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The Role of Feedback in Decision Making

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1. Introduction

To date there has been no comprehensive review of the kinds of decision making tasks and their requirements with respect to investigating preserved and impaired behavior in patients with Parkinson's (PD). The aim of this chapter is to address this by examining recent work in this domain. The chapter is divided into three main sections. The first will discuss tasks which have been typically used to study decision making in patients with PD. The aim here is to present an overview of critical features that are common to them along with the associated findings. The second section then focuses decision making behavior when patients are studied on dopaminergic medication, and when examined off medication. The concluding section discusses reinforcement learning models that have been used to account for differences in cognitive impairments in PD patients. The main claim that will be expounded is that some of the discrepancies found in the literature concerning impairments in decision making activities may be due to the structure of the task rather than the dopamine overdosing hypothesis *per se*.

2. Different flavours of decision making

To what extent does Parkinson's disease (PD) impair core cognitive functions such as decision making? The vast literature that has amassed in attempt to answer this question has spawned a diverse range of tasks, loosely classed as decision making tasks. These include, but are not limited to the following: the Iowa Gambling Task (Mimura et al, 2006; Poletti, et al, 2010), Game of Dice Task (Brand et al, 2004; Lubudda et al, 2010), Probabilistic Classification task (Bodi et al, 2009; Jahanshahi et al, 2010; Shohamy et al, 2004), Procedural learning transitive inference task (Frank et al, 2004), Conditional associative learning task (Gotham et al, 1988; Jahanshahi et al, 2000), Probabilistic reversal learning (Cools et al, 2006), and Dynamic decision making task (Osman et al, 2008; Witt et al, 2006).

To shed some light on the various approaches to understanding decision making in the clinical domain, Gleichgerrcht et al's (2010) recent review of decision making in patients with PD and Huntington's Disease, offered the following description of decision making "Decision-making is a complex mental function influenced by multiple cognitive and behavioral processes" (p 612). This clearly recognizes the multifaceted nature of decision making and its involvedness with other functions and though this is a popular characterization (Brand et al, 2004; Delazer et al, 2009; Mimura et al, 2006), it fails to describe the types of activities associated with decision making; it simply established that there are many of them.

Therefore, one might well do to ask the following question, if we strip the aforementioned decision making tasks to their essential features, what is it that constitutes a decision making task? More to the point, what are the types of processes that are under investigations when patients with Parkinson's are required to undertake one of these aforementioned decision making task? If the general findings from studies on PD patients performing the decision making tasks converge on the same general conclusions, which could be that performance is poor relative to healthy age matched controls (HCs), then that could be used to imply that some general aspect of decision making is affected. In actual fact, the evidence suggests that PD patients' performance is impaired under specific conditions (e.g., depending on feedback) but this is not consistently the case for all decision making tasks. Unless we understand what behaviors are engaged in these various tasks, and unless we can be sure that they are essentially tapping the same facets of decision making behavior, our conclusions are somewhat limited. All we can be sure of is that, at best, a broad class of tasks labeled as decision making tasks reveal impaired performance when carried out by patients with PD. At worst, we can be left concluding that a collection of tasks that are thought to involve decision making may actually be examining entirely different processes.

At a minimum then, we need to begin with some basic description of decision making. Most commonly, decision making needs to be thought of as a goal-directed pursuit that involves the ability to predict and manage outcomes (Osman, 2010). Without a goal we cannot direct our actions towards anything. Without a goal we cannot assess the relative success of our actions because we don't have a target by which to evaluate our behaviors against. To assist with the evaluation, interpreting the effects of actions on outcomes can come about through intrinsically driven or externally determined feedback (i.e. gains, losses; reward, punishment). This can often inform us of how much closer or further away we are from attaining our goal, but more often it will serve as an additional source of motivation. From this, we can outline the following three component parts of decision making: 1) sensitivity to the situation in terms of the rates at which rewards and punishments are experienced, (i.e. the amount of reward/punishment received, and the probabilities with which rewards and punishments occur), 2) evaluation of actions in relation to a desired goal (e.g., via rewards and punishments that our actions generate), 3) evaluation of future actions based on the outcome that we have achieved in trying to reach a desire goal (Doya, 2008, Schultz, 2006; Yu, 2007).

All of these components point to the fact that decision making is a sequential processes, in fact rarely is it the case that we make a one shot decision, we choose an action, that in turn has an effect, and shortly after we need to follow that up with yet another decision (Brehmer, 1992). Thus, decision making is often a sequential process. It involves inter-dependent decisions (e.g., choosing where to eat out, choosing where to sit in the restaurant, choosing what to eat and what to drink etc...), and the effects of our actions are inter-dependent (e.g., we invited 5 people to join us for dinner, instead, 7 people came, so we now need to find somewhere to accommodate 7 people instead of 5). Importantly, what should be stressed is that as a goal directed pursuit, decision making typically involves a more than one step.

Having established the critical components of decision making, it is important to also outline the general conditions under which decision making takes place. Trepel, Fox, and Poldrack (2005) draw on a broad distinction between two situations that those in the decision making sciences will recognize as "*Decisions under risk*" and "*Decision under*

uncertainty". In the former, people are engaged in planning actions against knowledge of the probabilities of the outcomes following their actions. For instance, betting on the roll of a dice, or placing money on a roulette wheel. Some estimation of the outcome can be calculated (e.g., the likelihood of the ball landing on black) and an action from it then follows. The estimation is a prediction of the outcome, and along with that we attach some value to it (e.g., betting money), or else there is some inherent value to it (e.g., the intrinsic value of correctly guessing that the roll of the dice would land a 4). The latter is a case in which people plan their actions from limited available knowledge of the possible outcomes, and in which the probabilities of the outcomes following actions is not known, or cannot be known. For example, deciding on when in the financial year to sell the house, or whether to make an investment by buying stocks in a major clothing company. Again, some estimation of the outcome is needed (i.e. how much of a profit will I make if I sell now/buy shares now rather than later). In the same way as decisions under risk, actions are informed by the estimation of the outcome occurring, and there are different values attached to the different possible outcomes that could follow. Similarly, the success of the decision is evaluated according to the eventual outcome. In sum, the simple distinction drawn between risk and uncertainty is that, either we can decide what actions to take in the face of knowing the probability of the desirable and undesirable outcomes, or we make a decision to act in situations in which the probabilities of outcomes are not known to us.

For the remainder of this section the focus will be on three types of tasks, two of which are commonly used to investigate decision making behavior in patients with PD, and one which is currently gaining in interest in the clinical field: the Probabilistic Classification task – alternatively known as the Weather prediction task (WPT), IOWA Gambling Task (IGT), and Dynamic decision making tasks (DDM). For each task, the aim is to examine the components of decision making, and the conditions under which decisions are being made. PD patient studies that are reported in this section refer to findings from patients on L-dopa medication.

