Learning from the past and expecting the future in Parkinsonism: Dopaminergic influence on predictions about the timing of future events

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1. Introduction

Our ‘beliefs’ about the external world allow for generating predictions about the possible timing of future events (temporal predictions, Nobre et al., 2007). However, temporal predictions carry a degree of uncertainty (temporal uncertainty) that scales with the length and variability (predictability) of the delay preceding an event (foreperiod; Gibbon et al., 1997). When the onset of a stimulus is predictable, reaction times (RT) speed-up (Niemi and Näätänen, 1981). But when the length and/or variability of foreperiods increases, temporal predictions become more uncertain, leading to slower RTs (Klemmer, 1956).

The neurotransmitter dopamine (DA) plays a central role in temporal processing and the formation of temporal predictions (Coulou et al., 2011; Meck, 1996). Along its role in encoding uncertainty about the occurrence of a stimulus, such as the delivery of a reward (de Lafuente and Romo, 2011), dopaminergic activity might also signal the uncertainty about when a stimulus occurs (e.g. time of reward delivery). For example, when long fixed foreperiods precede reward delivery (Bromberg-Martin et al., 2010; Nomoto et al., 2010), or when the foreperiods are variable (variable foreperiod), dopamine midbrain cells respond in relation to the temporal predictability of the reward delivery time (Pasquereau and Turner, 2015). Crucially, suppression of dopaminergic neurotransmission impairs temporal judgments (Soares et al., 2016) and the ability to form temporal predictions (Tomassini et al., 2015), possibly through a dopamine-dependent increase in uncertainty about the underlying temporal structure of events.

A role of dopamine for controlling temporal uncertainty (Fiorillo et al., 2003) suggests that dopamine depletion should impair the ability to form accurate temporal predictions (Friston et al., 2012). Here we tested this in Parkinson’s disease (PD) patients as a model for DA...
depletion, to elucidate the role of DA in regulating the levels of temporal uncertainty. PD is a movement disorder characterized by degeneration of midbrain DA cells and among the cognitive impairments observed in PD patients are the inability to combine past experience to guidedecisions (Perugini et al., 2016), along with altered processing of time durations.

However, it is still unknown whether DA depletion in PD patients impairs the ability to correctly represent temporal uncertainty and hence to form temporal predictions about future events. This is crucial because some impairments of movement control that characterize the disorder have been attributed to either an inability to react to novel events, or an over-reliance on new sensory information (Galea et al., 2012; Perugini et al., 2016). We addressed this question by comparing medicated (PD-on) and unmedicated (PD-off) PD patients, and aged-matched controls using a variable foreperiod task that allows to probabilistically predicting the timing of the stimulus onset (Gibbon et al., 1997; Luce, 1986). We measured RT across a range of predictability levels by manipulating the mean and variance of the foreperiod distributions in a block-wise fashion, thus linking actual stimulus-onset predictability to experienced temporal uncertainty (Fig. 1A-B).

By fitting RTs to a drift-diffusion model (DDM), we sought to identify the specific decision processes relating to changes in temporal uncertainty and their sensitivity to DA depletion. We applied a Bayesian hierarchical estimation of DDM, which is particularly suited for studies involving patients where trial counts are necessarily low (Wiecki et al., 2013), and which has been successfully employed to investigate PD (Cavanagh et al., 2011; Herz et al., 2017; Zhang et al., 2016). We compared three principled variants of DDM that reflected competing hypotheses about the link between DA and temporal uncertainty. One variant posits that more certain temporal predictions about stimulus-onset are reflected by lower boundaries. This leads to faster response initiation and hence faster reaction times (Näätänen, 1970). Conversely, high temporal uncertainty is reflected by higher decision boundaries, leading to more cautious, and hence slower responses (Forstmann et al., 2010; Fig. 1D). An alternative model that temporal uncertainty influences the ability to deploy attention (Nobre et al., 2007), as reflected by changes in the drift-rate of the accumulation (Forstmann et al., 2011). Higher drift-rates thus occur with high attentional engagement, and vice-versa. A third possibility is an interaction between drift-rate and boundary across conditions, suggesting that temporal uncertainty influences both response cautiousness and attention processes.

We tested this directly, hypothesizing that DDM parameters should vary across levels of temporal predictability reflecting changes in temporal uncertainty. We further hypothesized that dopaminergic depletion increases temporal uncertainty about temporal predictions, thus...

