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Cannabinoids and value-based decision making: implications for neurodegenerative disorders

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Abstract

In recent years, disturbances in cognitive function have been increasingly recognized as important symptomatic phenomena in neurodegenerative diseases, including Parkinson's Disease (PD). Value-based decision making in particular is an important executive cognitive function that is not only impaired in patients with PD, but also shares neural substrates with PD in basal ganglia structures and the dopamine system. Interestingly, the endogenous cannabinoid system modulates dopamine function and subsequently value-based decision making. This review will provide an overview of the interdisciplinary research that has influenced our understanding of value-based decision making and the role of dopamine, particularly in the context of reinforcement learning theories, as well as recent animal and human studies that demonstrate the modulatory role of activation of cannabinoid receptors by exogenous agonists or their naturally occurring ligands. The implications of this research for the symptomatology of and potential treatments for PD are also discussed.

Keywords

cannabinoid; cognition; decision making; dopamine; Parkinson's disease; reinforcement learning

Introduction

Disturbances in executive cognitive functions, including decision making, are prominent clinical features in various psychiatric disorders, such as attention-deficit hyperactivity disorder, mood and anxiety disorders, schizophrenia and substance use disorders [1]. In recent years, the notion that cognitive disturbances and impairments in decision making are important symptomatic phenomena in neurodegenerative disorders such as Parkinson's disease (PD) has gained increasing interest [2–5]. Interestingly, recent evidence suggests that these cognitive impairments might arise in the prediagnostic and early stages of PD [6–

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8] and are possibly caused by functional loss in the corticostriatal circuitry subserving cognitive functions [9].

In general terms, decision making refers to the selection of appropriate actions from various available options based on cost-benefit evaluations and subjective values of the outcomes of these actions. As such, decision making is a complex mental construct that is composed of several cognitive functions that should theoretically lead to adaptive behavioral outcomes or to maintain psychological or physiological homeostasis [10]. These functions and goaldirected action selection in decision making are driven by various neurotransmitter systems in the brain and have in particular been associated with dopamine function [11,12]. Over the last decades there has been a rise in decision making experimental data, partly due to the development and availability of laboratory tasks assessing aspects of real-life decision making in humans and preclinical animal models [13]. Altogether, these studies have greatly increased our understanding of the scientific basis and neurobiology of decision making, not the least because it is a subject that is studied from multiple disciplines including economics, psychology, neuroscience and computer science [14].

In addition to dopamine modulation of decision making, there is accumulating evidence of cannabinoid involvement in executive cognitive functions including decision making [15,16]. The endocannabinoid neurotransmitter system consists of at least two receptors, cannabinoid CB1 and cannabinoid CB2 of which primarily the former is highly expressed in the central nervous system. These Gi/o-protein coupled receptors, of which the vast majority is expressed presynaptically, are activated by their endogenous signaling molecules, such as anandamide (AEA) and 2-arachydonylglycerol (2-AG), and in response directly modulate the probability of release of several neurotransmitters including GABA, glutamate and indirectly dopamine [17,18]. Moreover, cannabinoid CB1 receptors are densely expressed in the brain including frontal cortical regions and several nuclei of the basal ganglia such as the striatum, globus pallidus and substantia nigra [19–21].

Interestingly, despite the cannabinoid CB1 receptor antagonist Rimonabant being withdrawn from the market, there is large therapeutic potential of cannabinoid mechanisms in several metabolic, psychiatric and neurodegenerative disorders [22,23].

This review aims at providing more insight into this convergence of cannabinoids, dopamine and value-based decision making in the context of neurodegenerative disorders and in particular PD. To this aim, we first will provide background on different theories of reinforcement learning as a framework for value-based decision making, and we will briefly discuss the role of dopamine in these processes. Next, we will discuss the involvement of the basal ganglia and importance of the endogenous cannabinoid system and its interactions with the dopaminergic system in decision making. Finally, we will review and discuss the available empirical evidence obtained from both clinical and preclinical studies of cannabinoid modulation of value-based decision making.

