Choice suppression through opponent but not independent function of the striatal indirect pathway

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Significance

There is significant clinical value to understanding how we reject or suppress making a choice, and the dorsomedial striatum (DMS) is a critical arbiter of this process. While optogenetic stimulation of DMS indirect pathway spiny projection neurons (iSPNs) can inhibit movement, it is unclear how iSPNs contribute to suppression of choices. A simple 'no go' function has been proposed for iSPNs, suggesting their activity enables choice suppression, but we found that chemogenetic activation of iSPNs impaired suppression of low value choices. This effect was explained by an algorithmic model in which the relative output of direct pathway (dSPNs) and iSPNs determines choice. Our findings have important implications for designing interventions to improve maladaptive decision-making in psychiatric disorders and addiction.

Abstract

The dorsomedial striatum (DMS) plays a key role in action selection, but little is known about how direct and indirect pathway spiny projection neurons (dSPNs and iSPNs) contribute to serial decision-making. A popular 'select/suppress' heuristic proposes that dSPNs encode selected actions while iSPNs encode the suppression of alternate actions. Here, we used pathway-specific chemogenetic manipulation during serial choice behavior to test predictions generated by the 'select/suppress' heuristic versus a network inspired OpAL (Opponent Actor Learning) model of basal ganglia function in which the relative balance of dSPN and iSPN output determines choice. In line with OpAL predictions, chemogenetic activation, not inhibition, of iSPNs

disrupted learned suppression of nonrewarded choices. These results cannot be explained by the classic view that choice suppression is an extension of iSPN stopping or 'no go' function. Together, our computational and empirical data challenge the 'select/suppress' interpretation of striatal function in the context of choice behavior and highlight the ability of iSPNs to modulate choice exploration.

Keywords: striatum, decision-making, reinforcement learning

Introduction

In everyday decision-making, we often select among options in a serial fashion, foregoing low value choices in order to arrive at a higher value choice. The inability to suppress poor choices is a core component of addiction, eating disorders, and obsessive-compulsive disorder (1-3). The mechanisms underlying choice suppression are therefore highly relevant to psychiatry and public health.

The DMS (homologous to the primate caudate) is a key brain structure for goal-directed action selection (4-8), and striatal dysfunction is associated with maladaptive choice behavior (9-13). However, it is still poorly understood how choice selection and suppression are implemented at the circuit level (14). Furthermore, much of the relevant functional data comes from two-alternative forced choice (2AFC) tasks (15-19), in which it is difficult to dissociate the selection of one choice (e.g. turn left) from the suppression of another (e.g. do not turn right). Therefore, studying DMS function in the context of a serial task in which animals move freely and select among multiple options may reveal new insights into the circuit mechanisms that underlie choice selection and suppression.

The DMS is primarily composed of dopamine D1 receptor expressing dSPNs and dopamine D2 receptor expressing iSPNs (20), whose activity reflect task features including movement, cues, and value (16, 21-26). Consistent with predictions from functional neuroanatomy (27-29) and theoretical work (30, 31), optogenetic stimulation of dSPNs promotes movement and reinforces actions ('go' functions) (32-34) whereas optogenetic stimulation of iSPNs inhibits movement and drives aversion ('no go' functions) (32-34). In a 2AFC task, dSPN stimulation promotes contraversive choices whereas iSPN stimulation promotes ipsiversive choices in a manner that is reward history dependent (18). While these data suggest that the function of dSPNs and iSPNs in decision-making are dichotomous, it is important to note that they are co-active during goal-directed movement (23, 35, 36). It has been suggested that the two pathways work in concert such that dSPNs promote desired actions/choices whereas iSPNs

suppress competing actions/choices (27, 29, 35, 37), but this interpretation, which we refer to as the ‘select/suppress’ heuristic, has not been directly tested in the context of serial choice.

Here we address this gap by testing a hypothesis that follows from the ‘select/suppress’ heuristic, that increasing iSPN activity should aid in the suppression of a choice whereas blocking iSPN activity should lead to a failure to suppress choice. To this end, we trained mice in an odor-guided serial choice task in which they approach multiple options before making a choice selection. Through trial and error, mice learn that only one of four odors is rewarded and learn to suppress choice to nonrewarded odors. After learning, we chemogenetically manipulated DMS dSPNs or iSPNs and examined choice behavior. To interpret our behavioral data, we compared predictions made by the ‘select/suppress’ heuristic and surprisingly opposite predictions that emerge from an algorithmic model of basal ganglia function, the Opponent Actor Learning (OpAL) model.