2.1 Weather prediction task (WPT)

The original motivation behind the WPT was to examine habit learning independently from the development of explicit reportable knowledge (i.e. declarative knowledge). To achieve this Knowlton et al (1994) designed a task in which stimuli and responses were associated probabilistically. Importantly, as with habit learning, this task was designed to encourage the incremental acquisition of knowledge of associations between stimuli and responses, because no one single encounter with a stimulus would reliably predict the outcome. So, when faced with the WPT task (See Fig. 1), a decision maker is shown one of 14 (15 – if all four cards are presented) possible combinations of four cards (Card 1 = Triangles, Card 2 = Circles, Card 3 = Diamonds, Card 4 = Squares). So, on a single trial, Card 1 and Card 3 could be shown, and on the next trial you might see Card 1, Card 3 and Card 4. The presentation of cards is pseudo-randomized, so that people are unable to experience runs of trials in which the same combinations of cards is presented in succession. Each individual card is associated with an outcome with a fixed independent probability, though card combinations do not appear with equal frequency, in fact some are more common than others. Importantly, the four cards have different cue validities. That is, one card is highly predictive (i.e. Card 4), and another card only weakly predictive of rain (i.e. Card 3), and similarly one card is highly predictive (Card 1) and weakly predictive (Card 2) of sun. In the course of the experiment which may involve between 100 – 350 trials, the two outcomes are equally likely to be correct.

What you are told when you are performing this task is that the different cards predict the weather, which can either be one of two states, sunny or rainy. What you have to do is work out on each trial based on the combination of cards presented, if it will rain or if it will be sunny by selecting one of the two options.

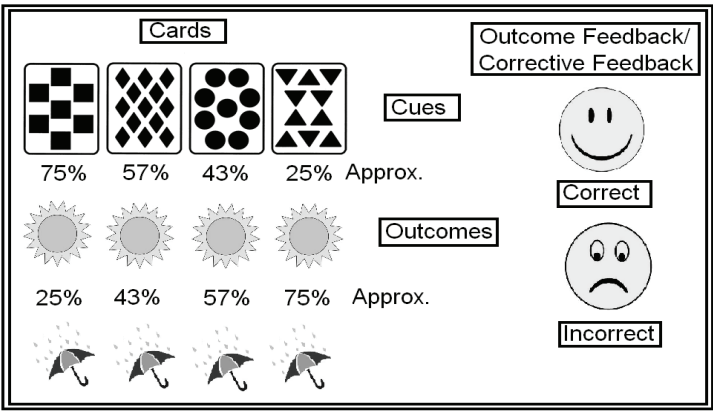


Fig. 1. Details of the Weather Prediction Task (WPT)

Typically, after your choice is made, your only way of knowing if you are correct is either seeing a smiley face, or a sad face; there is no presentation of labels to indicate what the outcome is. In this case corrective feedback and outcome feedback are presented as one and the same. In the task, our action/response is choosing what we think the outcome will be, and we can only do this based on limited knowledge – given that we are unaware of the precise probabilities of the outcomes associated with each card/card combinations. On a given trial, you can only infer from the correspondence of the feedback to your own prediction what the actual outcome is; where positive feedback is simply confirmation of our predictions, and negative feedback indicates that the basis of our predictions is incorrect.

So, what constitutes a decision in this task, what are the conditions in which decisions are being made, and how do PD patients perform in it? This task, and other variants like it, are referred to as probabilistic category learning tasks (Jahanshahi et al, 2010; Shohamy et al, 2004), predictive learning tasks (Knowlton et al, 1994), multiple cue probability tasks (Lagnado et al, 2006). In actual fact, they are all aspects of decision making, and so subject to evaluation of the three components outlined earlier. 1) In the WPT people are required to learn the rates at which rewards and punishments are experienced, because this indicates the success of learning the probabilistic relationship between the cues and outcomes. The findings are mixed with respect to this. Some show that impaired performance in PDs is localized to this component of decision making (Poldrack et al, 2001; Shohamy et al, 2004; Witt et al, 2002), whereas other have shown that the impairments are more general (Jahanshahi et al, 2010; Wilkinson et al, 2008). In one case, there was no overall difference in performance between PDs and HCs (Moody et al, 2004). 2) In the WPT actions are evaluated in relation to a general goal which is to learn cue-outcome associations in order to successfully predict the outcome on each trial. 3) Future performance is based on evaluating the rate of success of past predictions, as well as the usefulness of strategies from which cue-outcome knowledge informs actions taken. Both HCS and PDs show better performance when learning cue-outcome associations when they are given (i.e. presenting the cue pattern and the corresponding outcome) and then applied, compared with when they are acquired

through corrective feedback (Shohamy et al, 2004; Wilkinson et al, 2008). This could be taken to suggest that in general, corrective feedback interferes or competes with goal directed learning of cue-outcome associations in a probabilistic environment. This may be because learning probabilistic cue-outcome associations is demanding of executive functions, and so integrating corrective feedback requires additional resources that are simply not available. However, Wilkinson et al (2008) demonstrated that when removing the response deadline from the feedback and the no-feedback version, PD's showed equivalent learning in both conditions. Thus suggesting that actual feedback processing *per se* is not the reason for decrements in WPT performance. 4) Finally, because the probabilistic relationship between cues and outcomes is unknown, decision making in the WPT is under uncertainty. When compared with Amnesics, or patients with frontal lesions, PD's show poorer performance on the WPT task. Some have taken these findings to suggest that it is impairments to the striatum, and not the Medial temporal lobe or frontal lobes that are associated with impaired decision making under uncertainty in PDs (Knowlton, et al, 1996; Witt et al, 2002).

2.2 IOWA Gambling Task (IGT)

Bechara et al, (1994) devised a task that examined decision making under uncertainty in which the goal was obvious. People have to make advantageous decisions in order to make a profit, or else pay a penalty for a poor decision and lose money.

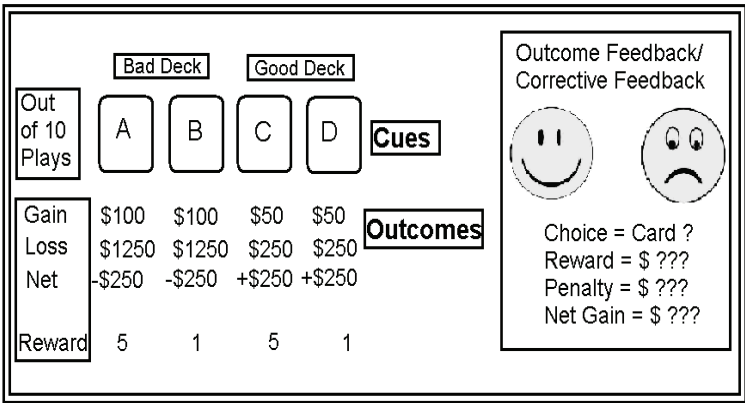


Fig. 2. Details of the IOWA Gambling task (IGT)

The IGT is highly motivating because it presents people with a situation in which at the start of the game they are given a fictional loan of \$2000 loan to play with. Not only is the task designed to examine decision making with gains and losses, it is designed to invoke emotions that could guide decision making in uncertain situations. In this sense the IOWA gambling task is not a risky decision making situation. Unlike other gambling tasks (Roulette, Poker) in which the probabilities of outcome can be estimated, in this task the decision maker is unaware of the probabilities of wins and losses associated with each deck. When presented with the task (see Fig 2), the decision maker is simply told that for each play (trial), they are to select a card from one of four decks A-D; which will not be placed back in the deck after selection. Two cards (A and B) have high rewards, and two cards have low rewards (C and D). However, they are unaware that over the course of 10 plays, cards selected consistently from a deck will result in a penalty that is high (Deck A or B, \$1250) or low (Deck C or D, \$250), with the difference between the two sets of decks based on the frequency of losses (5, or 1). The problem for the decision maker is that they are not told in

advance how many plays (actually 100) they will have, so they have to proceed cautiously by learning that two decks have high pays-outs and high penalties, and so to maximize their overall wins, they ought to go for decks with lower pay-outs and low penalties.