Theoretical history of reinforcement learning

Reinforcement learning (RL) is a well-supported computational framework for learning values in order to achieve optimal outcomes, which has gained popularity in the study of value-based decision making and its neural mechanisms [24]. The modern rendition of RL has grown from a fairly interdisciplinary history, beginning with animal learning paradigms of psychology and evolving through mathematical formulations and artificial learning research [25]. Both Bush and Mosteller's first formal mathematical model [26] and Rescorla and Wagner's subsequent version [27] postulated that learning only occurs at unexpected events [25,28]. Additionally, in the Rescorla-Wagner model, predictions for a given trial represent the sum of predictions from individual stimuli [25]. Despite its substantial

explanatory power, however, the Rescorla-Wagner model could not account for either second-order conditioning, of which a common example is the conditioned value of money to humans, or temporal relationships between stimuli within a trial [25].

The solution to these limitations came from two researchers working on artificial intelligence, who extended the Rescorla-Wagner model such that the decision-making agent seeks to estimate an average sum of all future rewards, rather than just the one in the immediate future [24,25]. These temporal-difference models (TD) are much more focused on goal-directed learning than their predecessors, and redefine the problem from one of learning values from past events to predicting the values of future events [24]. This distinction is important for thinking about the stimuli from which RL models learn; while Bush-Mosteller and Rescorla-Wagner models suggest learning from a weighted average of past rewards and the immediately experienced reward, TD models would learn from information that violates the agent's expectations for the sum of all future rewards [28]. For this theorized process of learning to occur, the TD model necessitates a neural mechanism for recording prediction errors.

Dopamine and reinforcement learning

Support from neural data and computational models have converged upon the midbrain dopamine system as encoding this key signal [29,30]. A substantial amount of research has implicated the dopamine system as a key player in value-based decision making, especially in instances of positive reinforcement [31]. Specifically, evidence has accumulated under the framework of a reward prediction error hypothesis (RPE), which posits that dopamine neuronal activity encodes the difference between expected and received rewards [29,30]. Within TD models of RL, the RPE embodies an essential mechanism for the proposed trialand-error learning process [24,32,33]. The seminal work of Schultz and his colleagues illustrated this principle through recordings from the midbrain dopamine neurons of awake, behaving monkeys [30,34]. These recordings showed that when a visual or auditory stimulus (conditioned stimulus) precedes a fruit or juice reward (unconditioned stimulus), the dopamine neurons increase their phasic burst firing upon receipt of the reward. However, this response occurs only during the learning phase. After the animal learns to predict a juice reward from the visual or auditory cue, an increase in dopaminergic burst firing is seen at the unexpected cue and not to the subsequently predicted reward. If the predicted reward is not delivered, a negative prediction error has occurred, and recordings show a corresponding decrease, or a pause, in the rate of dopaminergic firing [30,34,35]. These findings illustrated dopamine response to stimuli predicting rewards over the rewards themselves. Moreover, this pattern of dopaminergic activity specifically conforms to the RPE predicted by TD algorithms [29,30,36,37]. Further evidence has also shown that dopaminergic responses to conditioned stimuli are proportional to differing magnitudes and probabilities of predicted rewards [38–40], as well as rewards delivered after a delay [41–42]. Importantly, functional magnetic resonance imaging (fMRI) studies in human subjects have supported the biological and behavioral applicability of RL and TD models [e.g. 43–45].