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Fig. 1. Variable foreperiod task and the drift-diffusion model. (a) Following a warning stimulus (white circle), the onset of the imperative stimulus (colored arrows) required participants to make a keypress as quickly as possible. The time between the warning and imperative stimulus (foreperiod) changed across trials following a Gaussian distribution. (b) Mean and standard deviation of the foreperiod distribution were constant throughout a block of trials. Four different distributions were used in a blocked factorial design: foreperiod duration (Short, Long) x foreperiod variability (Low, High). The formation of precise temporal predictions was thus mainly limited by temporal uncertainty, which increased with foreperiod duration and foreperiod variability. (c) Example of a trajectory of the drift-diffusion model. The two boundaries represent action-triggering boundaries for ‘LEFT’ and ‘RIGHT’ responses. The diffusion process, reflecting the accumulation of sensorial evidence, starts at a point, $z$, between the two boundaries and after a non-decision time, $t_0$, rising up to one of the two action-triggering boundaries with drift-rate, $v$. The predicted RT is the sum of the duration of the diffusion process and $t_0$. (d) Hypothetical effects of temporal uncertainty on parameters of the model: temporal uncertainty may either modulate the sampling-rate of sensorial evidence accumulation (i.e. the drift-rate), increase the level of activation required to trigger an action (i.e. boundaries), or a combination of both. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
slowing response preparation (as indexed by slow RT), regardless of the actual predictability of stimulus onset. We further anticipate that the dopamine-induced deficit in estimating temporal uncertainty should be reflected by DDM parameters that do not adjust to changes of temporal predictability.

2. Materials and methods

2.1. Participants

Our 32 participants included sixteen patients with idiopathic PD and sixteen healthy controls. This sample size has proved powered enough in similar behavioural studies involving PD patients (Bellebaum et al., 2016; Hadj-Bouziane et al., 2012; Manohar and Husain, 2015).

PD patients and controls did not differ in age, education, gender distribution, and general measure of cognition (Table 1). Experimental protocols conformed to the guidelines of the Declaration of Helsinki and were approved by the research ethics committee of the Institute of Neurology at University College London.

Neurological and psychiatric symptoms were assessed using the Hoehn-Yahr Scale (Hoehn and Yahr, 1967), the Unified Parkinson’s Disease Rating Scale (UPDRS; Lang and Fahn, 1989), the Hospital Anxiety and Depression Scale (HADS; Zigmond and Snaith, 1983). Both patients and healthy controls were administered the Mini Mental State Examination Scale (MMSE; Folstein et al., 1975); a pre-defined cut-off score of 25 represented a degree of cognitive impairment considered too great for participation. Excluding PD medications for the patient group, neither patients nor controls were under the effect of drugs potentially interfering with central dopamine levels during the testing period.

2.1.1. Parkinson’s disease patients

PD patients were tested on and off (877 ± 220 min withdrawn) their usual dopaminergic medication. All patients were treated with either L-dopa monotherapy (n = 3) or L-dopa in combination with dopamine agonist (n = 13). L-dopa equivalent units (mean 713 ± 322) were calculated as described elsewhere (Tomlinson et al., 2010). A comprehensive description of the patients’ demographic data is provided in Table 1. Patients were assessed twice (days between testing sessions 12.9 ± 5.2), once in medicated state (PD-on) and once after overnight withdrawal (mean 14.7 ± 5.2 h) of dopamine medication (PD-off). To control for learning effects, the order of the assessment was counterbalanced so that half (n = 8) of the patients omitted their medication for the first session and the other half for the second session. All the patients had a stable response to L-dopa and showed no sign of dyskinesia during the experiment.

2.1.2. Healthy participants

Age-matched controls (six females, eight males; mean age 67.5 ± 7.3) had no history of neurological disorder and none of them were taking dopamine replacement medications.

2.2. Apparatus and procedures

2.2.1. Apparatus

Stimuli were presented using MATLAB (The MathWorks, Natick, MA) and Cogent Graphics routines (http://www.vislab.ucl.ac.uk/cogent.php) on a 19-in. LCD display (refresh rate 60 Hz) controlled by a Dell Precision T3500 (Dell Computer Corp., Austin, TX).

2.2.2. Behavioural procedure

We examined temporal preparation using a variable foreperiod task (Fig. 1a) in which the delay (foreperiod) between a warning stimulus (white circle) and an imperative stimulus (colored arrow) was varied across trials (Fig. 1A). Visual stimuli subtended approximately 5° of visual angle at a viewing distance of 60 cm. Participants had to respond to the appearance of the imperative stimulus as quickly and as accurately as possible by pressing either the left or the right arrow key with
their dominant hand (Right handed patients: 15/16; Right handed controls: 14/16). Here, the reaction times (RT) indicate the degree of preparation, such that greater preparation generates faster reaction times (Niemi and Näätänen, 1981).