A combination of outcome and corrective feedback is often used in the IGT. That is, on each trial, decision makers will know how much they gained/or lost (outcome feedback), and this is often accompanied by a smiley face or sad face depending on the outcome (corrective feedback). In addition, progress bars are presented on screen after a decision is made in order for people to see their cumulative wins and losses over the successive trials they have played. In sum, in the IGT, an action/response is reflected in the choice of deck that will help maximize wins and minimize losses. This is done in the absence of knowledge of the cue (decks)-outcome (wins and losses) associations, as well as the magnitude (high/low wins/losses) associated with each card selection. Uncertainty is compounded because the decision maker does not know how to incorporate feedback from their choice of decks, because they are unaware of how many total plays they are required to make. Given this fact, it may be the case that decision makers focus on the gain-loss frequency, rather than learning to make decisions that will contribute to a good final outcome (Chui & Lin, 2007).

It is clear from the outset that the condition under which decisions are made is an uncertain one for two reasons: 1) not knowing the probabilities associated with the outcomes, 2) not knowing how to distribute one's choices because of being unaware of the length of the game. For this reason, this makes the IGT rather different from the WPT task, though we will consider this in more detail later in the discussion. So, what constitutes a decision here and what other factors influence performance in PDs? As mentioned earlier, Bechara et al (1994) designed the IGT to examine the influence of emotions on decision making, and reported that in their non-clinical population, concurrent measurement of galvanic skin responses showed that the magnitude of elevated anticipatory skin conductance responses (SCRs) was associated with the magnitude of loss from cards selected (Bechara et al, 1997). However, there was no associated physiological response to losses from card selections in patients with orbitofrontal cortical dysfunction, and patients with Prefrontal damage were unable to shift from bad to good decks. The implications of these findings fit with the general function of this task, which is to show that autonomic processes may underlie our ability to interpret feedback in order to make decisions that maximize our outcome.

The IGT can also be evaluated with respect to the three proposed components of decision making. 1) In the IGT the rates at which rewards and punishments are experienced is critical to learning how to maximize one's earnings and at the same time avoid extreme losses. This is because over successive trials the decision maker learns the probabilistic relationship between cue and the magnitude of the outcome value. The findings are mixed with respect to this. Thiel et al (2003) showed that the distribution of choices for advantageous and disadvantageous decks was no different in PDs as HCs. Though it is important to note that their sample size was small, and the data was not presented in such a way as to determine any incremental improvements over successive trials. With respect to this, there are contradictory reports that overall trials PDs show improved card selection and equivalent rates of learning to HCs (Euteneuer et al, 2010), whereas there is also evidence suggesting that over blocks of trials practice only marginally improves performance as compared to HCs (Czerneki et al, 2002). However, in Czerneki et al (2002) participants performed the IGT twice, and only in the second repetition was there evidence of advantageous card selection even in HCs. This is unusual, since advantageous card selection typically emerges after 20

trials (Bechera et al, 1994; 1997), which suggests that the way in which Czerneki et al (2002) present the task slowed learning rates for both HCs and PDs. There is a range of information that a participant can receive as feedback (as shown in Fig 2), and not all studies report the exact presentation format or the actual range of information that is provided as feedback. Given that this can vary from one study to another, this appears to be one of the only main differences between any of the studies discussed here, with exception of the method of analysis of card selection behavior.

2) The goal of the IGT is unambiguous, and is made obvious to the decision maker from the start, so that each decision on each trial is an incremental step towards, or away from the target – i.e. maximize one's profits. Some have shown that PDs' overall winnings are substantially less than HCs, as indicated by failure to select the advantageous deck (Czerneki et al, 2002; Kobayakawa et al, 2008; Mimura et al, 2006). But, others have shown that the overall success in maximizing earnings is equivalent in both HCs and PDs (Euteneuer et al., 2010; Poletti, et al, 2010; Thiel et al, 2003). While Euteneuer et al (2010) showed that behavioral performance was the same, when comparing PDs with HCs on electrodermal response (EDRs) which indexes emotional/stress responses, they found that HCs showed higher anticipatory EDRs before choosing disadvantageous decks, whereas PDs showed lower anticipatory responses. 3) In the IGT future performance is based on evaluating the rate of success of past choices of the winning or losing deck, and this in turn indicates to the decision maker the usefulness of the strategies designed to reach the goal. Rossi et al (2010) compared IGT decision making behavior of PDs diagnosed as pathological gamblers (PG), with a group of non-gambling PDs. They showed that over successive trials, PDs that were PG tended to select deck B most often, preferring to opt for a high reward high loss strategy compared with PDs that showed a shift in strategy away from disadvantageous decks towards advantageous decks.

The implications here are that future decision making behavior under uncertainty is strongly influenced by sensitivity to previously rewarding outcomes. It maybe that PDs tend to base their strategies on large short term gains, while ignoring big losses, but over time can flexibly adapt their strategies. However, PDs with associated pathological gambling show inflexibility in adapting their strategies over time.

Despite the IGT being labeled as a gambling task, for reasons already discussed, excessive card selection of high gain/high loss decks does not reveal exceptional risk seeking behavior, because decisions are not made under risk. However, findings from a variant of the IGT task, do suggest that actually PDs are highly risk seeking. In the Game of Dice Task (GDT) the structure is transparent to the participant. They are aware of the probabilities and the rules for gains and losses. In GDT decision makers are required to improve on their initial loan of fictional money (\$1000), by rolling a virtual dice. The decision maker has to guess what number will come up by choosing a single number or a combination of numbers (2, 3, or 4). As the combination of numbers increases, the winnings and losses incrementally decrease. PD's tended to show that when experiencing high losses they often failed to shift to a better strategy compared to HCs (Brand et al, 2004). Moreover, when directly comparing the IGT with the GDT, PD's showed poorer performance on the GDT than the IGT (Euteneuer et al, 2010). However, the proportion of occasions in which they shifted strategies after experiencing losses was equivalent in both tasks, and EDRs for both tasks were lower after losses, but were at comparable levels to HCs after gains. Unfortunately, these studies do not include recall tests in which participants record the proportion of trials

in which they estimate their experienced high wins, high losses, low wins, and low losses. This measure would give some insight as to whether the low physiological responses to losses are also accompanied by poorer encoding of, and memory of losses. More to the point, it would help elucidate the reasons for the similar patterns of behavior in the IGT and the GDT.