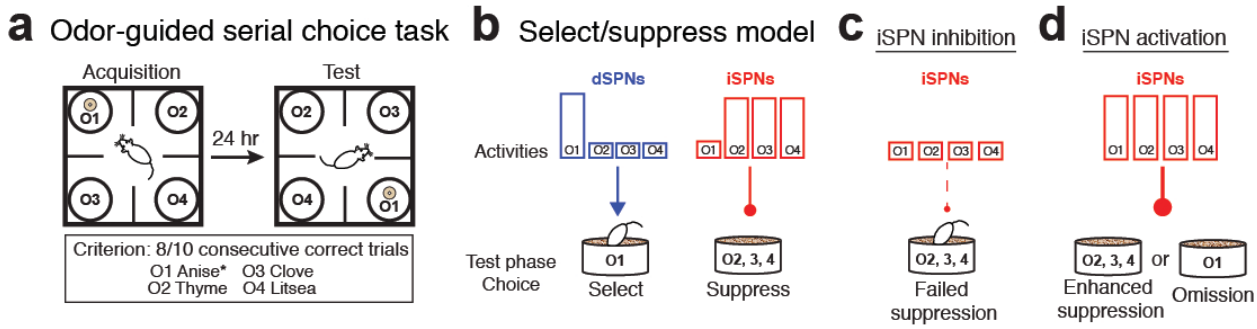
Results

In order to quantify selection and suppression of choices, we trained mice in an odor-guided serial choice task in which mice approach multiple distinctly scented pots in a serial fashion, rejecting pots until they choose one by digging in the scented shavings it contains (38) (Fig. 1A). Only one odor is rewarded (O1, “anise”), and the odor-action-reward contingency is learned through trial and error during an Acquisition phase. Mice consistently exhibit an initial preference for one nonrewarded odor (O4, “thyme), therefore, in addition to learning to choose O1, a large part of Acquisition is learning to suppress a choice. Twenty-four hours later mice enter a recall Test phase where their ability to select the rewarded odor (O1) and suppress choice to the remaining three nonrewarded odors is assessed (Fig. 1a, and Online Methods).

The ‘select/suppress’ model predicts inhibition of the indirect pathway should induce failure to suppress nonrewarded choices

If iSPNs are responsible for choice suppression as suggested by the ‘select/suppress’ heuristic (Fig. 1B), then inhibition of iSPNs during Test phase should lead to more errors, indicating a failure to suppress choice to nonrewarded pots (Fig. 1C). In this same framework, activation of iSPNs should facilitate suppression of nonrewarded choices and thus reduce errors, or alternatively, produce choice omission (Fig. 1D).

Fig. 1: Odor-guided serial choice task and ‘select/suppress’ heuristic predictions for iSPN manipulation



(**a**) 4 option odor-based serial choice task. (**b**) A ‘select/suppress’ model emphasizes the independent role of iSPNs in suppressing choices to nonnrewarded odor options. (**c,d**) The ‘select/suppress’ model predicts iSPN inhibition leads to failure to suppress low value choices while iSPN activation should enhance suppression of low value choices or increase omissions.

The OpAL model predicts that activation, not inhibition, of the indirect pathway should induce failure to suppress nonrewarded choices

