Examining Reward-Related Self-Regulation in Adolescents: A Multimodal Analysis

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Abstract

Real-time functional magnetic resonance imaging neurofeedback (rtfMRI-nf) is a powerful tool to measure self-regulation over targeted brain activity. This study examined whether rtfMRI-nf targeting nucleus accumbens (NAcc) modulation can measure developmental differences in reward-related self-regulation more directly than has been possible with existing measures. We used a multimodal approach to test whether NAcc activity during rtfMRI-nf differed between adolescents versus young adults over and above self-report and neurocognitive indices. In the adolescent group, we examined whether NAcc activity during rtfMRI-nf predicted future substance use, given linkages between reward responding and reward seeking behavior. Participants included adolescents (n = 56; ages 14–16) and young adults (n = 75; ages 25–27), who completed the Self-Regulatory Inventory (self-report assessment), an Emotional Go/No-Go task (neurocognitive assessment), and a rtfMRI-nf task (neural assessment). Adolescents reported substance use, including cannabis use, every six months for two years. Results from hierarchical regression models indicated that greater average NAcc activity during reward upregulation trials of the rtfMRI-nf task significantly predicted being in the young adult (vs. adolescent) group membership, even after accounting for sociodemographic, self-report, and neurocognitive measures. Among adolescents, cannabis users showed lower average NAcc activity during upregulation trials compared to cannabis non-users, suggesting deficits in the reward responsivity. In sum, findings highlight rtfMRI-nf as a complementary tool for measuring reward-related self-regulation and predicting cannabis use, with volitional control of the reward circuitry emerging as a potential neural risk marker for individualized prevention strategies.

Keywords: adolescence, development, self-regulation, real-time fMRI neurofeedback (rtfMRI-nf), nucleus accumbens (NAcc), cannabis use

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Adolescence is a developmental period marked by heightened sensitivity to rewards, underdeveloped cognitive control systems, and increased exposure to external social pressures—factors that collectively heighten vulnerability to impulsivity and risk-taking behaviors (Schreuders et al., 2018; Somerville et al., 2011; Steinberg et al., 2008). During this period, the same developmental plasticity that supports adaptive exploration and autonomy can also increase susceptibility to maladaptive behaviors, including substance use. Marijuana, in particular, is often initiated during adolescence and has been linked to lasting disruptions in reward processing and behavioral regulation (Martz et al., 2016; Schreuders et al., 2018).

At the core of these behavioral vulnerabilities is self-regulation—the capacity to manage one's thoughts, emotions, and actions in pursuit of long-term goals (Moilanen & DeLong, 2018). Strong self-regulatory capacity is associated with academic success, lower rates of psychopathology, and reduced engagement in risky behaviors (Memmott-Elison et al., 2020). However, self-regulation is not a unitary construct; it spans multiple domains and is shaped by both neurobiological development, environmental influences, and individual behavioral patterns—factors that contribute to variability in adolescents' ability to plan and regulate behavior (Steinberg et al., 2009).

To study this variability in a meaningful way, it is essential to identify the circuitry that underlie reward processing and cognitive control, as these neural mechanisms form the foundation of self-regulation. Neurodevelopmental models such as the dual systems (Steinberg et al., 2008) and opponent process frameworks (Casey et al., 2010) emphasize how an imbalance between relatively mature subcortical reward circuits and still-developing prefrontal control regions may shape adolescent risk-taking. These theoretical models offer a foundation for

understanding why some adolescents may be more vulnerable than others, but they do not fully explain individual differences in outcomes like substance use. Thus, capturing adolescents' reward-related self-regulation may require a multimethod approach, spanning self-report measures, neurocognitive task performance, and brain activation measured through neuroimaging that reflects both internal neural processes and observable behavior. Only by examining these components together can we determine whether real-time fMRI neurofeedback (rtfMRI-nf) reveals age-related differences in reward-related self-regulation, adds predictive value for distinguishing adolescents from young adults, and improves prediction of real-world outcomes such as adolescent substance use beyond self-report and neurocognitive tasks.