On each trial, the foreperiod duration was randomly sampled from a truncated Gaussian distribution (Fig. 1B). In a blocked 2 × 2 factorial design, we manipulated mean foreperiod duration (Short: 1500 ms; Long: 3000 ms) and foreperiod variability (i.e. standard deviation; Low: 100 ms; High: 600 ms). The two distributions for short foreperiods were truncated at 500 ms, here considered as the minimum time required for preparation (Hackley et al., 2009), and at 2500 ms (longest foreperiod) to preserve the distribution’s symmetry. To ensure comparable standard deviations between short and long distributions, both tails were also truncated to the long distribution at 2000 ms and 4000 ms.

Each experimental session consisted of 4 blocks of 120 trials each, separated by a short rest. A training block of 40 trials was conducted prior to the main experiment. The training block was identical to the experimental counterparts, but with the foreperiod sampled from an exponential (non-ageing) distribution with mean 1000 ms (Niemi and Näätänen, 1981). The order of conditions (blocks) was balanced across sessions and participants following a Latin square design. The whole experiment comprised one session for the controls and two sessions, one on and another off medication, for the PD patients.

2.3. Data analysis

2.3.1. Reaction times

RT were calculated as the delay between the onset of the imperative stimulus and the key press. Responses shorter than 100 ms or exceeding the individual median RT by more than 3 median absolute deviations (MAD) were considered invalid and excluded from further analysis. A Poisson regression characterized the relationship between RT and temporal predictability in terms of intercept and slope of a linear function fitted to the RT of each participant (Banca et al., 2014):

\[
\log(E(RT|TP)) = \beta_0 + \beta_1 TP
\]  

(1)

\(TP\) (temporal predictability) varies from 4 (high) to 1 (low). The intercept (\(\beta_0\)) corresponds to the expected RT when temporal predictability is highest and quantifies absolute differences in temporal uncertainty (indexed by RT) between groups not attributable to our manipulation. The slope (\(\beta_1\)) measures the sensitivity of RT to variations in temporal predictability and represents the strength of the relationship between subjective temporal uncertainty and temporal predictability. Specifically, positive slopes indicate that temporal uncertainty increases when reducing temporal predictability whereas slopes close to zero indicate no relationship.

In addition, we tested whether PD-off patients were able to modulate their RTs with the passage of time (foreperiod-effect; Luce, 1986) showing faster RT for foreperiods near the end of the trial than for early ones. A linear regression between foreperiod’s length and RT quantified the foreperiod-effect between groups, with negative slopes indicating faster RT for longer foreperiods. This was to confirm that performance in PD-off was not determined by impaired motor preparation or/temporal processing.

2.3.2. Drift-diffusion modelling

In the drift-diffusion models (DDM) the decision process is described by four parameters (Fig. 1C): the separation between the two decisions boundaries (b) corresponding to the two choice alternatives (e.g. left vs right button), the rate of activity accumulation arising towards the boundaries (v; drift rate), a priori bias towards one of the two decisions (z), and non-decision time \(t_0\) representing the time used for stimulus encoding and response execution latencies. The model predicts the RT for each alternative as the latency for the accumulating activity to reach the corresponding boundary.

Here, we used a stimulus-coding approach where the lower and upper boundary correspond to left and right responses, respectively.

We applied a hierarchical Bayesian approach (http://ski.clps.brown.edu/hddm_docs/, Wiecki et al., 2013) to fit the model to the empirical RT. The hierarchical approach treats participants as random variables drawn from the group-level distribution, and uses Bayesian statistics to estimate the posterior distribution of the DDM parameters at the group-level, while accounting for differences at the participant-level (Wiecki et al., 2013). This approach is robust in estimating parameters with limited data, and thus particularly well suited for studies involving clinical populations given the substantial constraints on the duration of the task for patients (Zhang et al., 2016).

To test such hypotheses, we first compared 3 variants of the DDM varying systematically whether only the boundaries (Model 1), the drift-rate (Model 2) or a combination of both (Model 3) were allowed to change between levels of temporal predictability. We did not expect a priori biases since the two alternatives were presented in random order, and counterbalanced by condition. Non-decision time was kept constant across levels of temporal predictability, given prior evidence of a dissociation between motor performance (i.e. kinematic parameters) and temporal uncertainty (Tomassini et al., 2015; Pasquaereu and Turner, 2015), but was allowed to vary across groups to reflect dopamine-related changes. All parameters were estimated separately for each group.