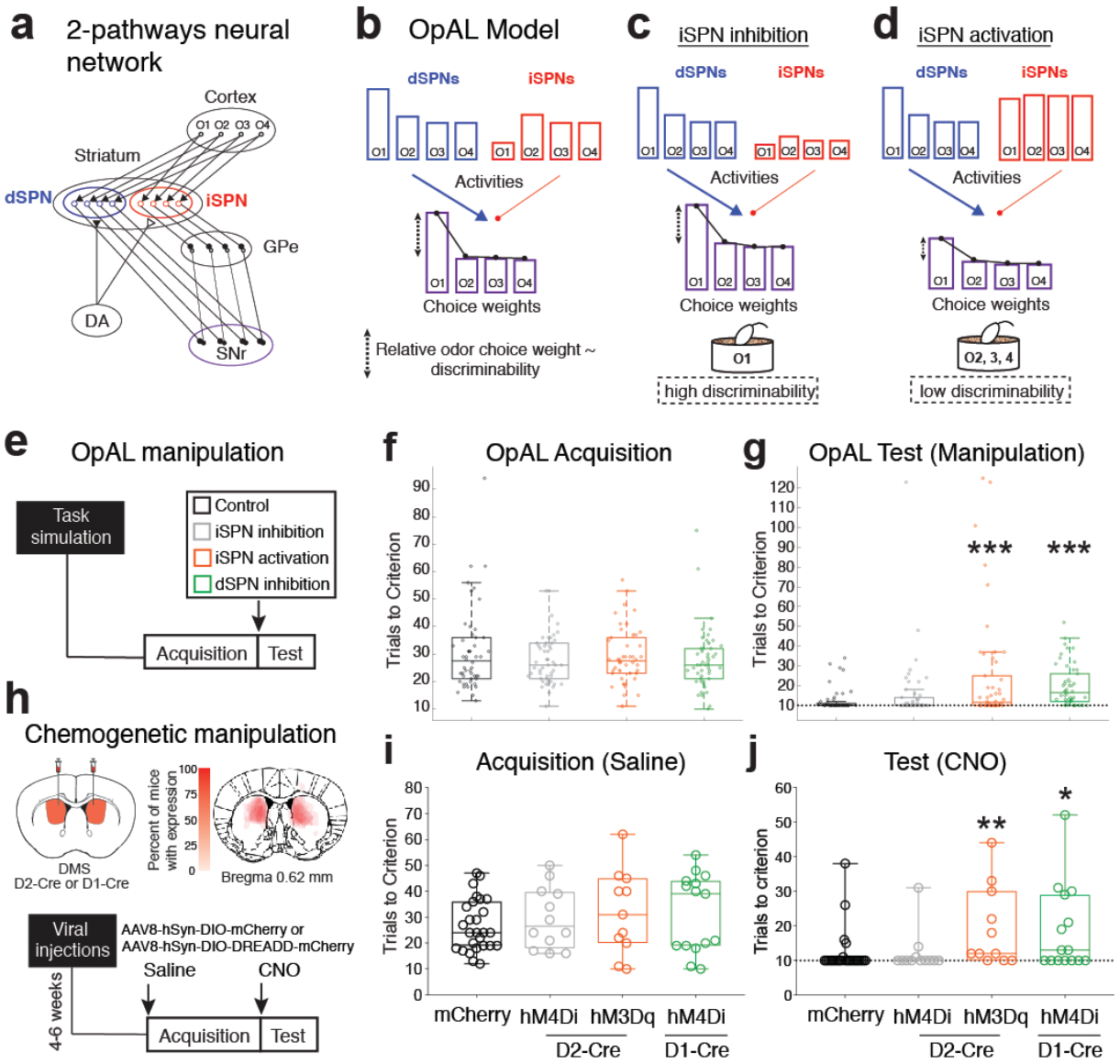
Alternate, network-inspired models of basal ganglia function (31) and recent *in vivo* data suggest that an independent division of labor does not properly account for how action and choice arise from the activity of dSPN and iSPN populations (24, 39-43). A model that accounts for the opponent nature of the two pathways may generate different and more accurate predictions. Therefore, we turned to OpAL, an algorithmic model of a biologically plausible basal ganglia network (Fig. 2A) in which choice is a function of the weighted difference between dSPN and iSPN population activity (Fig. 2B, see Methods). OpAL predicted that decreasing iSPN activity would not alter the relative difference between choice weights, leaving discriminability among odors options high (Fig. 2C) but predicted that increasing iSPN activity would minimize the difference in choice weights between the rewarded odor and the nonrewarded odors, lowering discriminability (Fig. 2D) (Fig. S1). We simulated performance in the odor-guided serial choice task by adjusting iSPN population activity during Test phase via parameters that mimicked chemogenetic activation or inhibition (Fig. 2E). OpAL simulations predicted that activation of iSPNs would increase Test phase errors (i.e. choices to nonrewarded odors) while inhibition of iSPNs should not affect performance (Fig. 2F,G). Therefore, OpAL made predictions regarding iSPN function that were opposite to those generated by the 'select/suppress' heuristic.

Chemogenetic manipulation experiments confirm activation, not inhibition, of the indirect pathway induces failure to suppress nonrewarded choices

To directly test the predictions made by the 'select/suppress' heuristic and OpAL model we turned to *in vivo* chemogenetic manipulation. D1-Cre or D2-Cre mice were injected bilaterally into the DMS with 0.5 µL of virus and 4-6 weeks later were trained in the 4 option odor-guided serial choice task (Fig. 2H). Mice that expressed Cre-inducible mCherry were used to control for any effects of surgery, AAV infection, and CNO administration on behavior. The efficacy of activating and inhibitory DREADD manipulation was confirmed in slice electrophysiology experiments; CNO activation of hM4Di suppressed iSPN synaptic release and CNO activation of

hM3Dq depolarized iSPNs (Fig. S2). Viral targeting was confirmed and mapped for all mice tested (Fig. S3). No differences in Acquisition learning, measured as trials to criterion (TTC), were observed across groups (Kruskal Wallis test, $H=1.42$, $p= 0.70$) (Fig. 2I). Twenty-four hours after Acquisition, mice were administered CNO (1.0 mg/kg, i.p.) and run in the recall Test phase. In the Test phase, mCherry control and D2-Cre inhibitory DREADD (hM4Di) groups exhibited robust recall of the rewarded choice and successful suppression of the nonrewarded choices, with most mice reaching criterion in the minimum number of trials required (median TTC = 10, IQR = 0) (Fig. 2J). Meanwhile, mice expressing activating DREADD in iSPNs (D2-hM3Dq) and mice expressing inhibitory DREADD in dSPNs (D1-hM4Di) took significantly more trials to reach criterion compared to mCherry controls (Kruskal-Wallis test, $H=12.4$, $p= 0.006$; Dunn's uncorrected post hoc test, $^{**}p<0.01$ D2-hM3Dq vs. mCherry, $^{*}p<0.05$ D1-hM4Di vs. mCherry) (Fig. 2J). These data were consistent with the predictions made by the OpAL model (Fig. 2G).