2.3 Dynamic Decision Making tasks (DDMs)

Dynamic decision making tasks are designed to transpose problems faced in applied contexts into experimentally controlled situations in which the decision maker is faced with complex dynamic situations (Brehmer, 1992). However, participants are typically naïve to the context, and so decision making is not based on established expertise, but developing expertise. In these tasks skill is defined as the ability to systematically choose cue values that will change the outcome value in order to reach a target criteria and maintain it. The decision maker is told from the outset that they need to learn the relationship between the cues and outcomes. This is because either after a period of training (Osman, et al, 2008) or right from the outset (Witt et al, 2006) they make interventions on the cues in order to control an outcome in a dynamic environment. In this sense, the goal of the task is explicit and there is no uncertainty about the length of the decision making period. However, the conditions under which decisions are made is uncertain because people are unaware of the associated probabilities or noisy functions that describe the cue-outcome relationship. The process by which a decision maker learns about the task is revealed by the values of the cue that they change and the corresponding changes to the outcome value. Also, by directly manipulating the cues via changing their values, the decision maker is able to acquire knowledge about the underlying structure or rule that connects cues to outcomes.

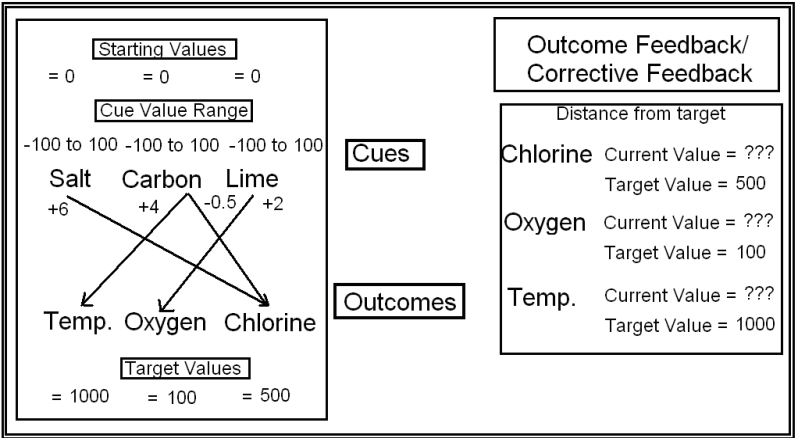


Fig. 3. Details of the Dynamic Decision Making task (DDM)

In the example presented in Fig. 3 the relationships between the cues (Salt, Carbon and Lime) and outcomes (Temperature, Oxygen, Chlorine) is based on a causal structure, in which the cue-outcome associations are linear but noisy (e.g. increasing the value of Lime by 100, will increase Oxygen by 102). The context for the example in Fig. 3 is based around a water purification plant in which participants are asked to imagine that they are trainee operators, and that they need to work out what levels of salt, carbon and lime are needed to purify the water. Their goal is to reach and maintain specific outcome values which indicate the safest purity levels (Oxygen = 100, Temperature = 1000, Chlorine = 500) (Burns &

Vollmeyer, 2002; Osman et al, 2008). At the start of the task all values are set to 0. So, manipulating the cue values will change the outcome values directly, which are observed on every trial. More importantly, the changes to the outcome value are cumulative over trials. That is, while the cue values are reset to 0 the outcome values are retained from the previous trial. In this sense, a poor decision on Trial 2 will need to be corrected on Trial 3 and possibly Trial 4 in order to bring the outcome values back on target, and keep them there.

Not all DDM tasks precisely follow the cue-outcome structure as described here. For instance, some DDM tasks only involve one cue and one outcome, but the functional relationship between the two is still complex (Berry & Broadbent, 1988). Nevertheless, the basic features of the tasks are consistently the same. Cue-outcome relations are opaque to the decision maker and through direct manipulations of the cues (which are typically continuous values) changes to the outcome occur, and the goal is to reach and maintain specific outcome states. Moreover, the type of feedback presented in DDM tasks usually involves presentation of the target value, which is the residing goal throughout the task, and the outcome values directly following from cue manipulations. In so doing, the decision maker is alerted to the discrepancy between the achieved outcome values and the target outcome values.

The same criteria for evaluating the WPT and the IGT as decision making tasks will now be applied to DDM tasks. To begin, given that the DDM task includes a number of features that are unknown to the decision maker at the start, decision making proceeds under uncertainty just as with the IGT and the WPT. So, what constitutes a decision in this task and how do PD patients perform? 1) DDM task requires people to track the rates at which rewards and punishments are experienced, because this indicates the success of learning the relationship (e.g., probabilistic, dynamic, non-linear, linear) between the cues and outcomes. A positive outcome is reflected in a decrease between achieved and target outcome, and a negative outcome is reflected in an increase between achieved and target outcome. Thus, rates of rewards and punishments are experienced in a manner that is different from the IGT or the WPT; this point will be discussed in more details later in this section. In the main, there is consensus that PDs show intact goal directed decision making when compared to HCs (Osman et al, 2008; Witt et al, 2006). PDs are able to consistently reach and maintain a specific goal by making interventions that involve selecting appropriate cue values.

2) DDM tasks are principally goal directed decision making tasks. In fact, accuracy in decision making and outcome and corrective feedback are all based on the success of reaching and maintaining a specific goal. The task is set up to inform the decision maker precisely about their status in the task with respect to a given goal. The difficulty of the task is determining the right cue interventions that are needed when the outcomes deviate from the target. The evidence suggests that this component of decision making is also intact in PDs (Osman et al, 2008; Witt et al, 2006). To complement this, similar findings have also been reported with amnesic patients performing DDM tasks (Squire & Frambach, 1990), and PD patients performing a predictive task in which the reward structure of the task is dynamic (Rutledge et al, 2009). While successful control behaviors have been demonstrated in PD patients, there is evidence to suggest that structural knowledge (i.e. causal cue-outcome associations, or functional relationship between cue-outcomes) of the task is impaired (Osman et al, 2008; Witt et al, 2006). This has led some to suggest that complex planning behaviors are needed to decide on which cues to intervene on. But, given that PDs are unable to provide accurate verbal reports of their cue-outcome knowledge, planning is

based on knowledge that is not consciously accessible (Witt et al, 2006). In line with Witt et al's proposals, McKinlay et al. (2010) presented PDs with a test battery including decision making and problem solving tasks designed to engage executive functions. PDs showed preserved goal directed behaviors, though the authors suggest that performance reflected conscious access to knowledge in their tasks.

3) In DDM tasks future performance is based on evaluating the rate of success of past predictions, as well as the usefulness of strategies from which cue-outcome knowledge informs actions taken. Using previous strategies to make future decision has been examined in DDM tasks, however the evidence is mixed. Osman et al (2008) found that PDs were no different to HCs, and both were able to successfully transfer their decision making strategies from one version of a DDM task to a similar version in which the cover story differed. This is all the more notable given that the training phase of each DDM task performed was different. Some first experienced trials in which they directly manipulated cues (active learning) while others experienced trials much like Wilkinson et al's (2008) WPT. In their task learning cue-outcome associations was observational based, in which all trial information was presented (i.e., Cue Values, Outcome Values and Target values) without the decision maker making any decisions. However, Witt et al (2006) failed to show transfer of decision making skills in PDs. Despite the fact that both tasks were structurally identical and only differed with respect to the cover story, there was no benefit in performance following initial exposure to the first version. However, Witt et al (2006) found that HCs also failed to show transfer, and this same finding has been found with amnesic patients (Squire & Zola-Morgan, 1991) and young healthy controls (Berry & Broadbent, 1988). The main reason for the mixed findings is that the DDM task used by Osman et al (2008) and those used by Witt et al (2006) are structurally different. In the former case, there is a complex structure that may be intuitively easier to because it is causal, whereas in the latter study the structure is a non-causal rule, and therefore transfer may in fact be facilitated as a result of causal reasoning.