For all variants, Markov Chain Monte Carlo simulations were run to generate 50,000 samples from the estimated joint posterior parameter distribution and the first 5000 samples were discarded as burn-in. Convergence was assessed by visual inspection of the Markov chains and by calculating the R-hat Gelman-Rubin statistics (Krypotos et al., 2015).

Model comparison was performed by comparing the deviance information criterion (DIC) value of each variant (lowest DIC indicates the best fit; Spiegelhalter, 2002), and revealed that our data were best fitted when only the boundary parameter varied across conditions (i.e. Model 1; See results below for more details; See Table A1 in the appendix for the parameters of the winning model). Hence, from here onward, we will only refer to this model. To further evaluate the quality of model fitting, we ran posterior predictive checks by averaging 500 simulations generated from the model’s posterior to confirm it could reliably reproduce pattern in the observed data (see appendix Table A2 and appendix Fig. A1 for results of posterior checks).

We predicted that impaired behavioural performance should arise from the inability to correctly map temporal uncertainty to different levels of temporal predictability. Following the same logic of the RT analysis, we characterized the relationship between temporal uncertainty (indexed by the boundary parameter) and temporal predictability in terms of intercept (\(\beta_0\)) and slope (\(\beta_1\)) of a linear function fitted to the estimated boundary of each participant. Since the intercept occurs when the predictability of stimulus-onset is highest, it represents the expected boundary’s value when temporal predictability is highest and provides insight on the ‘baseline’ levels of temporal uncertainty across groups. The slope quantifies the modulatory effect of temporal predictability on temporal uncertainty, as reflected by the boundary parameter, with slopes close to zero indicating a weak modulatory effect. The anonymised behavioural data, and source code used for the analyses can be found at https://github.com/ale-tom/PD_HDDM.

2.3.3. Statistical analyses

Within group effects of medication (PD-on, PD-off) were assessed using one-tailed paired t-tests. Between groups effects were tested using one-way ANOVAs with post-hoc planned comparisons (Controls vs PD-
We report $\eta^2$ as a measure of main effect size and Cohen's $d$ for the effect size of $t$-test comparisons. For all analyses, level of statistical significance was fixed at 0.05.

Statistical inference on model parameters was made by comparing the proportion ($q$) of the posterior distribution of each parameter that overlaps between groups. Significance was assigned if less of the 16.7% ($q < 0.0167$) of the distributions overlapped, corresponding to $q = 0.05$ (Wiecki et al., 2013) after applying Bonferroni correction (Banca et al., 2014).

### 3. Results

#### 3.1. Clinical assessments

Patients were in the mild to moderate stage of the disease, with more pronounced symptoms when in the off state (Hoehn and Yahr scale, $t_{15} = 2.61, p = 0.02$). As expected, scores of the motor section of the UPDRS were significantly higher ($t_{15} = 6.19, p < 0.001$) when measured off compared to on medication. None of the patients had dementia diagnoses (MMSE scores > 25) and none suffered from clinical depression (HADS scores < 7). See Table 1 for further details.

#### 3.2. Basic reaction time effects

Participants performed the task without difficulty as shown by the small overall proportion of excluded trials (control: 2.5% PD-on: 8.6%, PD-off: 9.3% of responses). Less errors were made by the control group (mean 3% ± 2%) compared with the PD-off (mean 18% ± 25%) and PD-on groups (mean 19% ± 24%), although patients and control subjects did not differ significantly (ANOVA, $F(2,44) = 3.14$, $p = 0.053$). The data from one healthy volunteer were excluded due to technical problems during data acquisition.