Fig. 2: OpAL model and chemogenetic manipulation data show iSPN activation not inhibition impairs suppression of low value choices



(**a**) Schematic of cortico-basal ganglia network. The 4 odor options are represented as separate action channels in direct and indirect pathways. (**b**) OpAL model with example of choice among the 4 odor options in the serial choice task. (**c**) OpAL predicts that iSPN inhibition will increase choice weights across odor options but that the relative value difference (discriminability) between odor choice weights will be maintained. (**d**) OpAL predicts that activation of iSPNs will minimize the difference in choice weights across odor choices and make choice more exploratory. (**e**) OpAL simulated trial histories for the odor-guided serial choice task, with manipulation (control, inhibition, or activation) applied to dSPNs or iSPNs only during the Test phase. (**f**) OpAL simulated trials to criterion during Acquisition phase did not differ across groups ($p>0.05$, Kruskal Wallis test). (**g**) In OpAL simulated data, iSPN activation and dSPN inhibition during Test phase significantly increased trials to criterion compared to controls (***$p<.0010$, Kruskal Wallis test). OpAL simulation of iSPN inhibition during Test phase did not significantly affect performance (p=

0.11, Kruskal Wallis test). (**h**) Chemogenetic manipulation of DMS iSPNs or dSPNs in D2-Cre or D1-Cre mice. (**i**) All groups performed similarly in the Acquisition phase (H=1.42, df=3, p=0.70, Kruskal Wallis test). (**j**) There was a significant effect of virus on performance during the Test phase (H=12.46, df=3, **p<0.01, Kruskal Wallis test), with D2-Cre mice expressing DIO-hM3Dq and D1-Cre mice expressing DIO-hM4Di taking significantly more trials to complete the Test phase (**p<0.001, mCherry vs. D2-hM3Dq, *p<0.05, mCherry vs. D1-hM4Di, post hoc uncorrected Dunn's multiple comparison test).

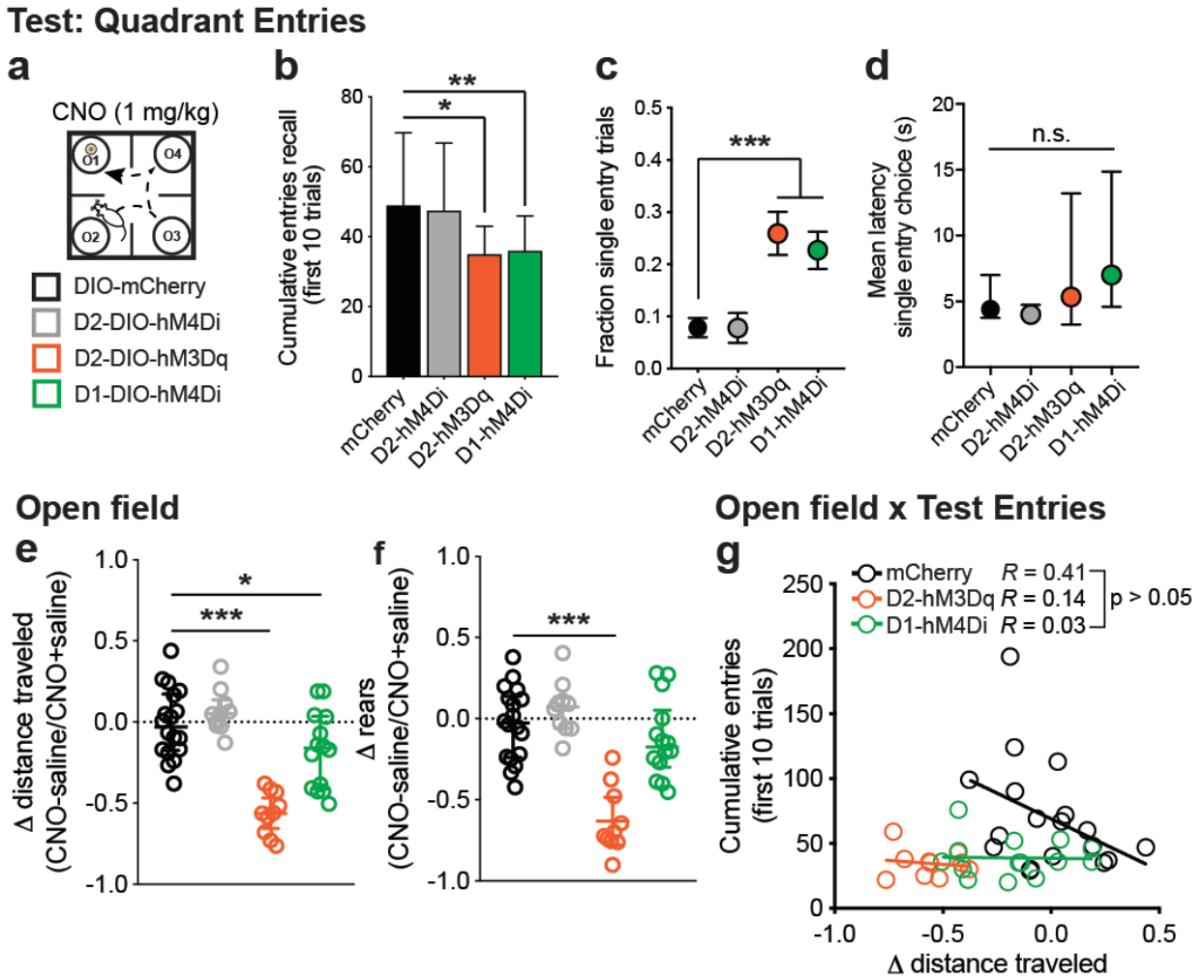
Acute chemogenetic manipulation alters choice strategy in a manner not explained by locomotor effects