2.4 Summing up: Different flavours of decision making

2.4.1 What are the similarities between the WPT, IGT and the DDM?

The WGT, IGT and DDM require the decision maker to examine events (cues) that probabilistically predict an outcome. By accruing knowledge of the associations between cues and outcomes they can utilize it in such a way as to predict or control an outcome. When a response is made in which an outcome is predicted, feedback directly related to the outcome (outcome feedback) is presented given after the response is made. Finally, correct responses may in principle be taken to be rewarding outcomes, that is, a correct response serves as a reward in and of itself, or a reward structure is in place in the task in which virtual money can be gained or lost. However, from the discussion thus far it is clear that whilst they share a number of fundamentally similar features, the WPT, IGT and DDM tasks differ in a number of important ways.

2.4.2 Are there differences between the WPT, IGT and DDM based on the brain systems they engage?

Overall, compared to HCs, PDs tend to show poorer performance in the WPT. Some have argued that this is because the task engages the striatum and medial temporal lobes (MTL), which are regions that are impaired in PDs (Poldrack et al, 2001; Shohamy et al, 2004). In

contrast, the IGT has generated mixed findings, and so it is unclear what can be inferred. Euteneuer et al (2010) claimed that the IGT and its close cousin the GDT engage the limbic-orbitofrontal striatal loop because both tasks involve some emotional processing because of their reward structures. Given that in PDs there are impairments to this system, this candidate explanation could account for why it is that in both tasks, PDs show lower physiological responses to emotional outcomes, albeit specific to negative outcomes. The DDM poses somewhat of a problem in understanding what brain systems are engaged because PD's performance is comparable to that of HCs. Moreover, this has been shown in two entirely different versions (structurally, contextually, perceptually): the water purification system (Osman et al, 2008) and the sugar factory task (Witt et al, 2006). The general claim has been that DDM tasks engage neocortical structures that are recruited when binding complex information. The problem is however, that the DDM task is likely to engage more than just neocortical structures, but which other structures is as yet not clearly specified. An alternative route that has been taken is to focus on the regions that are unlikely to be engaging. Given that PD is associated with neurodegeneration in the striatum, particularly the posterior putamen, the implication is that DDM tasks do not engage midbrain regions, and so processes associated with them, such as incremental error-corrective learning and reward/feedback learning aren't necessary to perform the task (Witt et al, 2006). However, this simply cannot be the case for DDM tasks given the task analysis earlier in this section.

Goal directed processes tend to be preserved in PDs, but incremental acquisition of cue-outcome knowledge which enables the quick execution of highly practiced knowledge (i.e. habits) is impaired (McKinlay et al, 2010; Redgrave et al, 2010; Shohamy et al, 2006). Redgrave et al (2010) propose that some of the impairments observed in decision making may reflect intact goal directed learning (e.g., rostromedial striatum) that cannot be expressed autonomically because of a dysfunctioning habit learning systems (e.g., midbrain). In other words the acquisition of information (e.g., WPT- cue patterns that predict rain, IGT -cues that predict High gain/High loss) is not severely affected by PD, but what is severely affected is the speed up that would typically occur through repeated application of this information. In PDs the rate at which knowledge can be expressed is affected because the mechanism that forms habits is impaired. For example, there is evidence that PDs can learn probabilistic information in an incremental way in a sequence learning task (Wilkinson & Jahanshahi, 2007), but that the magnitude of learning is reduced as compared with HCs. In their task goal directed, Wilkinson and Jahanshahi (2007) showed that PD's learning involved acquisition of the probabilistic cue (stimulus) - outcome (response) associations, but expression of this knowledge through speed up of responses was impaired (Wilkinson & Jahanshahi, 2007).

To bring these points to bear more specifically to PD performance in the decision making tasks, some have claimed that failure to exhibit incremental cue-outcome learning (as in the WPT, or in some cases the IGT) is the result of slower rates of learning (McKinlay et al, 2010; Redgrave et al, 2010; Rutledge et al, 2009). Indeed, the most consistent core cognitive deficits reported in PDs are speed of processing, along with visuo-spatial ability and some components of executive functioning (McKinlay et al, 2010). McKinlay et al (2010) propose that deficits in general memory, planning, and attention are much more variable, and one reason for this could be as a result of the particular methodology used to study these processes. Similarly then, decision making may also be included in this latter category of

processes in which methodology plays a big role in explaining the mixed findings. Alternatively, poor performance in decision making tasks may reflect a more profound problem that begins with deficits in encode cue-outcome knowledge as well as later problems in expressing it (Poldrack et al, 2001). If one accepts this claim, then failing to encode cue-outcome knowledge is as a result of impairments to processing feedback (Poldrack et al, 2001; Shohamy et al, 2004, 2006). However, one problem with this view is that, with exception of the WPT, which can be accounted for on this basis, studies using the IGT revealed mixed findings with respect to impaired performance in PDs, and the DDM actually shows intact decision making in PDs.

2.4.3 Where do the differences lie between the WPT, IGT and DDM?

Goals: Each of the three decision making tasks involve a goal, but the tasks differ with respect to the specificity of the goal. In the WPT the goal is general, and that is to simply learn to accurately predict the outcome from the cue patterns. The goal of the IGT is more specific and requires the decision maker to maximize their earnings and minimize their losses. But, the decision maker isn't told what the maximum earnings are that they can achieve. In the DDM task, the goal is often specified from the outset, so the decision maker is aware what the precise target is. Thus, the goal of the task, or rather the specificity of the goal may be a contributing factor to the differences in performance in the WPT, IGT and DDM. Planning behaviors are not thought to be severely affected in PD, and one reason for this is that tasks used to examine and successfully show unimpaired performance involve problem solving tasks with an obvious specific goal (McKinlay et al, 2008). McKinlay et al (2008) deconstructed the components of the tower of London task which is a problem solving tasks that involves following specific rules that state how a series of discs can be moved from one peg to another. They found that so long as the goal isn't ambiguous – more to the point, if the actual hierarchy of goals/sub-goals is made clear, then goal directed processes remain intact in PDs. In contrast, PD's failure to encode or re-organize representations, and their lack of flexibility and poor incremental learning has been extended to account for impaired decision making in general (Owen, 2004; Poldrack et al, 2001; Shohamy et al, 2004, 2006). However, it may well be the case that the goal structure of the tasks in these studies interferes with PD's ability to perform decision making well; this says more about the task than the nature of the cognitive impairments in decision making.

Uncertainty: The discussion of the WPT, IGT and the DDM suggest that they are tasks that induce uncertainty. A decision maker in the WPT is unaware of the probability of cue-outcome associations (i.e. how often certain cue patterns will appear) and the cue-outcome probabilities (the association between cues and certain outcomes). In the IGT the decision maker is unaware of the cue-outcome probabilities, and also how many opportunities they have to make decisions. In the DDM the cue-outcome probabilities are unknown, and also the structural features or functional relationships between cues and outcomes (causal associations between cue-outcomes, rules describing cue-outcome associations). In general it seems that three tasks generate uncertainty about the cue-outcome associations, but they differ markedly with respect to other sources of uncertainty.