Our behavioural results show that although participants were not aware of the different foreperiod distributions, PD-on and controls were able to learn the underlying temporal structure of the task and used temporal predictions in anticipation of forthcoming stimuli (Fig. 2 A–B). Indeed, our Poisson regression revealed that, in controls, RTs were modulated by the temporal predictability of stimulus-onset (slopes of Poisson regression, one-sample $t$-test against zero: control: $t_{15} = 2.588, p = 0.002$) with slower RT when the temporal predictability was lowest. By contrast, PD-off patients showed slow RT regardless of the level of predictability (slope of Poisson regression, one-sample $t$-test against zero; PD-off: $t_{15} = 0.562, p = 0.582$; between-group comparison: $\beta_1$: $F_{2,46} = 5.557, p = 0.007, \eta^2 = 0.187$; controls vs PD-off post-hoc; $t_{24.33} = 0.52, p = 0.002, d_\text{H} = 1.3$; corrected for heteroscedasticity). Crucially, after dopaminergic administration, patients’ performance was restored to normality (regression slope). One-sample $t$-test against zero: PD-on: $t_{15} = 5.369, p < 0.001$; PD-on vs PD-off: paired $t$-test: $t_{15} = 3.767, p = 0.001, d_\text{H} = 0.96$; Controls vs PD-on: two-sample $t$-test: $t_{20} = 1.310, p = 0.2$). Since we assume that the changes in RT across levels of predictability index changes in temporal uncertainty, our data suggests that temporal uncertainty has saturated after DA depletion.

Poisson regression also revealed significant differences in the RT intercept ($\beta_0$: $F_{2,46} = 4.696, p = 0.014, \eta^2 = 0.173$) between groups. The intercept in Fig. 2A-B quantifies RTs when the stimulus onset can be easily predicted and is consistent with PD-off patients being overall slower than PD-on (paired $t$-test; $t_{15} = 3.767, p = 0.001, d_\text{H} = 0.96$) and controls (post-hoc; $t_{24.33} = 0.52, p = 0.002, d_\text{H} = 1.3$; corrected for heteroscedasticity). However, foreperiod analyses confirmed that PD-off were still able to modulate their response speed depending on the passage of time. Foreperiod effects were marginally weaker for PD patients (both on and off medication) than controls (see inset Fig. 2C), however such differences were not statistically significant (two sample $t$-test: control vs PD-on, $t_{29} = -0.572 p = 0.57$; Control vs PD-off, $t_{29}$...
Thus, the lack of difference in RT across predictability levels contradistinctive of DA depletion cannot be attributed to a general impairment of motor preparation or to experience the passage of time. Together these results indicate that PD patients were not per se unable to form temporal predictions, but that this ability requires sufficiently restored levels of DA, as after administration of dopamine medication (see Table 2 for an overview).

### 3.3. Drift-diffusion model

Changes in boundary separation alone were able to account for changes in RTs across different levels of temporal predictability and our experimental groups, as reflected by lowest DIC values for this model (Model 1; Fig. 3A). This result shows that the estimated boundary can be considered as a proxy measure of the temporal uncertainty experienced by the subject. Furthermore, no significant differences between groups were observed in either drift-rate (Control vs PD-on: $q = 0.86$; Control vs PD-off: $q = 0.29$; PD-on vs PD-off: $q = 0.03$) and non-decision time (Control vs PD-on: $q = 0.73$; PD-on vs PD-off: $q = 0.89$). These results confirm that our behavioural observations on PD-off did not result from an unspecific effect on alertness or the ability to move.

Following the same logic of the behavioural analysis, we characterized the relationship between temporal predictability and DDM boundaries in terms of intercept ($\beta_0$) and slope ($\beta_1$) of a linear function fitted to the estimated boundary of each participant. The results from the linear fitting of boundaries paralleled the results from the behavioural analysis (Fig. 3). Both intercept ($F_{2,46} = 8.497$, $p = 0.001$, $\eta^2 = 0.278$) and slope ($F_{2,46} = 5.856$, $p = 0.006$, $\eta^2 = 0.209$) differed significantly between groups. Intercepts ($\beta_0$) were significantly larger in PD-off, compared to PD-on (paired $t$-test; $t_{15} = 2.826$, $p = 0.006$, $d_z = 0.71$) and controls (post-hoc: $t_{44} = 4.013$, $p < 0.001$, $d_z = 1$).

### Table 2

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Control</th>
<th>PD-on</th>
<th>PD-off</th>
<th>Control vs PD-on</th>
<th>Control vs PD-off</th>
<th>PD-on vs PD-off</th>
</tr>
</thead>
<tbody>
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<td>Behavioural</td>
<td>Intercept ($\beta_0$)</td>
<td>$334 \pm 1.11$</td>
<td>$354 \pm 1.18$</td>
<td>$395 \pm 1.20$</td>
<td>$p = 0.15$</td>
<td>$p = 0.002$</td>
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<tr>
<td></td>
<td>Slope ($\beta_1$)</td>
<td>$0.015 \pm 0.02$</td>
<td>$0.023 \pm 0.02$</td>
<td>$-0.004 \pm 0.03$</td>
<td>$p = 0.18$</td>
<td>$p = 0.014$</td>
</tr>
<tr>
<td>Model</td>
<td>Intercept ($\beta_0$)</td>
<td>$0.869 \pm 0.16$</td>
<td>$0.931 \pm 0.10$</td>
<td>$1.065 \pm 0.14$</td>
<td>$p = 0.21$</td>
<td>$p &lt; 0.001$</td>
</tr>
<tr>
<td></td>
<td>Slope ($\beta_1$)</td>
<td>$0.040 \pm 0.05$</td>
<td>$0.059 \pm 0.05$</td>
<td>$0.001 \pm 0.05$</td>
<td>$p = 0.15$</td>
<td>$p = 0.015$</td>
</tr>
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Table shows mean ± SD.

