older compared to younger adults (Figure 2(C)). These deficits seem to be particularly pronounced in situations in which unexpected reward on the second stage indicates that the decision strategy on the first stage has to be adjusted. In these situations, older adults choose the suboptimal option, whereas younger adults engage in a strategic exploration of the decision space using their knowledge of the task transition structure. The neurophysiological mechanisms that lead to these deficits in model-based behavior in older adults are not yet clear. Work in younger adults suggests that fronto-partial areas may play a critical role in learning model-based representations (Gläscher, Daw, Dayan, & O'Doherty, 2010; Lee, Shimojo, & O'Doherty, 2014). Consistent with these findings, recent results from our group suggest that deficits in the learning of task transition structures (that is, learning how to navigate in a task in order to reach a goal) are associated with a reduced recruitment of the lateral prefrontal cortex (Eppinger, Heekeren, & Li, 2013b). Taken together, the current data point to substantial deficits of older adults in model-based learning and decision making. These deficits may affect choice behavior in experiential decision making tasks, particularly in environments that involve nonstationary reward and transition structures.

CONCLUSIONS

We conclude with a brief summary of the psychological and neurobiological processes underlying learning and decision making deficits and with a description of potential interventions to improve learning and decision making in older adults.

Most of our everyday decisions involve uncertainty about the potential outcomes. To reduce uncertainty we have to sample different options and associated rewards (different types of apples or different stocks or bonds for investment). Therefore, in decisions from experience we have to learn the outcome probability of an option. In this chapter we explored the psychological and neurophysiological underpinnings of learning impairments, which are relevant for the understanding of age-related changes in decisions from experience. In particular, we focused on age-related changes in the neurocomputational mechanisms of reinforcement learning. Recent results in this emerging field of research suggest that age-related impairments in learning of the expected utility of options might be due to a reduced updating of reward value representations in the vmPFC (Eppinger et al., 2011; Hämmerer & Eppinger, 2012). Whether these effects are due to reduced dopaminergic projections from the midbrain to the

ventral striatum or whether they result from a diminished representational capacity of the vmPFC in older adults (or both) is currently unclear (Eppinger, Schuck, et al., 2013). Thus, based on the current data it seems straightforward to link age-related deficits in decisions from experience to these impairments in model-free reinforcement learning. However, model-free reinforcement learning tends to be relatively slow and inflexible, due to the large number of repetitions that needs to approximate the value of options. Therefore, it seems reasonable to assume that decisions from experience also involve faster and more flexible learning mechanisms that allow the decision maker to rapidly adjust behavior to changes in the environment, such as changes in reward probabilities. Current decision theories assume that these learning mechanisms involve the representation of a forward model of the decision space that includes all possible combinations of states, actions, and outcomes (Balleine & O'Doherty, 2010; Daw et al., 2005). The decision maker uses this model representation to choose the option that yields the highest long-term outcome in a given situation. Thus, these learning and decision making mechanisms provide the basis for flexible decisions. However, they also come at the cost of being computationally demanding and effortful (Otto, Gershman, Markman, & Daw, 2013). Recent behavioral and fMRI data suggest that model-based learning and decision making is impaired in older adults (Eppinger, Heekeren, & Li, 2012; Eppinger, Walter, et al., 2013). These impairments seem to be associated with a substantial under-recruitment of the lateral prefrontal cortex during the learning of higher-order contingencies in the decision space. Certainly, more research is needed to define and understand age-related changes in model-free and model-based decision mechanisms as well as their interactions and boundary conditions (Lee et al., 2014).

Most of the studies that directly targeted the dopamine system using PET have focused on age differences in WM updating and executive control, but more or less ignored motivational functions (Bäckman, Nyberg, Lindenberger, Li, & Farde, 2006). This is surprising, given the well-established role of DA for motivation and the fact that we seem to have a much better mechanistic understanding of reward-based learning and decision processes than WM or executive control. Future studies should fill this gap, ideally by combining neurocomputational approaches with functional neuroimaging. Ultimately, the goal of this research should be to link results back to everyday life situations that involve decisions from experience, to allow not only to learn about the involved mechanisms but also to learn how to improve decision making under uncertainty across the life span.