Outcome/Reward/Feedback: The tasks can also be differentiated on the basis of the outcomes and their rewards. In the WPT, the decision maker predicts an event (i.e. sunny, rainy) from a given cue pattern, and then the accuracy of the prediction is indicated either by positive or negative feedback (i.e. smiley face, sad face). In the IGT, the decision maker selects a deck

and the outcome is either positive (a gain of \$50 or \$100) or negative (loss of \$1250 or \$250), and in either case they differ in magnitudes. In the DDM, the decision maker manipulates a cue by selecting a cue value, and this changes the outcome value. Based on the manipulation, the outcome value will either be closer to target as compared to the previous trial (Positive outcome), or the outcome can deviate further away from target as compared with the previous trial (Negative outcome). The IGT and the DDM are similar to each other than with the WPT. First, a decision has a direct consequence on the outcome, given that for both the IGT and DDM the outcome value is dependent on the choice of cue selected. In fact in the DDM, this is even more pronounced, because in this task the decision maker can directly change the cue value. Second, for both the IGT and the DDM a good decision is in itself the reward (i.e. IGT – increasing outcome value; DDM – closer to target). Third, the magnitude of the reward can vary in both the IGT and the DDM (i.e. IGT – high/low, DDM – closer to target/exactly on target). For the WPT a decision has no consequence on the outcome itself. This is an important matter because the decision maker doesn't choose the cues and so cannot influence the outcome. Their decision making simply involves a prediction, the status of which is indicated through feedback.

3. The effects of medication on decision making

As mentioned, the core cognitive impairments associated with PD's are speed of processing, visuo-spatial processing, and also executive functioning (Cools et al, 2001; Muslimovic et al, 2005; Owen, 2004). The problem is that, executive functioning is not one thing it involves a combination of activities that are used to different degrees for different tasks. Similarly, as we have considered thus far, decision making has many components, and tasks that are designed to engage decision making processes reveal mixed findings in terms of the extent of impairments found in patients with PD. For this reason it is hard to infer what role medication plays in alleviating or impairing components of the decision making process. As mentioned, the findings from all reported studies discussed thus far involve patients on medication, typically Levodopa (L-Dopa). Dopamine deficiency in the (e.g., putamen and dorsal caudate) midbrain is the hallmark of PD (Hornykiewicz & Kish, 1984), and so dopamine replacement therapy with L-Dopa or dopamine agonists is the most effective method of alleviating motor symptoms (e.g., tremors, rigidity, bradykinesia, akinesia, balance and walking) associated with PD.

As well as mobility, dopamine replacement therapy improves cognitive functioning associated with brain areas which have depleted levels of dopamine (e.g., putamen and dorsal caudate). For instance, improvements have been reported in tasks involving object and spatial recall (Cooper et al., 1992), fluency in generating semantically associated words (Gotham et al, 1988) and task switching between letter naming and digit naming tasks (Cools et al, 2001). However, dopamine replacement therapy also increases dopamine levels in unaffected areas (e.g., prefrontal cortex and ventral striatum). The prefrontal cortex is speculated to be involved in processing probabilistic cue information (Forstman et al, 2010; van Veen et al., 2008) and the ventral striatum has been associated with classification of probabilistic cue-outcome associations (Cools, et al, 2006). In support, dysfunction of cognitive processes include deterministic cue-outcome learning (Gotham et al., 1988) and probabilistic cue-outcome learning (Cools, et al, 2006; Cools et al., 2001; Shohamy et al, 2006; Swainson et al, 2000; Swainson et al, 2006). Findings of this kind have been used to support the dopamine overdosing hypothesis, which proposes that dopamine levels in unaffected

brain regions are “overdosed” and this then leads to dysfunction of processes such as cue-outcome learning (e.g., Cools et al, 2001; Gotham et al, 1988). Recall, the features of cue-outcome learning are the basic building blocks of the three main decision making tasks (WPT, IGT, DDM) discussed in this chapter. Therefore, by implication, decrements in performance on these tasks while on medication may be explained by the overdosing hypothesis.

3.1 The effects of on vs. off L-Dopa medication in the WPT

One might predict that if impairments to decision making performance in PDs is observed while on L-Dopa medication, as is the case with the WPT, then if the overdosing hypothesis bears out, PDs off L-Dopa medication should show improvements in the WPT performance. This is exactly what has been shown (Shohamy et al, 2002; Jahanshahi et al, 2010). Jahanshahi et al (2010) found that the same patients on medication, then performed the task after having withdrawn from medication, showed equivalent predictive accuracy to HCs. However, patients tested off and on medication were able to discriminate between strong and weak cards as well as HCs. Importantly, critical behavioral differences between those off and on medication were found to be the result of the types of strategies that were implemented (Speekenbrink et al, 2010). HCs and PDs off medication showed hypothesis testing type behavior, partly resulting in more flexibility in switching strategies when experiencing poor outcome feedback, whereas PDs on medication switched to poorer strategies. This strongly implies that the impairments in performing the task are not located at an encoding level, given that all participants learnt which cues strongly and weakly predicted a particular outcome.

In two analogous probabilistic cue-outcome learning tasks (Probabilistic Selection task, Probabilistic Discrimination task) which share many similarities with the WPT, similar improvements in predictive accuracy have been reported while PDs are off medication (Frank et al, 2004; Shohamy et al, 2006). The facilitatory effects of withdrawing from medication are thought to improve feedback processing, in particular negative feedback (Frank et al, 2004; Shohamy et al, 2006). In support, in WPTs or equivalent tasks, PD patients on medication show impaired performance, whereas when no feedback is presented in identical tasks, there is no reported impairment in performance (Shohamy et al, 2004; Shohamy et al, 2006); though some have speculated that this result is because the time limit to respond was removed in the no feedback version (Wilkinson et al, 2008). From this, Shohamy et al (2006) proposed that the overdosing hypothesis can be used to explain the discrepant effects of feedback on performance because midbrain dopamine systems are implicated in reward-related error-correcting incremental learning processes. Thus, increasing dopamine levels interferes with error processing in tasks that provide feedback, whereas presenting PD patients with versions without feedback eliminates error corrective processing and in turn the detrimental effects of overdosing on incremental learning. To complement this, Frank (Frank et al, 2004; Frank, 2005) has claimed that positive and negative feedback have differential effects on dopamine release. In sum, it is not clear whether probabilistic cue-outcome learning is impaired in PDs on medication because of critical features of the task that require flexibility in strategy application, or failure to process negative feedback. PDs on medication may perseverate on poorer strategies, or have greater difficulty switching to better strategies, which indirectly suggest failure to process negative feedback.