Limitations of the dopamine RPE hypothesis

Despite the accumulation of support for the dopamine RPE hypothesis, there are also noteworthy limitations which include contradictory data [46,47], as well as overarching problems concerning, for example, the treatment of Pavlovian vs. instrumental learning paradigms, limitations of the simple behavioral tasks currently in use, and facets of dopamine function that extend beyond its short-latency phasic firing [46]. Within the broad RL framework itself, the role and expression of a dopaminergic RPE are couched in subtly varying theories of value learning and action selection [32,33,48–50]. Additionally, there are

several alternate theories that posit non-RPE explanations for dopamine function, with varying degrees of empirical support [31]. Such alternatives include the salience [51], incentive salience [52,53] and agency [54] hypotheses, which propose dopamine responses to salient stimuli, separate systems for "wanted" compared to "liked" stimuli, or sensory prediction errors that reinforce agency and novel actions, respectively. These hypotheses of dopamine function have proven difficult to disentangle, perhaps due in large part to a more general problem in the experimental treatment of latent variables, such as "rewards," "predictions," or "salience," which are not directly observable and must therefore be related to an observable variable [55].

The axiomatic approach and its advantages

Caplin and Dean proposed an axiomatic approach as a solution to clarify the role of dopamine in decision making, and more specifically RL [55]. Borrowed from economics, this standard methodology encapsulates core theoretical tenets in compact mathematical statements [56]. These axioms then serve as testable predictions, the criteria to which empirical data must conform in order to admit the theory in question. Caplin and Dean applied this method to the RPE hypothesis of dopamine function [28,55–57].

Experiments conducted under the axiomatic framework addressed the major problems attributed to traditional regression-based tests [55,57]. Importantly, the axioms nonparametrically define latent variables in terms of the variable of interest, namely the dopaminergic response, in order to avoid jointly testing auxiliary assumptions concerning the operationalization of latent variables and to allow categorical rejections of the entire class of RPE models if the data violate any given axiom [57]. Additionally, the strict mathematical formalization of relevant variables facilitates the differentiation between alternate explanations of dopamine activity [55,57]. Moreover, the axiomatic approach allows for hierarchical testing so that axiomatic representations can also be made for more refined sub-hypotheses. Finally, if the data violate one or more axioms, these axioms can become focal points for precise revisions to the model, creating a close link between theory and data [55].

Thus far, experiments conducted within this axiomatic framework have supported an RPE model of dopamine function in various areas of the brain. The first formal axiomatic test of a dopamine RPE found such a signal in the activity of the nucleus accumbens, a principal target of midbrain dopamine neurons discussed below [58]. Additionally, fMRI scans of the caudate, putamen, amygdala, medial prefrontal cortex, and anterior cingulate cortex showed that activity in these regions also satisfied the axiomatic RPE model [59]. Meanwhile, the anterior insula was found to be in strong violation of the RPE axioms, and seems to encode salience instead [58,59]. These parallel findings illustrate a common theme in theories of dopamine function, which emphasize that dopamine needs not be restricted to serving only one function, nor that a particular function can be served only by dopamine [28,31]. It should be noted that while the regions imaged have been identified as receiving direct dopaminergic projections, the blood oxygen level dependent (BOLD) fMRI signal is not a corollary of dopamine activity alone. Furthermore, BOLD signals in the midbrain dopamine structures did not provide evidence for an RPE model, although the researchers note that this finding may be partly due to the difficulty of imaging these structures [58]. Nevertheless, these experiments provide proof of method for the axiomatic approach. Furthermore, the axiomatic approach can be applied to any data series, including BOLD or electrophysiological recordings, such that future studies can effectively build upon these initial findings [57].

In summary, Caplin and Dean's axiomatic approach to the reward prediction error hypothesis addressed several central complaints against RPE. Also, the successful use of this axiomatic model illustrates the advantages of a neuroeconomic approach and, in general, the increased power that can be leveraged through cross-disciplinary interaction [14,60]. The development of RL theories similarly exemplifies the benefits of interdisciplinary cooperation in advancing the study of decision making. RL theories and the axiomatic approach also share another common characteristic in that both investigational frameworks exhibit a close interplay between theory and empirical evidence, particularly in demonstrating the role of dopamine in value-based decision making. In RL theories, the convergence of computational models and neural data enhanced the study and understanding of RL and helped identify the dopamine system as encoding an RPE in accordance with TD models [29,30,48]. Additionally, while axiomatic methods have been applied most extensively to the dopamine RPE model, the advantages of this approach can be extended more broadly to different components of decision making as well as different neural systems [57].