Neurodevelopment of Self-Regulation Systems in Adolescents and Young Adults

Reward Responding and the Nucleus Accumbens

Understanding these developmental differences requires a closer examination of the neural systems that support reward processing and cognitive control. Central to this inquiry is the nucleus accumbens (NAcc), a key region within the reward circuitry, whose function may help explain age-related variability in self-regulation and risk-taking. Situated within the ventral striatum, the NAcc is a critical node in dopaminergic reward circuitry and is deeply involved in goal-directed behavior, reward anticipation, and motivational salience (Casey & Jones, 2010; Dickerson & Adcock, 2021; Floresco, 2015; Knutson & Cooper, 2005). Through its connections with the prefrontal cortex, the NAcc helps guide motivated behavior by signaling both the anticipation and receipt of rewards, translating motivational value into everyday decisions (Somerville et al., 2010). Disruptions in this dopaminergic system have been implicated in a range of psychiatric and developmental disorders, including substance use disorders (Maia & Frank, 2011). The NAcc is particularly relevant here because its heightened responsivity to

rewards may underlie the motivational imbalances often observed during adolescence, a period when subcortical regions such as the striatum undergo synaptic pruning earlier than higher-order association cortices (Somerville et al., 2010). As a neural marker of reward sensitivity, it offers insight into the mechanisms shaping individual differences in self-regulation during this critical developmental window.

Building on this, the NAcc undergoes dynamic functional changes during adolescence, with numerous studies identifying an adolescent-specific peak in reward sensitivity. Converging neuroimaging work shows that NAcc activation in response to rewards follows an inverted U-shaped trajectory across adolescence, with peak responsivity generally occurring between ages 13 and 17 (Casey & Jones, 2010; Schreuders et al., 2018; Somerville et al., 2011; Steinberg et al., 2008). Behavioral findings echo this neural pattern: sensation seeking rises sharply in early adolescence (about 12–15 years) before declining, whereas impulse control improves more gradually into young adulthood (Steinberg et al., 2008). Galvan et al. (2006) further support this imbalance by showing that the NAcc in adolescents mirrors adults in its reward sensitivity and connectivity. However, because prefrontal control systems and their connections are still developing, this mismatch results in more exaggerated responsivity within the reward system, likely heightening sensitivity to immediate rewards in the absence of mature regulatory control.

According to the dual systems framework (Steinberg et al., 2008), a rapid pubertal surge in dopaminergic signaling within the NAcc drives sharp increases in reward seeking, while the regulatory-control system lags behind structurally. The opponent process model echoes this imbalance, indicating that subcortical regions undergo synaptic pruning and maturation earlier than higher-order association areas such as the prefrontal cortex (Casey & Jones, 2010; Somerville et al., 2010). Consistent with both views, neuroimaging evidence indicates that

regions within the reward system, such as the NAcc, become disproportionately active compared to still-maturing top-down control systems during adolescence, which may bias decision-making toward immediate over long-term gains (Galvan et al., 2006; Sawyers et al., 2008; Steinberg et al., 2008). However, findings are mixed regarding the directionality of NAcc responsivity; while some studies identify exaggerated activation to rewards (e.g., Galvan et al., 2006; Schreuders et al., 2018), others report blunted responses in tasks requiring sustained effort or top-down regulation, implying that adolescent reward reactivity may be highly context- and task-dependent (Sawyers et al., 2024).

Self-Regulatory Development in the Prefrontal Cortex

The prefrontal cortex (PFC), a region essential for executive functions such as inhibitory control, planning, and decision-making, follows a slow and gradual maturation into adulthood. During adolescence, processes like synaptic pruning and myelination strengthen connections within and between brain regions, enhancing the integration and efficiency of regulatory systems (Steinberg et al., 2008). Because integration between control systems and subcortical regions develops more slowly, adolescents experience a period of heightened vulnerability to risk-taking, as relatively mature subcortical structures generate strong motivational signals that are insufficiently modulated by still-developing prefrontal control systems (Somerville et al., 2010; Steinberg et al., 2008). This developmental imbalance contributes to emotionally driven and reward-sensitive behavior often seen at this stage.