* $p < 0.05$.

Fig. 3. Model comparison and hierarchical drift-diffusion modelling of variable foreperiod task (a) Model comparison. The deviance information criterion (DIC) between the best fitting model (Model 1 - free parameter: boundary) and the two alternative models (Model 2 - drift-rate; Model 3 – boundary and drift rate) is shown. (b) Influence of predictability on evidence accumulation. Intercept and slope of a linear function were fitted to the estimated boundary of each participant. (c) Model fit. Estimated boundary values were strongly correlated to empirical RT averaged across trials within each predictability level (Spearman correlation); * $p < 0.05$; Error bars represent ± 1 SEM.
suggesting high levels of temporal uncertainty after dopamine deple-
tion even when stimulus-onset was highly predictable. Slopes ($\beta_1$) were
significantly smaller in PD-off relative to PD-on (paired $t$-test; $t_{15}$ =
3.202, $p = 0.003$, $d_z = 1.23$) and controls (post-hoc: $t_{44} = 2.259$,
$p = 0.015$, $d_z = 0.81$). There were no significant differences between
PD-on and controls ($\beta_2$: $t_{12.561}$, $p = 0.21$; $\beta_1$: $t_{10.035}$ $p = 0.15$). The lack of
difference between controls and PD-on groups suggests that a widening of
decision boundaries along with a failure to adjust to changes in
temporal predictability result from DA depletion.

A strong correspondence between estimated boundary values and
the empirical RT (Fig. 3C; Control: rho = 0.82, $p < 0.001$; PD-on: rho =
0.78, $p < 0.001$; PD-off: rho = 0.81, $p < 0.001$) confirmed that the
observed behavioural impairments were well explained by changes in
the sole boundary parameter of the DDM (see Table 2 for a compar-
ison).

Finally, the goodness of fit of the regression analyses was first
quantified for each individual using Pearson’s correlation coefficient
and then Fisher transformed to meet distributional assumptions for
parametric tests across groups. A one-way ANOVA on the Fisher-
transformed correlation coefficients showed no difference in the
goodness of fit across groups for neither empirical reaction times ($F(2$,
44) $< 0.001$, $p = 1.00$; mean $R^2 \pm$ stdev: Controls = 0.83 ± 0.004,
PD-Off = 0.83 ± 0.004, PD-On = 0.83 ± 0.009) nor model boundary
parameter ($F(2$, 44) = 1.07, $p = 0.35$; mean $R^2 \pm$ stdev: Controls =
0.84 ± 0.007, PD-Off = 0.83 ± 0.007, PD-On = 0.84 ± 0.005).

4. Discussion

Parkinson's disease (PD) is characterized by an impaired use of prior
information to guide perceptual (Perugini et al., 2016) and value-based
decisions (Frank et al., 2004; Shiner et al., 2012). Here we demonstrate
that after DA medication withdrawal, PD patients are impaired when
using prior experience about the time of occurrence of events to prepare responses in anticipation of an event. Critically, dopamine adminis-
tration restores performance to levels comparable to the control group.

PD is a movement disorder often accompanied by bradykinesia
(Sheridan and Flowers, 1990). A general inability to produce fast
movements in PD-off patients could alternatively explain our results.
However, most previous studies (Girotti et al., 1986; Jahanshahi et al.,
1992; Starkstein et al., 1989; but cf Zappia et al., 1994) have shown no
difference in simple motor RT prior and after medication. Furthermore,
PD-Off patients were able to modulate their speed showing increasing
motor preparation with the passage of time. This suggests that brady-
kinetic symptoms in PD may result from a change in implicit 'motor
motivation', as opposed to a general inability to move fast (Mazzoni
et al., 2007). In previous work (Tomassini et al., 2015) adopting the
same temporal manipulation, dopamine blockage in healthy partici-
pants produced strikingly similar results on temporal processing as
observed here, without affecting the speed of reaching movements. In
the present study, we furthermore observed that non-decision times
estimated by the DDM (accounting for perceptual and motor processes)
did not differ between groups. Differences in performance across groups
were therefore neither driven by dopamine-related inability to produce
fast movements, nor by deficits in temporal processing per se. Instead,
our results indicate that DA depletion impairs the integration of prior
temporal information for the preparation of actions.

