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Research report

Drift diffusion model of reward and punishment learning in schizophrenia: Modeling and experimental data

Ahmed A. Moustafa[a,*], Szabolcs Kéri[b,c,d], Zsuzsanna Somlai[e], Tarryn Balsdon[a], Dorota Frydecka[f], Blazej Misiak[f,g], Corey White[h]

[a] School of Social Sciences and Psychology, Marcs Institute for Brain and Behaviour, University of Western Sydney, Penrith, NSW, Australia
[b] Nyírő Gyula Hospital–National Institute of Psychiatry and Addictions, Budapest, Hungary
[c] University of Szeged, Faculty of Medicine, Department of Physiology, Szeged, Hungary
[d] Budapest University of Technology and Economics, Department of Cognitive Science, Hungary
[e] Semmelweis University, Department of Psychiatry and Psychotherapy, Budapest, Hungary
[f] Wroclaw Medical University, Department and Clinic of Psychiatry, Wroclaw, Poland
[g] Wroclaw Medical University, Department of Genetics, Wroclaw, Poland
[h] Department of Psychology, Syracuse University, Syracuse, NY, USA

HIGHLIGHTS

- It is the first drift diffusion model of behavioral data from schizophrenia patients.
- Unlike controls, schizophrenia patients show punishment learning deficits.
- Schizophrenia patients show slow motor/encoding time.
- Unlike controls, schizophrenia patients use a strategy favoring accuracy over speed.

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ABSTRACT

In this study, we tested reward- and punishment learning performance using a probabilistic classification learning task in patients with schizophrenia ($n = 37$) and healthy controls ($n = 48$). We also fit subjects' data using a Drift Diffusion Model (DDM) of simple decisions to investigate which components of the decision process differ between patients and controls. Modeling results show between-group differences in multiple components of the decision process. Specifically, patients had slower motor/encoding time, higher response caution (favoring accuracy over speed), and a deficit in classification learning for punishment, but not reward, trials. The results suggest that patients with schizophrenia adopt a compensatory strategy of favoring accuracy over speed to improve performance, yet still show signs of a deficit in learning based on negative feedback. Our data highlights the importance of applying fitting models (particularly drift diffusion models) to behavioral data. The implications of these findings are discussed relative to theories of schizophrenia and cognitive processing.

1. Introduction

International diagnostic systems classify schizophrenia (SZ) as a psychotic disorder, with several positive symptoms such as delusions and hallucinations, as well as negative symptoms, such as affective flattening, alogia or avolition. However, cognitive deficits are also increasingly recognized as the core component of SZ symptomatology. These deficits occur in multiple domains of cognitive functioning, with moderate to large effect sizes for impairments across memory, motor performance, attention, IQ, executive function and working or verbal memory, compared to controls [1]. Notably, these deficits precede the onset of overt psychosis and are a risk factor for the onset of SZ [2]. Several lines of evidence also indicate that cognitive impairment may predict functional outcomes, such as self-care, community functioning, and social problem solving and furthermore, that cognitive impairment may be a better predictor of these outcomes than psychotic symptoms [3,4].

* Corresponding author at: Department of Veterans Affairs, New Jersey Health Care System, East Orange, New Jersey, United States of America.
E-mail address: a.moustafa@uws.edu.au (A.A. Moustafa).

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Research has indicated that SZ patients show learning and decision making deficits, especially in the context of rewards and punishment. A deficit in updating the expected value of choices, especially loss, and disruption in associative learning underlying the representation of expectancies has been shown in the Iowa Gambling task (IGT) [5–7], the Monetary Incentive Delay task [8], the Wisconsin Card Sorting Task (WCST) [9], delayed reward discounting, and reinforcement learning paradigms (Gold et al. [19]). However, the deficit does not present in the same manner as the loss insensitivity of an orbitofrontal cortex lesion, as, in the WCST, patients do not always select significantly less from advantageous decks (as seen in patients with orbitofrontal cortex lesions [10]. Rather patients make more perseveration errors, indicating a role of learning or as Shurman et al. suggest, working memory (see also [11,12]). Furthermore, imaging studies have revealed reduced activity in the ventral striatum during the anticipation of gain or loss compared with normal controls [13,14], and reduced error-related negativity (ERN) in probabilistic learning tasks (Morris and co-workers) indicating an underlying deficit in signaling prediction errors for value based learning and decision making.