Striatal involvement in value-based decision making

In addition to the well-established involvement of prefrontal cortical regions in decisionmaking [9,61], rodent studies have provided a vast amount of evidence supporting the pivotal role of the ventral striatum in decision making processes involving cost-benefit assessments. For example, excitotoxic lesions of the nucleus accumbens impair effort-based and delay-based decision making, as well as decision making under risk as has been excellently reviewed elsewhere [13]. On the other hand, lesioning the dorsal part of the striatum, does not seem to affect value-based decision making in rats [62].

Neuroimaging studies in healthy volunteers also strongly suggest that the ventral striatum represents an important component of the decision-making circuit. More specifically, the subjective value of delayed rewards in intertemporal choice paradigms is represented in the nucleus accumbens [e.g. 63–68]. In one of these studies, however, evaluations related to effort were found not to require ventral striatal activation [68]. Nevertheless, task-related activity of the ventral striatum has also been observed in decision-making under risk [69] and uncertainty [70].

Thus, the role of the basal ganglia in value-based decision-making stemming from BOLD studies, seems largely restricted to the ventral striatum/nucleus accumbens. In this regard, a recent primate study indicates that the caudate nucleus might also be important for costbenefit analyses. With their experiments, involving single-neuronal recordings in rhesus monkeys, Cai and colleagues revealed that neurons in both the ventral and the dorsal striatum encode reward value during an intertemporal choice task [71]. Taken together, currently available data primarily highlight a pivotal role of the ventral striatum in the corticostriatal circuitry subserving value-based decision-making.

Cannabinoids have a modulatory role on dopamine systems in a manner that is relevant to value-based decision making

As pointed out previously, an accumulating body of evidence suggests that dopamine plays an integral role in value-based decision making [11,12]. While the precise behavioral outcome resulting from dopamine release likely varies depending on the pattern of dopaminergic neural activity and the postsynaptic target [13,72], subsecond bursts of mesolimbic dopamine release in the core region of the nucleus accumbens are theorized to modulate cost-benefit assessments by carrying information concerning reward value [73]. When animals are required to make value-based decisions using predictive environmental

information (i.e., cues) for example, the concentration of subsecond dopamine release increases as a function of the expected reward magnitude [40,74–76]. These cue-evoked dopamine release events are sufficient in concentration to occupy low-affinity dopamine D1 receptors within the nucleus accumbens [77,78] and, through subsequent modulatory actions, are thought to strengthen reward seeking in a manner resulting in the procurement of larger reward [79–81].

Cannabinoid CB1 receptor agonists modulate subsecond dopamine release by disinhibiting midbrain dopamine neurons. Both the primary psychoactive component of *Cannabis sativa*, Δ9-tetrahydrocannabinol (Δ9-THC), and synthetic compounds that exhibit a high affinity for the cannabinoid CB1 receptor (e.g., WIN 55,212-2) increase subsecond dopamine release events [82,83]. These exogenous cannabinoids are unable to directly stimulate dopaminergic neural activity however, due to an absence of cannabinoid CB1 receptors on midbrain dopamine cell bodies [84]. Rather, they are thought to increase bursts of dopaminergic neural activity by suppressing GABAergic release and, thereby, indirectly disinhibit dopamine neurons [85]. In support of this theory, applying cannabinoid CB1 receptor agonists to ventral tegmental area (VTA) brain slices decreases GABAergic inhibitory post-synaptic currents in a $GABA_A$ receptor dependent manner [86], while the expected increase in dopaminergic neural activity is blocked by pretreatment of GABA^A receptor antagonists [87].