During each trial of the odor-based serial choice task, mice were free to enter each of the 4 quadrants and sample the odors present in each pot, quantified as entries, before making a bi-manual dig to indicate choice (Fig. 3A). Mice expressing activating DREADD in iSPNs (D2-hM3Dq) or inhibitory DREADD in dSPNs (D1-hM4Di) consistently made fewer entries during the Test phase compared to mCherry controls and mice expressing inhibitory DREADD in iSPNs (D2-hM4Di) (Fig. 3B). Both D2-hM3Dq and D1-hM4Di mice were more likely to choose the first odor they encountered (classified as single entry trials) compared to mCherry control and D2-hM4Di mice (Fig. 3C). We examined whether single entry trials could be explained by impulsivity or lack of motivation. We found that on single entry trials, mice used odor value information to guide choice, inconsistent with impulsivity (Fig. S4). In addition, overall choice latency (Fig. S4) and single entry trial latency did not differ across groups (Fig. 3D). D2-hM3Dq and D1-hM4Di mice completed more trials and had similar numbers of omission trials compared to mCherry controls (Fig. S5) suggesting they remained motivated.

To examine if single entry trials could be related to changes in movement, we measured the effect of CNO on spontaneous locomotion and rotarod performance. CNO administration significantly reduced spontaneous locomotion in mice expressing activating DREADD in iSPNs (D2-hM3Dq) by ~50% compared to mCherry control mice (Fig. 3E). Mice expressing inhibitory DREADD in dSPNs (D1-hM4Di) showed a less dramatic reduction in distance traveled on CNO, whereas mice expressing inhibitory DREADD in iSPNs (D2-hM4Di) did not differ from mCherry control mice on CNO (Fig. 3E). However, the effect of CNO on spontaneous locomotion did not

correlate with entries made during Test phase (Fig. 3G) suggesting that the influence of CNO on behavior in the Test phase is not simply motor-related. In addition, CNO did not alter rotarod performance in any groups tested (Fig. S6).

Fig. 3: Chemogenetic manipulation of direct and indirect pathway neurons alters odor option sampling in a manner dissociable from motor effects

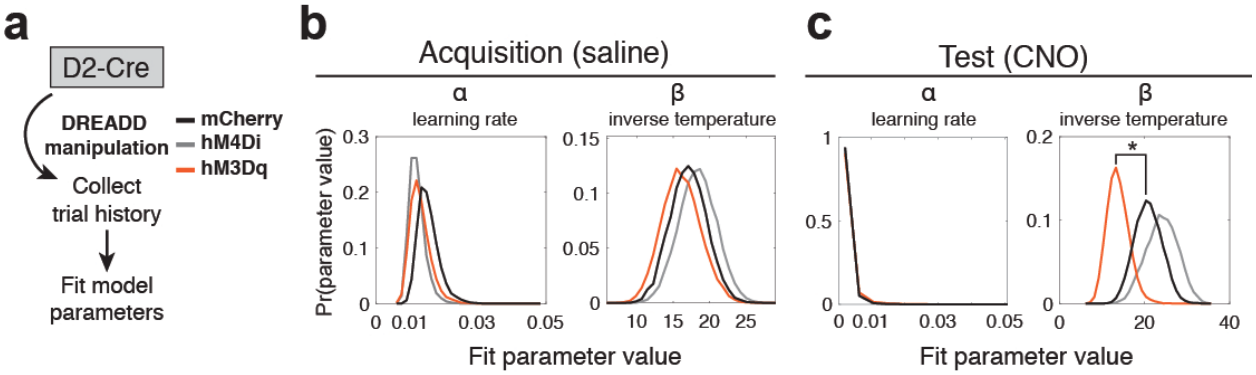


(**a**) Test phase quadrant entries. (**b**) D2-Cre mice expressing activating DREADD (D2-hM3Dq) or D1-Cre mice expressing inhibitory DREADD (D1-hM4Di) made fewer entries during Test phase on CNO compared to mCherry control mice on CNO (*p<0.05, **p<0.01 Kruskal Wallis ANOVA). (**c**) D2-hM3Dq and D1-hM4Di mice made significantly more single entry trials ($F(3,40.65)= 9.55$, ***p< 0.0001 main effect of group Brown-Forsythe ANOVA; **p<0.01 unpaired t-test with Welch's correction). (**d**) Latency of single entry trials did not differ across groups. (**e**) Spontaneous locomotion was significantly reduced in D2-hM3Dq mice on CNO (1 mg/kg) compared to saline ($F(3,48)= 22.38$, ***p<0.0001, one-way ANOVA, ***p<0.0001, uncorrected Fisher's LSD) and D1-hM4Di mice to a lesser extent (*p<0.05, uncorrected Fisher's LSD). (**f**) CNO administration significantly reduced the number of vertical rears made by D2-hM3Dq mice ($F(3,48)= 21.87$ ***p<0.0001, one-way ANOVA, ***p<0.0001 mCherry vs. D2-hM3Dq uncorrected Fisher's LSD). (**g**) Locomotor modulation on CNO did not correlate with the number of entries mice made on CNO during Test phase for any group.