However, there are also inconsistent results. For instance, Morris et al. [15], later found that although response-related ERN was reduced in SZ patients compared to controls, their feedback-related ERN was intact. Furthermore, whilst Polli et al. [16] found that SZ patients could immediately correct their errors in an antisaccade task, a later replication of this result accompanied by fMRI [16] showed reduced error-related activity in both dorsal and rostral Anterior Cingulate Cortex (ACC) (even once medication was taken account of), which has been associated with perseveration errors. Some studies have found little to no effect of reward. For instance, Waltz et al. [17] found that whilst SZ patients showed reduced activity for reward in a passive conditioning task, they showed intact responses to unexpected reward omissions, which is supported by a further conditioning experiment by Dowd and Barch [18]. Of note these experiments did not require participants to make value based decision. The differences in these results and even behavioral studies emphasize the need for a more subtle understanding of what is going on; one cannot simply compare a saccade task with a reward learning task with a conditioning task. Clearly there are instances in which SZ patients show significantly different behavior and neural responses from normal controls and it is important to understand the nuances of what might be driving these differences in some cases, and why they lay dormant in others.

In an attempt to account for abnormalities in reward learning, Gold et al. [19] compared performance of SZ patients and normal controls on a number of various tasks, including the International Affective Picture System ratings, delayed reward discounting, the Wisconsin card sorting task, rapid reversal learning and reinforcement learning paradigms. Their results indicated that processing deficits may be explained by an inability to fully represent value. Gold et al. [19] linked this internal representational difference to the differences in patients' pleasantness ratings when they are asked to imagine a scene to when they are shown the scene as a picture. Patients displayed normal positive emotion when presented with visual stimuli, but displayed poor pleasantness ratings when asked to imagine a scene, suggesting further that reports of anhedonia in SZ patients may come down to testing procedures that require a level of value representation that is impaired in patients.

A further avenue of research to discern the nature of cognitive impairments in SZ patients may be found by deconstructing the decision making process to further dissociate at what stage SZ patients differ from normal controls. In this study, we applied a drift diffusion model (DDM), to behavioral data from patients with SZ to understand the information processing mechanism of impaired learning and decision making. We hypothesized that SZ patients will be impaired at learning from negative feedback, as suggested by prior studies, although here, we use a DDM model that takes into account both accuracy and reaction time. Further, given prior studies and observations of general slowness and motor impairments (see [49]) in SZ patients, we hypothesize that patients will show a combination of increased response caution (favoring accuracy over speed) and slower motor execution time in comparison to controls.

1.1. Drift diffusion models

When comparing task performance between groups, it is important to note that multiple decision components could differ among participants. Thus, for example, observing slower responses for the SZ group could be indicative of a difference in response caution rather than a deficit in reward learning. In these situations, reaction time models like the drift diffusion model (DDM) [20] can be fitted to data to circumvent this problem. Notably, DDM can include parameters that can be mapped on to psychological constructs, allowing researchers to make comparisons of the intactness or disruption of different decision components in ways not possible with behavioral data alone.

Because DDM is mathematically specified, it makes precise predictions about how the different components relate to reaction time and accuracy. Importantly, this process can be inverted, whereby observed behavioral data are fitted with DDM to estimate the values of the decision components driving the behavior. This technique has been ubiquitously applied to investigate processing differences across a range of domains [21,22] (White et al.). By estimating the values of the decision components for each participant, researchers are able to make group comparisons of these psychologically meaningful parameters.

There are two main advantages to a DDM analysis over traditional RT or accuracy comparisons: increased specificity and increased sensitivity. For specificity, the DDM allows identification of which decision components account for behavioral performance in the task. For example, slower RT could be due to slow motor response (non-decision time), increased caution (boundary separation), and/or poorer task performance (drift rates). The model allows these components to be separately estimated to disentangle how they contribute to the observed behaviour. For sensitivity, past work has shown that DDM parameters are more sensitive to small differences than RT or accuracy. Several studies have shown that DDM parameters can detect differences that are not significant in the behavioural data (see [23,24]). This is because DDM controls for the effects of each decision component, meaning that any differences in response caution or bias are controlled for when estimating task performance (i.e., drift rates, see [24,25]). For example, imagine that Participant A has poorer learning ability than Participant B, but is more cautious when responding. This could lead to equivalent accuracy between them, as the lower accuracy from poor learning is offset by the higher accuracy from increased caution. Thus comparing accuracy values alone is insufficient to detect processing differences between them. In contrast, using the DDM approach circumvents this problem because it estimates multiple components of the process simultaneously, allowing the conclusion that the participants differ in both caution and learning.

In this regard, DDM provides a principled method for comparing different aspects of the decision process between SZ patients and controls. This DDM approach was employed in the present study to investigate which components differ between SZ patients and controls in the reward and punishment learning task.