Potential Interventions to Ameliorate Learning Deficits in Older Adults

Naturally, findings on age-related deficits in DA function and their consequences for behavior raise the question about pharmacological

interventions in old age that might ameliorate cognitive deficits. Data from a recent study suggest that the DA precursor L-DOPA, which is commonly used to treat later-stage Parkinson's disease, partially restores striatal Pe signaling in older adults (Chowdury et al., 2013). However, in this study older adults did not seem to benefit from this treatment in terms of performance, which raises questions about the usefulness of an intervention using L-DOPA. Furthermore, it should be noted that L-DOPA may induce negative side effects such as nausea, arrhythmia, and extreme emotional states, and the consequences of longer-term use of such medications are unclear. Additionally, the outcome of pharmacological studies using dopamine agonists is less straightforward than one would wish. Another study that used an L-DOPA manipulation in combination with a task that taxes interference control showed a negative effect in younger adults (possibly due to excessive DA levels) and no effect on performance in older adults (Onur, Piefke, Lie, Thiel, & Fink, 2011). Similar to these results, a study using DA agonists and antagonists during memory encoding in older adults did not show significant differences in drug effects on memory when compared to younger adults (Morcom et al., 2010). Thus, the results of studies using pharmacological interventions in combination with cognitive tasks are mixed, and the effects are generally weak. One apparent problem with most of the pharmacological interventions is that the mechanisms by which these drugs interact with the neuromodulatory system are very complex and probably not specific to a certain cognitive function. Furthermore, the drug effects may depend on individual difference in baseline DA levels as well as genetic predispositions. These factors add another level of complexity to the development of potential pharmacological interventions. Drugs that are assumed to enhance cognitive function but are less specifically associated with dopamine, such as Modafinil, have, to our knowledge, not been systematically investigated in age-comparative studies.

Another way to interact with the DA system is to provide primary and secondary reinforcers in the context of cognitive or motivational tasks to support performance. Recent work in younger adults suggests that performance-dependent reward incentives support executive control abilities (such as the ability to switch between tasks or to perform two tasks in parallel) (Savine & Braver, 2013). Similar effects were obtained with respect to episodic memory performance for rewarded, as compared to non-rewarded, information (Adcock, Thangavel, Withfield-Gabrieli, Knutson, & Gabrieli, 2006; Wittmann et al., 2005). An age-comparative ERP study (Eppinger et al., 2010) showed that reward during learning enhances subsequent memory performance to a similar degree in younger and older adults. Similar findings were obtained by Mather and Schoeke (2011). Work by Anguera and colleagues (2013) suggests that training using a video game enhances cognitive control abilities and improves prefrontal brain function. These effects may partially be due to the rewarding

properties of the computer game. Taken together, these results seem to support a seemingly trivial conclusion, namely, that younger as well as older adults seem to learn and perform better in situations that involve incentives. The boundary conditions of these effects as well as the underlying neurophysiological mechanisms, however, are not yet determined.

To summarize, in this chapter we provided a link between age-related impairments in decisions from experience and age-related deficits in different types of reinforcement learning. Moreover, we showed that computational approaches in combination with neuroimaging can provide an important tool to advance our mechanistic understanding of age differences in decision making. Accumulating evidence suggests that age differences in Pe signaling may be one of the mechanisms underlying age-related impairments in model-free reinforcement learning (Chowdury et al., 2013; Eppinger, Schuck, et al., 2013; Samanez-Larkin et al., 2014). These effects are most likely due to age differences in dopaminergic neuromodulation. In contrast, age deficits in more complex types of learning, such as the learning of task structures or state spaces, seem to be associated with a reduced recruitment of prefrontal areas (Eppinger, Heekeren, & Li, under review). Both learning deficits may contribute to age-related changes in decisions from experience, particularly in uncertain and ambiguous decision situations. Given the ubiquity of these situations in our daily life, future research should try to improve decision making abilities in older adults by supporting learning mechanisms.

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