The finding that exogenously administered cannabinoid CB1 receptor agonists modulate dopamine signaling related to value-based decision making implies that the endogenous cannabinoid system might also contribute. 2-AG, an endogenous cannabinoid and full CB1 receptor agonist [88], is an ideal candidate to modulate subsecond dopamine release during value-based decision making. The synthetic enzymes (e.g., diacylglycerol lipase-α(DGLα)), required to generate 2-arachydonlylglycerol [89,90] are abundantly expressed in midbrain dopamine neurons [91] and are activated exclusively during periods of high neural activity [92], as occurs during cue-evoked dopamine signaling. Based on what is found in other brain regions we speculate that when dopamine neurons fire in high frequency bursts (>20Hz), thereby generating subsecond surges in dopamine concentration in the NAc [93], intracellular Ca^{2+} increases within the dopamine cell bodies and leads to the on-demand synthesis of 2-AG via activation of DGL-α [90,92,94]. Once synthesized, 2-AG retrogradely activates presynaptic cannabinoid CB1 receptors [95], thus suppressing GABA-mediated inhibition of IPSC amplitude, which could theoretically lead to depolarization-induced suppression of inhibition [95]. This conceptualization of how 2-AG modulates dopamine neural activity is consistent with the growing consensus that 2-AG is the primary endogenous cannabinoid involved in regulating synaptic plasticity [89,90].

Augmenting 2-AG concentrations increases the motivation to procure reward, strengthens reward seeking and facilitates cue-evoked dopamine signaling. Motivation to obtain food reward, as assessed using a progressive ratio schedule, is enhanced by either systemically treating animals with 2-AG [96] or by reducing its enzymatic degradation using monoacylglycerol lipase inhibitors (e.g., JZL184) [97]. Likewise, increasing 2-AG levels in the brain energizes responding for reward, as assessed by a decrease in response latency, when reward delivery is predicted by the presentation of conditioned stimulus [97]. This 2- AG induced facilitation in reward seeking is accompanied by greater cue-evoked dopamine release events detected in the nucleus accumbens [97]. Importantly, increasing 2-AG concentration in the VTA alone is sufficient to enhance cue-evoked dopamine signaling and reward seeking [97], thus supporting the theory that 2-AG is critically involved in regulating dopamine signaling within local microcircuits in the midbrain during reward directed behavior (Figure 1).

Consistent with findings from rodent studies, the human brain contains high densities of the cannabinoid CB1 receptor in frontocortical and striatal regions [98]. In accordance, accumulating evidence from human neuroimaging studies employing both fMRI and Positron Emission Tomography (PET) approaches indicates that marijuana and THC modulate the activation of prefrontal cortical and subcortical brain regions subserving dopamine function and decision making processes [99]. Furthermore, and relevant to valuebased decision making as outlined earlier, THC induces release of dopamine in the human striatum [100] matching findings in laboratory animals [82,83].

Although the effects of cannabinoids have been well-documented for a variety of executive cognitive functions including attentional processes, time estimation and working memory [15,16], to date relatively fewer studies have focused on cannabinoid effects on decision making in humans under laboratory settings. The value of delayed rewards or uncertain rewards, as assessed in a delay discounting and a probability discounting task, were not affected by acute challenges with THC in humans [101]. In these decision making tasks the subjective value of the reward was either altered by imposing hypothetical delays on the availability of the reward (delay discounting) or by manipulating the likelihood and predictability of reward (probability discounting). These findings are paralleled by preclinical data demonstrating that the synthetic cannabinoid CB1 receptor agonist WIN55,212-2 does not alter delay discounting in rats [102]. Furthermore, challenges with various cannabinoid CB1 receptor antagonists (SR141716A and O2050) do not modulate the value of delayed reward in rats, suggesting that endogenous cannabinoid tone is not critically involved in this form of delay-based decision making [102,103]. In contrast to the effects of THC in humans, THC alters the value of delayed rewards in rats and shifts the preference towards more self-controlled choice [103]. The observation that SR141716A fully reversed the effects of THC indicates a cannabinoid CB1 receptor-mediated mechanism in promoting diminished delay discounting.