Trial-by-trial RL modeling suggests that enhancing iSPN activity alters Test phase performance by increasing choice stochasticity

Finally, to determine how chemogenetic manipulation affected underlying choice processes, we compared multiple reinforcement learning (RL) models (44) fit to trial-by-trial changes in behavior using a hierarchical fitting process (Fig. 4A; SI methods). The best fit model for our behavioral data included phase-specific parameters for the learning rate α and the inverse temperature parameter β, which captures choice stochasticity (see Table 1 for alternate model comparison). Focusing on D2-Cre mice, we found that Acquisition phase α and β parameters did not differ across groups (Fig. 4B), whereas the Test phase β parameter was significantly lower for mice expressing activating DREADD in iSPNs (D2-hM3Dq) compared to mCherry control and inhibitory DREADD (D2-hM4Di) (Fig. 4C). These data suggest that chemogenetic activation of iSPNs in DMS makes choice policy more stochastic/exploratory. Model fits of OpAL simulated trial histories converged on the same results, with iSPN activation associated with decreased Test phase β (Fig. S7). RL model fits to OpAL simulated data also suggested that inhibition of dSPNs reduce the Test phase β parameter, but RL fits to D1-hM4Di mice were not significantly different from D1-mCherry mice (Fig. S7).

Fig. 4. iSPN activation increases choice stochasticity



(**a**) Acquisition and Test phase trial history data from D2-Cre DREADD mice and controls were modeled using an RL model, and best fit parameters were inferred using hierarchical Bayesian model fitting. (**b**) Test phase alpha and β parameters did not significantly differ among manipulation groups ($p>0.05$ Kruskal Wallis ANOVA). (**c**) Test phase β was significantly lower in D2-hM3Dq group compared to mCherry control (*$p<0.05$ Kruskal Wallis ANOVA).

Discussion

In the present study, we found that manipulating iSPN activity had surprising effects on learned choice behavior that were not accounted for by a popular 'select/suppress' model. We showed that chemogenetically inhibiting dSPNs or activating iSPNs impaired suppression of nonrewarded choices, whereas inhibiting iSPNs did not affect choice behavior. These behavioral results were predicted by the OpAL network model, in which choice is determined by the relative balance of direct and indirect pathway activity (31). RL model fits to OpAL simulated data and mouse behavioral data showed that activating iSPNs reduced the inverse temperature (β) parameter, consistent with more exploratory choice. In the context of our deterministic task, this manifested as failure to suppress nonrewarded choices. Our computational and empirical data demonstrate that the combined output of direct and indirect pathways, and not the independent function of either, is critical for learned choice suppression.

Previous studies provide clear evidence that optogenetic stimulation of DMS iSPNs can drive aversion and inhibit movement (32, 33, 45, 46), suggesting that choice suppression might be an extension of indirect pathway 'no go' function. However, recording data collected during decision-making has shown that dSPNs and iSPNs are simultaneously active when animals choose an action (23, 35, 36). The 'select/suppress' heuristic accounts for this coactivation by suggesting that dSPNs select specific actions while iSPNs simultaneously suppress alternate actions. However, it is problematic to infer *in vivo* function from optogenetic simulation effects that override endogenous activity patterns, especially if learning is stored in corticostriatal synaptic weights (6, 47, 48). Therefore, in the current study we chose to use chemogenetic manipulation tools in order to preserve aspects of endogenous activity that may have been altered during Acquisition phase learning.

While many studies have focused on the role of the striatum in selecting rewarded actions (16, 18, 25) and stimuli (49), fewer have studied its role in avoiding low-value actions (50-53) and stimuli (54). Here, our goal was to understand how activity in DMS dSPNs and iSPNs influences

the ability to suppress an initially encountered low-value choice in order to make a subsequent high-value choice. In our odor-guided serial choice task, as in many natural decision-making settings, the value of a given action/choice (here, dig) was contingent on available stimulus information plus choice and outcome history. RL model fits to odor choice trial histories enabled us to investigate how chemogenetic manipulation altered the relationship between odor value estimates and choice. The multiple choice task design enhanced our ability to interpret underlying choice processes. The fact that the mice were freely moving and were never required to hold still removed a common confound between choice suppression and motor freezing. Lastly, the task was acquired in a single session without extensive training that is often found in rodent operant tasks. This should enhance relevance to DMS function, which is engaged in early flexible goal-directed learning (22, 55, 56). Collectively, these more ethological task features may have permitted novel observations about the role of the indirect pathway in choice suppression behavior (57).