3.2 The effects of on vs. off L-Dopa medication in the IGT

Despite the popularity of the task, only Czerneki et al (2002) examined the effects on decision making while patients were medicated on L-Dopa and when they had withdrawn from it for 24hrs. Recall that in Czerneki et al's (2002) study all groups (PDs on medication, PDs off medication, HCs) performed the IGT twice. While HCs showed a net improvement across repetitions, PDs showed no relative improvement in selecting from the advantageous decks more often. These findings strongly suggest that increasing dopamine levels in the midbrain as well as unaffected regions doesn't have any adverse effects on IGT performance any more than restoring levels of dopamine in unaffected regions through withdrawal of dopaminergic medication. To add to this, while Czerneki et al's (2002) is the only study that has contrasted the effects of on vs. off medication on IGT performance, Pagonabarraga et al (2007) examined the effects of different levels of dosage of L-Dopa on IGT performance. They compared PDs on medication that were receiving L-Dopa on a daily basis (405 +/- 300 mg) and showed stable responses to medication, and PDs on medication also receiving L-Dopa but showing a fluctuating responses to medication, or wearing-off responses which involve increases in L-Dopa dosage (930 +/- 411 mg). Pagonabarraga et al (2007) found that there was no influence of type of dosage on IGT performance, although they found that in general PDs performed worse than HCs. Nevertheless, this too is an example in which medication, and more to the point, the overdosing hypothesis cannot exclusively explain PD's performance in the IGT. Finally, Perratta et al (2005) compared PDs with early stages of the disease (i.e. less than a score of 3 on the Hoehn and Yahr Scale score), and those with late stages of the disease (i.e. more than a score of 3 on the Hoehn and Yahr Scale score) on the WPT and the IGT. They found that on the WPT, HCs and the early PD group showed equivalent performance on 100 blocks of trials they carried out, but that late PDs showed worse performance than both other groups, and accuracy decreased in the last 30 trials. It is important to note that it is rather atypical to only present participants 100 trials, however, even in Jahanshahi et al (2010) study in which they used 200 trials. However, in line with Perratta et al's findings, they reported a marginal negative correlation between performance and Hoehn and Yahr stage of illness and performance on the WPT. When focusing on the IGT, Perratta et al (2005) found that stage of illness made no difference in performance, and that for early and late PDs, performance was equivalent. With the exception of one block of trials, PDs also showed equivalent performance to HCs. While Perratta et al's (2005) manipulation did not include an on vs. off medication manipulation, one could argue that those in early stages of PD would be more susceptible to overdosing in regions such as the ventral striatum and orbitofrontal cortex which remains relatively spared in early stages of PD. Given that the ventral striatum has been associated with probabilistic cue-outcome associations, then one might predict that both the WPT and the IGT would be affected. However, only performance in the WPT was in fact impaired. Moreover, the location of impairments was against what would be predicted by the overdosing hypothesis. Those in late stages of PD were affected rather than those in early stages of PD. Clearly then, across these different studies, there is a strong indication that L-Dopa medication does not impair performance on the IGT, and that withdrawing from medication does not improve performance above baseline.

3.3 The effects of on vs. off L-Dopa medication in the DDM

The use of DDM tasks in clinical populations is in its infancy, and so only two studies can potentially inform the debate concerning the effects on vs. off medication on performance in

these tasks. Osman et al (in preparation) have shown that comparing PDs on L-Dopa medication and off L-Dopa medication while performing a DDM did not differentially affect performance, and that both groups performed as well as HCs. However, they did find that those off medication and HCs adopted similar strategies when choosing how many cues to intervene on in order to control the outcome. Both these groups tended to manipulate one cue at a time and observe the effects of their manipulation on the outcome. This is a more effective strategy for acquiring cue-outcome knowledge in a dynamic environment, because it is hard to isolate which factors may contribute to changing the outcome value (Osman, 2010). In contrast, PDs on medication tended to manipulate all the cues most of the time in order to control the outcome, which makes learning the association between cues and outcomes harder depending on the cue values that are selected. That is, all three cues may be manipulated, but cue 1 could be set at 75, cue 2 set at 50 and cue 3 set at 50. If on trial two cue 1 is set to 100, and cue 2 and cue 3 are set to 50, then this is the same strategy as varying one cue at a time. In general, performance, as indicated by consistently achieving and maintaining a specific outcome for a course of trials was not differentially affected by the presence or absence of dopaminergic medication.

Though not a DDM task, Rutledge et al's (2009) study involved a dynamic environment in which the rewards associated with certain cues would change throughout the course of the task. Participants were told they were on a fishing vessel and that they were required to choose between one of two crab traps to send into the water. They received real monetary rewards for each successful decision they made. The relative reward rates would change in blocks of 70-90 trials (i.e., 6:1, 3:1, 1:3, 1:6), and the identity of the high reward option alternated between blocks of trials. The task essentially involves making a prediction about which crab trap will yield the highest catch which will in turn lead to high rewards. They found that PDs on as well as off medication earned as much as HCs that were aged matched, though younger HCs earned the most money and more than PDs from either group. When examining rates of learning and sensitivity to transitions in rewards over trials, they found that PDs on medication showed different rates of learning to those off medication. Moreover, Rutledge et al's (2009) reported that when comparing learning rates when receiving positive outcomes, PDs on medication showed higher learning rates than PDs off medication. For negative outcomes, learning rates were lower than for positive outcomes, and for both groups learning rates were the same.

3.4 Summing up: The effects of medication on decision making

In line with the general pattern of findings discussed in the previous section, the effects of withdrawing from medication seem to impact most reliably on performance in the WPT. For the IGT and the DDM the implications are that brain regions that would be overdosed with dopamine through drug treatment are not engaged in these tasks. Alternatively, it may be that the way in which the tasks are structured enable patients to exhibit more robust aspects of decision making which may well be preserved in PD, or at least, less affected than other cognitive functions that consistently reveal decrements in performance. The examination of the different tasks in the previous section reveal that both the IGT and the DDM are more clearly defined in their goals than the WPT is. Also, the feedback presented in the IGT and the DDM share more features in common, than with the feedback presented in the WPT. However, this is largely because of one critical factor. The decisions that are made in the IGT and the DDM affect the outcome and rewards/punishments, whereas in the WPT, the

decision only affects rewards/punishments. If one is making choices that have direct consequences for the outcome, then predictions about the effects that those choices will bring, could in turn lead to differences in processing feedback as compared to when the outcome is already predetermined. In addition, feedback indicates the effects of incremental changes in positive and negative outcomes in the IGT and DDM. While Shohamy et al (2004) and Shohamy et al (2006) claim that the WPT is an incremental cue-outcome learning task, in actual fact feedback in this task does not revealing incremental changes in the outcome or rewards or punishments. Rather, the WPT reveals the success of a decision on a discrete trial basis. The concluding section of this chapter will consider these points in more detail.

4. Reinforcement learning models and feedback

The effects of dopamine replacement therapy on decision making provides important clues as to the components of decision making that are impaired and spared. From what we know of the way dopamine neurons behave, they tend to show different activity associated with different outcomes. If one is expecting an outcome and receives it, then there is tonic activity in dopamine neurons. However, there is short phasic activation in the presence of unexpected rewarding outcomes (e.g. presentation of money), which over time shift towards the predictor of the reward (e.g., cards from a particular deck). Activation tends to decrease in the presence of negative outcomes (e.g., loss of money) or when there is a discrepancy between the expected reward and the actual reward (Hollerman & Schultz, 1998; Schultz, Apicella, & Ljungberg, 1993).