Interestingly, the sensitivity to reinforcement in humans is sensitive to alteration by challenges with THC. In a concurrent random interval procedure, where one response option led to a fixed monetary gain and the other to decreasing monetary gain, THC promotes preference for the latter, less beneficial, choice in subjects occasionally using marijuana [104]. In extension of these findings, THC also induces risky decision making in occasional marijuana users in a task where subjects choose between a non-risky option (small monetary gain, probability of 1.0) and a risky option (larger monetary gain and monetary losses, probability 0.5) leading to zero expected value [105]. Thus, under conditions with uncertainty about the likelihood of punishment, activation of cannabinoid CB1 receptors influences the sensitivity to reinforcement as well as punishment. These findings have been further substantiated by several recent studies implementing neurocognitive risk-based decision making tasks such as the Iowa Gambling Task and related gambling tasks in healthy volunteers and marijuana users [106,107]. Briefly, in the Iowa Gambling Task originally developed by Bechara and coworkers [108] subjects have to make a cost-benefit assessment based on their decisions and are able to draw cards from one of four decks to obtain monetary reward. The expected value of cards drawn from two "risky" decks is negative and will lead to a net loss of money as a result of high gains and even higher losses, whereas the expected value of drawing cards from the other two "safe" decks is positive and will lead to monetary reward. Heavy marijuana use has been associated with an increased preference for risky decisions leading to monetary loss [109] and a positive correlation has been reported between the magnitude of use and risky decision making [107], although comparable effects of THC on decision making are not consistently observed in frequent

marijuana users [110]. In line with the former findings, in a related gambling task, THC challenges in healthy volunteers increased the choice of decisions with a zero-expected value and altered aspects of processing decisions, for instance by reduced attention towards losses and faster reaction times related to gambles with large gains [106]. This has recently been further confirmed using computational models of the Iowa Gambling Task showing that heavy cannabis users are indifferent to loss magnitude and perceived both small and large losses as equal minor negative outcomes [111]. Thus, cannabinoid activity modulates human cost-benefit assessments and the motivational processes therein, and this is possibly explained by its modulatory role on dopamine function. Neuroimaging studies have further uncovered how marijuana use and THC exposure might impact the neural circuits implicated in gambling behavior and risky decisions among which the orbitofrontal cortex and dorsolateral prefrontal cortex are key regions [108]. PET studies have demonstrated that although acute THC exposure is known to increase activity and regional blood flow in these subregions of the prefrontal cortex [112], disturbed decision making in 25-day abstinent heavy marijuana users has been associated with lowered activity in the orbitofrontal cortex and dorsolateral prefrontal cortex [113]. This contrasts recent PET data showing that in 1 day abstinent heavy marijuana smokers regional blood flow in the ventromedial prefrontal cortex and cerebellum was increased during performance in the Iowa gambling task [114]. In keeping with the aforementioned behavioral findings of altered cost-benefit processing induced by THC [106] or in heavy marijuana users [111], fMRI approaches indicate accompanying reductions in brain activation in regions such as the anterior cingulate cortex, medial frontal cortex and cerebellum, particularly during loss of reward [115,116]. Notably, despite the high densities of cannabinoid CB1 receptors in basal ganglia structures in the human brain [19], their involvement and possible differential activation by exogenous cannabinoids in risky decision making is not as pronounced as that of prefrontal cortical regions from the current neuroimaging work. In this respect, it would be highly interesting for future studies to employ neuroimaging approaches in e.g. PD patients with a history of marijuana use and focus on prefrontal cortical activation. Whereas the pathophysiological mechanisms in PD are predominantly subcortical, alterations in cortico-striato-thalamocortical loops [117,118] may give rise to the cognitive disturbances observed in PD. Indeed, this notion is supported by neurocomputational models that strongly predict empirical findings in PD [119–121].