Our data support and add new circuit dimension to previously proposed dopaminergic mechanisms underlying choice exploration. We found that when iSPNs were activated, choice became more stochastic/exploratory, meaning that mice were more likely to “explore” (i.e. choose) a lower value odor as opposed to “exploit” the highest value odor, as estimated by RL model fits. This was captured by a lower inverse temperature parameter, which tunes explore/exploit balance in the estimated odor value to choice conversion. This observation is consistent with a previous study that found D2R antagonism in the primate caudate reduced the inverse temperature parameter and increased exploratory choice (58). Our findings are also compatible with computational accounts that predict that lowering tonic dopamine, which facilitates iSPN activity and suppresses dSPN activity (59, 60), shifts explore/exploit balance towards exploration (61, 62). Finally, if behavioral switching is viewed as exploring action space, our iSPN data may relate to recent studies that report iSPN activity increases in response to outcomes preceding switch trials (25, 64).

Unexpectedly, we observed that dSPN inhibition or iSPN activation increased the number of trials in which mice chose the first odor they encountered (Fig. 3). Several observations suggest that these single entry trials were separable from changes in locomotion and were not due to random impulsivity. Chemogenetic manipulation did not affect rotarod performance and the effects of manipulation on spontaneous locomotion in the open field did not correlate with entries in the serial choice task (Fig. 3). We reasoned that if purely impulsive, the odors chosen on single entry trials would be random, i.e. independent of odor Q values. However, we found that single entry trial choices were significantly influenced by Test phase odor Q values (Figure S3). Therefore, we interpret that the increase in single entry trials is the result of a more exploratory choice process that occurs when chemogenetic inhibition of dSPNs or chemogenetic activation of iSPNs minimizes the difference in choice weights across odors.

It is possible that there are latent variable(s) in our task that are not captured by OpAL or our current RL models. For example, reduced entries prior to choice could reflect changes in cost/accuracy tradeoff and share mechanistic overlap with individuals with Parkinson's disease who are capable but choose not to exert the effort required to move rapidly in a motor speed/accuracy tradeoff task (65, 66), consistent with dissociable cognitive and motor impairments (67). Similarly, reduced entries may relate to the putative role of DMS in invigorating actions on the basis of net expected return and state value signals (68, 69). In addition, in our odor-guided serial choice task, reward contingency was 100%, and negative feedback was signaled by the absence of reward as opposed to punishment. OpAL predicts that inhibition of the indirect pathway more heavily influences choice behavior in environments in which animals balance reward and punishment or are rewarded in a probabilistic manner (31). Therefore, the deterministic nature of the task used here may have emphasized the contribution of the dSPNs over iSPNs, potentially explaining why inhibiting iSPNs produced no detectable effects in this task.

Overall, our data support existing models of basal ganglia function in which trial and error

choice drives learning that is later stored or read out in the balance of activity emerging from DMS dSPNs and iSPNs (70). The fact that learned choice behavior is specifically disrupted by chemogenetic inhibition of dSPNs and activation of iSPNs (but not by inhibition of iSPNs) is consistent with these manipulations counteracting reported patterns of long-term potentiation (LTP) onto dSPNs and long-term depression (LTD) onto iSPNs following goal-directed action learning (6). Further work will need to be done to inform how LTP and LTD are allocated to specific neural ensembles of dSPNs and iSPNs to sculpt choice.

In summary, our findings suggest that the indirect pathway does not independently mediate choice suppression. Instead, choice appears to arise from the difference in dSPN and iSPN population activity, and conditions that reduce this difference increase choice stochasticity/exploration. Importantly, we demonstrate that manipulations that simply enhance activity in the indirect pathway do not facilitate adaptive choice suppression, and in fact can have the opposite effect. These data highlight the importance of using network concepts and models over simple heuristic accounts of circuit function to understand decision-making. We are hopeful that these findings will inform studies of addiction and other conditions in greater capacity for choice suppression is desirable.

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Author contributions

K.D., A.G.E.C., and L.W. designed the research. K.D. performed all experiments and analyzed data. A.G.E.C. contributed analytic tools, designed and performed OpAL simulation and RL model analysis to which B.H. contributed. K.D., A.G.E.C., and L.W. wrote the manuscript.

Declaration of interests

The authors declare that there are not conflicts of interest.

Methods:

Mice

C57BL/6 BAC transgenic mice expressing Cre recombinase under the regulatory elements for the D1 and D2 receptor (Drd1a-Cre and D2-Cre ER43) were obtained from Mutant Mouse Regional Resource and bred in our colony. All procedures were approved by the Animal Care and Use Committee of the University of California, Berkeley and complied with the NIH guide for the use and care for laboratory animals.