There are currently two reinforcement learning models that are used to account for the differential activation patterns in dopaminergic neurons. The Reward Prediction Error (RPE) model (Montague et al, 2004; Rangel, et al, 2008; Rutledge et al, 2009; Shultz et al, 1997) claims that learning about cue-outcome associations comes about through the generation of expectations about future events; these expectancies influence the rate of learning of the associations. By developing expectancies, one can gain information about the accuracy of one's prediction in the form of prediction errors. If one sees a combination of tarot cards and predicts rain, but the actual outcome is sun, then the expectancy of rain receives a negative prediction error through outcome feedback. Thus, the outcome itself can either positively or negatively deviate from one's expectancies. In each state (positive error, negative error) there is a corresponding pattern of activation in dopamine neurons. The Response-Selection model (Frank et al, 2004; Frank, 2005) instead proposes that choices become associated with relevant predictive cues. Receiving positive feedback from one's actions increases activity in dopamine neurons and this reinforces the selected response (go signal). Negative feedback decreases activity in dopamine neurons and this reinforces an inhibition of the selected response (no-go signal). The critical difference between the two models is that in the former updated cue-outcome knowledge is based on prediction errors, whereas in the latter model it is based on response errors. Both reinforcement models have incorporated the overdosing hypothesis into their accounts. The RS model proposes that intact brain networks have a greater baseline of dopamine which decreases the dynamic range of phasic peaks and dips. This is thought to specifically impair processing negative feedback, and as a result there is less suppression of no-go signals. The RPE model claims that increase in dopamine through L-dopa modulate RPE magnitude, to the extent that the RPE is amplified, and in turn increases the rate of learning of cue-outcome associations, which in turn can be detrimental because of hypersensitivity to rewarding outcomes. This perspective does not place specific deficits on processing of particular forms of feedback, but rather different forms of reward.

4.1 Impaired feedback processing may not be the answer

Dopaminergic neurons have been associated with reward processing, and the striatum is thought to play an important role in reinforcement learning, which is why presenting PDs with decision making tasks that involve rewards structures and incremental feedback reveals important clues about cognitive dysfunction associated with the disease. However, surveying the findings from three different decision making tasks, in which all involve incremental learning of cue-outcome associations, and processing feedback - sometimes with rewards attached, the picture that emerges is not in obvious support of impaired feedback processing in PD.

A task like the WPT does not involve continuous incremental choice-outcome behavior, because there aren't any choices made that would lead to outcome changes; in fact, this applies to Cool et al's (2001) probabilistic reversal learning task, and Franks et al's (2004) Probabilistic selection task. It may be the case that in tasks of these kinds, settling on a consistent decision strategy to start with is one of the most important ways of performing well in them. Maintaining a consistent strategy enables the decision maker to accurately interpret the feedback from each discrete prediction made. Of course, this is less of a concern when the decisions and their effects can be tracked easily over trials, as in the case of the IGT and DDM. Thus, either because the decisions made in these tasks have consequences on the outcomes, or because one can observe the cumulative effects on ones decisions, learning to make decision from cue-outcome associations is facilitated regardless of whether PDs are on or off medication. PDs on medication tend to show hypersensitivity to novel outcomes (Bodi et al, 2009) and an amplified PRE (Rutledge et al, 2009), both of which become relaxed while off medication. Paying special attention to novel changes and having an enlarged error signal when estimating changes in an outcome in combination could explain the fact that performance is poorer in the WPT while on medication, because both contribute to poor strategy selection. That is, PDs would be more susceptible to changing their strategies or even show random responding while on medication because they are acting on each discrete change that they experience from trial to trial, and prompted to do so from an amplified error signal. In fact, PDs on medication show more random guessing early in the WPT task (Speekenbrink et al, 2010), and take considerably longer to switch to a single strategy that they can test which enables them to better track cue-outcome associations over trials (Jahanshahi et al, 2010; Speekenbrink et al, 2010).

Overall, the studies reviewed suggest that cue-outcome associations learning are preserved in spite of stage of PD, level of medication, and withdrawal from medication. Thus, acquisition of probabilistic cue-outcome knowledge in PD is not impaired, but rather the implementation of cue-outcome knowledge may in fact be facilitated or hampered by the nature of the task. It may be the case that implementing cue-outcome knowledge is facilitated in tasks in which the effects of one's decisions are cumulative, either through direct manipulation of the cue values (DDM) or selecting cues in order to achieve a specific goal (IGT). As a result, midbrain regions are still needed in order to perform the task, but the IGT and the DDM may not show disrupted performance when PDs are on or off medication, because the observed cumulative effects of one's decisions are enough to facilitate incremental learning via the continuous updating of action effects on rewards/punishments.

One might ask: Why is actual choice so important? The Pre-supplementary motor area (Pre-sma) has been associated with action-effect bindings and control of voluntary

actions, and has projections to the striatum (Potsuma & Dagher, 2006), which we know is disrupted in PD. Pre-sma is associated with binding of actions to their effects. Intentional action-effect binding involves forming an association between an action (i.e. choosing which cue to manipulate and by which value) and the effect of that action (i.e. the corresponding change in the outcome value) is feedback and this reveals changes in the outcome. This process is an important basis for which to incrementally learning cue-outcome associations (Moore et al, 2010). Therefore, agency is an important aspect of decision making (Osman, 2010), which is why perhaps PDs benefit from tasks in which they are required to make choices, and can adjust their strategies because they incrementally observe the effects of their own decisions.

5. Conclusion

At a more general level, stage of PD, level of medication, and medicated vs. non-medicated do not substantially impair the basic incremental cue-outcome learning mechanism that decision making activities are reliant on. Even in cases in which PD patients on medication are shown to have deficits in decision making, with extended exposure to the decision making task, they are able to eventually switch their strategies to better ones. Unless detailed analysis of the task and its requirements are conducted, and compared with other existing decision making tasks, little progress will be made in understanding the extent of impairments in decision making in patients with PD. The studied reviewed here suggests that tasks with a dynamic element to them reveal intact complex decision making. This in turn provides should provide greater impetus to improve on the kinds of assessments used to determine the range of abilities that are still preserved in patients with PD.

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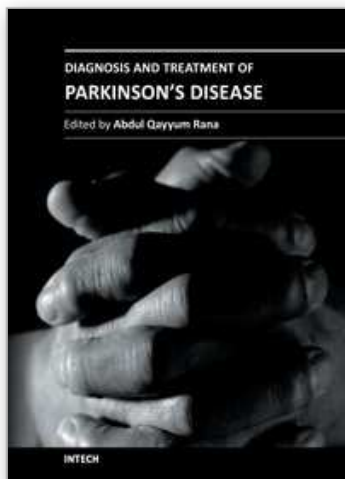
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Diagnosis and Treatment of Parkinson's Disease

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Parkinson's disease is diagnosed by history and physical examination and there are no laboratory investigations available to aid the diagnosis of Parkinson's disease. Confirmation of diagnosis of Parkinson's disease thus remains a difficulty. This book brings forth an update of most recent developments made in terms of biomarkers and various imaging techniques with potential use for diagnosing Parkinson's disease. A detailed discussion about the differential diagnosis of Parkinson's disease also follows as Parkinson's disease may be difficult to differentiate from other mimicking conditions at times. As Parkinson's disease affects many systems of human body, a multimodality treatment of this condition is necessary to improve the quality of life of patients. This book provides detailed information on the currently available variety of treatments for Parkinson's disease including pharmacotherapy, physical therapy and surgical treatments of Parkinson's disease. Postoperative care of patients of Parkinson's disease has also been discussed in an organized manner in this text. Clinicians dealing with day to day problems caused by Parkinson's disease as well as other healthcare workers can use beneficial treatment outlines provided in this book.

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