Here we used a Bayesian framework as a theoretically grounded
way to solve problems in the presence of uncertainty (Körding and
Wolpert, 2006), and in which to explain the impairments observed in
non-medicated patients. Within this framework, decisions rely more on
more precise (i.e. less uncertain) sources of information (Friston et al.,
2012; Mamassian and Landy, 2010; Stocker and Simoncelli, 2006).

More specifically, in conditions of high temporal predictability parti-
cipants will form reliable prior-beliefs about the most likely time of a
stimulus (Acerbi et al., 2012; Ahrens and Sahani, 2011; Jazayeri and
Shadlen, 2010), and use that information to prepare their responses.
When reducing this predictability, priors become more uncertain and
thus an optimal behaviour would require up-weighting the actual ap-
pearance of the stimulus rather than relying on one's temporal predic-
tions. Accordingly, if dopamine depletion causes the overestimation of
uncertainty about temporal predictions, a Bayesian agent will inflexibly
rely on the external stimulus to determine when to make a response
(Friston, 2014). This interpretation agrees with work (Perugini et al.,
2016) suggesting that PD patients rely less on prior information to make
decisions. Conversely, dopaminergic up-regulation should result in a
bias towards prior expectations (Cassidy et al., 2018). Hallucinations, a
cardinal feature of schizophrenia, are known to depend on excessive
striatal dopamine (Weinstein et al., 2017). A Bayesian model of hallu-
cinations posits that dopaminergic up-regulation can lead to a system-
tic underestimation of the uncertainty of predictions resulting in
hallucinatory percepts reflecting excessive biases toward sensory ex-
pectations (Friston, 2005). Such idea could also be extended to tem-
poral predictions, so that a Bayesian agent under hyper-dopaminergic
state would inflexibly rely on a priori expectations to determine when
to make a response. Future work on schizophrenic patients or pharma-
cological challenge (e.g. amphetamine) could assess such hypothesis.

The boundary parameter of our model captured the internal un-
certainty about temporal predictions: Large boundaries under condi-
tions of high temporal uncertainty index more cautious, and thus
slower, responses (Forstmann et al., 2010). In agreement with our re-
sults, the effect of dopaminergic depletion on changes in DDM bound-
aries has been linked to basal ganglia function (Bogacz et al., 2010;
Forstmann et al., 2008; Frank and O'Reilly, 2006; Hanks et al., 2014;
Heitz and Schall, 2012; Herz et al., 2017). Accordingly, inflexibly large
boundaries in PD-off indicate a dopamine-sensitive increase in un-
certainty about when a stimulus is bound to appear (Tomassini et al.,
2015). These results agree with previous work demonstrating a failure
in adjusting the amount of sensory evidence needed to make a decision in PD (Perugini et al., 2016). They further echo earlier findings using
healthy ageing as model for dopamine depletion, demonstrating inflex-
ible decision boundaries in older relative to younger adults (Forstmann et al., 2011) performing speed-accuracy-trade-off tasks.

In older adults, adopting conservative decision criteria is presumed
to be a compensatory strategy to prevent errors (Ratcliff et al., 2007,
and references therein). One possible interpretation to our results is that
dopamine-deficient individuals try to balance their performance by
reducing temporal uncertainty with associated costs in terms of RT. In
other words, an agent accumulates as much information as possible to
reduce its internal uncertainty (Tajima et al., 2016), at the cost of
slower responses.

In conclusion, we show that DA depletion increases the subjective
levels of temporal uncertainty damaging the ability to use prior in-
f ormation in order to prepare to future events.

A better understanding of the mechanism linking temporal un-
certainty and motor preparation may enable new therapeutic ap-
proaches to deal with impairments of movement control that char-
acterize PD.