Stereotaxic Virus Injection

rAAV8-hsyn-DIO-mCherry, rAAV8-hsyn-DIO-hM3Dq-mCherry, or rAAV8-hsyn-DIO-hM4Di-mCherry [University of North Carolina at Chapel Hill or by Addgene viral service] were bilaterally infused into DMS (in mm from bregma): 0.90 anterior, +/-1.4 lateral, and -3.0 from surface of the brain for behavioral and slice electrophysiological studies. Additionally, DMS was transduced with a 2:1 mixture of rAAV8-hsyn-DIO-hM4Di-mCherry and rAAV5-Ef1α-DIO-hChR2-EYFP for slice electrophysiological studies. 4-6 weeks were allowed for viral expression before behavioral training or electrophysiological recordings.

Behavioral Testing

Adult male and female mice (6-10 weeks) were used in behavioral assays. Mice were first tested in 4 choice odor-guided serial choice task and then $\geq$ 2 weeks later were tested in locomotor

and/or rotarod tasks so that performance on CNO [obtained from NIMH Chemical Synthesis and Drug Supply Program (NIMH C-929)] could be compared within animals across tasks.

OpAL model

OpAL is an actor-critic-like RL algorithm which assumes two sets of weights are being tracked, D and I (corresponding to the direct pathway and indirect pathways, respectively; initialized at 1.5 for the preferred odor D weight, 1 for all other weights), in addition to a classic critic value V (initialized at 0.25 as the initial expected value of each option). Critic values are updated according to the classic RL equation:

$V_{t+1} \leftarrow V_t + alpha_C * delta_t$; $delta_t = r - V_t$ (r=1/0).

D and I weights are updated with a three factor, non-linear learning rule that emphasizes gains and losses, respectively:

- $D_{t+1} = D_t + [alpha_D * D_t] * delta_t$
- $I_{t+1} = I_t + [alpha_I * I_t] * [-delta_t]$
- To simplify the modeling of excitatory DREADD effects, we enforce an upper limit L to the D and I weights.
- The final choice is a softmax probability based on combined weights $Wt = beta_D * D_t - beta_I * I_t$, supposed to represent the output of the cortico-basal ganglia loops.

Chemogenetic tools modulate activity of dSPNs and iSPNs neurons, and we model their effects on D and I weights respectively. We assume that inhibitory DREADD multiplicatively decrease the corresponding pathway's activity:

- $W_t = beta_D * DREADD_I * D_t - beta_I * I_t$ in the case of dSPN DREADD
- $W_t = beta_D * D_t - beta_I * DREADD_I * I_t$ in the case of iSPN DREADD

For the simulations, the inhibitory $DREADD_I$ parameter is fixed at 0.5.

For excitatory DREADD, we assume that the tool promotes firing in neurons whose activity would otherwise be subthreshold, thus increasing low weights more than high weights. Specifically, we model W activity as:

- $W_t = beta_D * D_t - beta_I * (I_t + DREADD_E * (L - I_t))$ in the case of iSPN DREADD

Where L is the activity limit. For all simulations, L is fixed at 2, and the excitatory $DREADD_E$ parameter is fixed at 0.8.

To investigate the effects of chemogenetic manipulation on behavior, we simulated 100 times with parameters set to $alpha_C = alpha_D = alpha_I = 0.1$, randomly chosen parameters $1 < beta_D < 3$, and $1 < beta_I < 1.6$, reflecting greater influence of the direct than indirect pathway on the final choice.

RL model

We modeled Acquisition and Test phase behavior using a reinforcement learning model driven by an iterative error-based rule (74, 75). The model uses a prediction error (δ) to update the value (V) of each odor stimulus, where δ is the difference between the experienced feedback (λ) and the current expected value (λ= 100 for rewarded, λ= 0 for unrewarded) scaled by a learning rate parameter (α), with $0<\alpha<1$. Because mice exhibit innate preferences for odors, we set initial odor values to fixed parameters [v1,v2,v3,v4] for all 75 mice tested.

To model trial-by-trial choice probabilities, the stimulus values were transformed using a softmax function to compute the relative probability of each choice. The inverse temperature parameter (β) determined the stochasticity of the choices. We used hierarchical Bayesian model fitting to infer the best fitting parameters, using the package STAN in Matlab (76). We assumed that odor values were shared by all animals, and that other parameters (α and β for each phase) were drawn from group level distributions defined by the experimental manipulation. We performed statistical tests on the distribution of samples obtained for the group-level hyperparameters. We compared the alternative models using the WAIC (77, 78) and found that

the best fit model included phase-specific (non-zero) α and β parameters; all RL model comparisons are presented in Supplementary Table 1.

Statistics

Groups were compared using one-way ANOVA if data were normally distributed or Kruskal Wallis test if data were not normally distributed. When the ANOVA or Kruskall Wallis test yielded significant results ($p < 0.05$), a post-hoc LSD or Dunn's test was used to compare DREADD manipulation groups to the mCherry control group. Because our experiments were designed to compare the behavior of DREADD manipulation groups to that of mCherry controls, we did not correct for multiple comparisons.

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