Concluding remarks

This review aimed at 1) providing a background in reinforcement learning as a framework to increase our understanding of different components of value-based decision making and 2) highlighting the importance of cannabinoid signaling that, via its modulatory actions on the dopaminergic system, modulates value-based decision making. Particularly, in view of neurodegenerative disorders such as PD this topic is gaining increasing interest. First, there is now accumulating evidence that executive cognitive disturbances, including value-based decision making, are prominent features of the disorder even in the early stages [2–5,8]. For example, there are several studies that have demonstrated impaired performance in gambling tasks such as the Iowa gambling task in PD [8,122–124], although this finding has not been replicated in all studies [125–127]. These observed disturbances in decision making in PD might result from the ongoing neurodegenerative processes in the dopaminergic system and nuclei of the basal ganglia and cortical connectivity that are an essential part of the corticostriatal loops subserving reinforcement learning and decision making [9,128].

Second, in view of the clinical management of PD, targeting the endogenous cannabinoid system might provide new therapeutic opportunities in addition to the existing dopaminemimetic compounds. Although the latter class of drugs is clinically effective in ameliorating the motor symptoms of the disorder, prescription of dopamine agonist medications, and in

particular levodopa, in PD might result in serious adverse side-effects such as levodopainduced dyskinesias [129]. Furthermore, levodopa use has also been linked to the development of pathological gambling and impaired decision making in PD [5,130]. With regard to endogenous cannabinoids and PD [22,131], AEA levels in cerebrospinal fluid are elevated in non-medicated PD patients [132] and cannabinoid CB1 receptor binding is increased in the basal ganglia in post-mortem brains of PD patients [133]. These findings are supported by earlier work in animal models of PD showing enhanced endocannabinoid signaling (AEA, 2-AG) in various nuclei of the basal ganglia such as the striatum, substantia nigra and globus pallidus related to disturbances in motor behavior [134,135]. Thus, enhanced activity of the endogenous cannabinoid system is associated with the motor symptomatology of the disorder and this would favor the development of novel cannabinoid CB1 receptor antagonist-based strategies as a therapeutic intervention for PD. Whether this observed enhanced activity of the endogenous cannabinoid system in PD also contributes to the aforementioned decision making disturbances in the disorder is an interesting question that certainly warrants further investigation. The observed adverse effects of cannabinoid CB1 receptor agonists such as THC on value-based decision reviewed here, and the proposed endogenous cannabinoid-dopamine interaction in value-based decision making (Figure 1), may offer an explanation for these phenomena. In view of this notion, second generation cannabinoid CB1 receptor antagonist targeted medications are likely of therapeutic potential and may possibly exert a dual mode action through amelioration of motor disturbances as well as improving impaired decision making in PD. A potential caveat of such a pharmacotherapeutic approach, that certainly requires further investigation, might reside in the observed enhancement of striatal glutamatergic signaling by cannabinoid CB1 receptor antagonism in an experimental model of PD [136], the former which has been associated with the pathophysiology of levodopa-induced dyskinesia in PD [137].

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Figure 1.

A theoretical ventral tegmental area microcircuit during value-based decision making. After encountering a cue predicting a large reward, conditioned glutamate release occurs in the ventral tegmental area **(1)**, thus resulting in Ca^{2+} influx into the dopamine neuron **(2)** and activation of G-protein coupled receptors (e.g., mGluR1/5) **(3)**. G-protein coupled receptor stimulation activates phospholipase C (PLC), which ultimately leads to the formation of inositol trisphosphate (IP3) and diacylglycerol (DAG) **(4)**. IP3 binds to IP3 receptors, resulting in the mobilization of intracellular Ca^{2+} stores (5). Elevated intracelullar Ca^{2+} activates the enzyme diaacylglycerol lipase-alpha (DGL-α) **(6)**, which hydrolyzes DAG to

form 2-AG **(7)**. 2-AG traverses the plasma membrane into the extrasynaptic space **(8)**, where it retrogradely activates cannabinoid CB1 receptors on presynaptic GABA terminals **(9)**. Activation of the Gi/o subunit of CB1 receptor suppresses GABA release **(10)**. Decreased GABA activation of GABAA receptors **(11)** on dopamine neurons disinhibits the dopaminergic neural activity, thus facilitating cue-evoked dopamine signaling during reward-directed behavior.