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competing financial interests and no conflict of interest.
Appendix

See Table A1
Model parameters for the winning model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Control</th>
<th>PD-on</th>
<th>PD-off</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boundary (a)</td>
<td>0.9709 ± 0.15</td>
<td>1.078 ± 0.14</td>
<td>1.067 ± 0.12</td>
</tr>
<tr>
<td>a standard deviation</td>
<td>0.1455 ± 0.01</td>
<td>0.1455 ± 0.01</td>
<td>0.1455 ± 0.01</td>
</tr>
<tr>
<td>Drift-rate (v)</td>
<td>0.026 ± 0.039</td>
<td>0.085 ± 0.033</td>
<td>0.002 ± 0.032</td>
</tr>
<tr>
<td>v standard deviation</td>
<td>0.0331 ± 0.023</td>
<td>0.0331 ± 0.023</td>
<td>0.0031 ± 0.023</td>
</tr>
<tr>
<td>Non decision time (t0)</td>
<td>0.232 ± 0.009</td>
<td>0.226 ± 0.008</td>
<td>0.240 ± 0.009</td>
</tr>
<tr>
<td>t0 standard deviation</td>
<td>0.0353 ± 0.004</td>
<td>0.0353 ± 0.004</td>
<td>0.0353 ± 0.004</td>
</tr>
<tr>
<td>Bias (z)</td>
<td>0.70 ± 0.008</td>
<td>0.70 ± 0.008</td>
<td>0.70 ± 0.008</td>
</tr>
<tr>
<td>z standard deviation</td>
<td>0.143 ± 0.032</td>
<td>0.143 ± 0.032</td>
<td>0.143 ± 0.032</td>
</tr>
</tbody>
</table>

Table shows mean ± SD.

See Table A2

Table A2
Posterior predictive checks.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Observed</th>
<th>Predicted</th>
<th>MSE</th>
<th>Credible</th>
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</thead>
<tbody>
<tr>
<td><strong>Left stimulus</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.372</td>
<td>0.494</td>
<td>0.031</td>
<td>Yes</td>
</tr>
<tr>
<td>Std</td>
<td>0.105</td>
<td>0.202</td>
<td>0.016</td>
<td>Yes</td>
</tr>
<tr>
<td>10th quantile</td>
<td>0.271</td>
<td>0.316</td>
<td>0.007</td>
<td>Yes</td>
</tr>
<tr>
<td>30th quantile</td>
<td>0.315</td>
<td>0.376</td>
<td>0.012</td>
<td>Yes</td>
</tr>
<tr>
<td>50th quantile</td>
<td>0.35</td>
<td>0.431</td>
<td>0.021</td>
<td>Yes</td>
</tr>
<tr>
<td>70th quantile</td>
<td>0.395</td>
<td>0.521</td>
<td>0.042</td>
<td>Yes</td>
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<tr>
<td>90th quantile</td>
<td>0.494</td>
<td>0.742</td>
<td>0.111</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Right stimulus</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.376</td>
<td>0.494</td>
<td>0.03</td>
<td>Yes</td>
</tr>
<tr>
<td>Std</td>
<td>0.111</td>
<td>0.202</td>
<td>0.008</td>
<td>Yes</td>
</tr>
<tr>
<td>10th quantile</td>
<td>0.272</td>
<td>0.316</td>
<td>0.001</td>
<td>Yes</td>
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<tr>
<td>30th quantile</td>
<td>0.316</td>
<td>0.367</td>
<td>0.002</td>
<td>Yes</td>
</tr>
<tr>
<td>50th quantile</td>
<td>0.352</td>
<td>0.431</td>
<td>0.006</td>
<td>Yes</td>
</tr>
<tr>
<td>70th quantile</td>
<td>0.397</td>
<td>0.531</td>
<td>0.018</td>
<td>Yes</td>
</tr>
<tr>
<td>90th quantile</td>
<td>0.502</td>
<td>0.744</td>
<td>0.058</td>
<td>Yes</td>
</tr>
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</table>
Comparison between statistics of the observed RT and statistics of the data predicted by the winning model. The mean-squared error (MSE) is a measure of how far the summary statistics of the observed data differ from the predicted data. MSE values close to zero indicate a good match between observed and simulated data. The Credible column shows whether the predicted data lie within the 95% credible interval from the observed data.

See Fig. A1

Fig. A1. Posterior predictive data distribution from the winning model. The distributions along the positive and negative x-axis show the latency distribution for the left and right response, respectively. Each panel shows the normalized histograms of the observed data and the model predictions (black lines). The model predictions were generated by averaging 500 simulations of the same amount of model predicted data as observed in the experiment using posterior parameter estimates. Each row shows the distribution for each group (color-coded) whereas the columns are arranged according to the level of temporal uncertainty. The plots show a good agreement between the observed data and the model predictions across temporal uncertainty levels in all three groups.

References