Functional neuroimaging research has provided support for this imbalance, highlighting developmental differences in the coordination of reward and control systems. Sawyers et al. (2024) showed that adolescents exhibit less efficient top-down engagement of the dorsolateral prefrontal cortex during reward-based tasks requiring attentional regulation. During demanding

tasks such as the Monetary Incentive Reaction-Time Choice task, a reward-based paradigm that compares brain activation in response to effortful versus random chance rewards, adolescents demonstrated weaker connectivity between prefrontal regions and the NAcc and diminished striatal activation compared to adults. These findings imply that adolescents may struggle to sustain cognitive regulation over their behavioral responses—especially in situations where consequences hinge on self-regulatory performance. In contrast, adults, whose prefrontal circuits are more mature and tightly coupled with striatal regions, are better equipped to integrate reward processing with cognitive control demands (Sawyers et al., 2024).

Adolescents frequently struggle to regulate their behavior when confronted with highly salient environmental cues, which can contribute to risky or harmful decision-making due to underdeveloped prefrontal control (Somerville et al., 2010). While this imbalance can contribute to impulsive or risky behavior, it is not a fixed trajectory; contextual salience, task demands, and individual differences can shape how strongly this neural imbalance influences behavior.
While existing research has deepened our understanding of developmental differences in self-regulation, most traditional tasks examine reward responsivity and cognitive control in isolation, overlooking how these systems interact dynamically. This separation limits our ability to fully capture the processes that drive regulation in real-world contexts, where motivational and control demands often co-occur. As such, there is a need for approaches that assess individuals' ability to volitionally modulate reward-related brain activity in real time, offering a more integrated and ecologically relevant view of self-regulation than static measures alone.

Neuroimaging Measure of Self-Regulation: Real-Time Modulation of the Nucleus Accumbens

Capturing how self-regulation unfolds in real time requires tools that go beyond the static or fragmented snapshots offered by traditional neuroimaging approaches. Most existing methods

assess brain activity before or after a regulatory task, limiting insight into how individuals modulate behavior in the moment. rtfMRI-nf addresses this gap by allowing participants to observe and actively modulate their brain activity as it occurs. This closed-loop technique typically uses visual feedback—such as thermometers or bars—to represent activation in targeted brain regions (Thibault et al., 2016). By providing a direct behavioral index of volitional control over neural processes, rtfMRI-nf offers a powerful method for assessing individual differences in brain-based self-regulation, particularly within the reward system.

Work by Greer et al. (2014) demonstrated the feasibility of using rtfMRI-nf to volitionally control activity in the NAcc. Participants who received neurofeedback were able to selectively upregulate NAcc activation during reward imagery, an effect that was not observed in control conditions and diminished once feedback was removed. Notably, this volitional control was accompanied by co-activation in the medial prefrontal cortex, suggesting that neurofeedback may facilitate engagement of regulatory circuits that support goal-directed reward processing. These findings underscore the potential of rtfMRI-nf to capture real-time interactions between subcortical and prefrontal regions involved in self-regulation.

Neurocognitive Measure of Self-Regulation: Inhibitory Control over Rewarding Stimuli

Inhibitory control is a core component of self-regulation, enabling individuals to suppress inappropriate or prepotent responses in order to support goal-directed behavior. A well-validated paradigm to assess this process is the Go/No-Go task. This task is particularly well-suited to probing adolescent self-regulation, as it challenges individuals to inhibit responses to emotionally salient cues—a context in which adolescents are known to struggle due to the dynamic interplay between affective and cognitive systems.

The Emotional Go/No-Go task, an affectively enhanced version of the classic inhibitory control paradigm, not only engages response inhibition but also reveals affective biases. Participants tend to respond more quickly and commit more errors to emotionally positive stimuli—a pattern that is especially pronounced during adolescence, when reward-related affective systems are particularly active. Compared to adults, adolescents show greater difficulty inhibiting responses to these emotionally salient cues, as evidenced by increased false alarms and slower reaction times to happy-face (i.e., emotionally salient) trials (Somerville et al., 2011). Also using the Emotional Go/No-Go task, Hare et al. (2008) found that adolescents made more commission errors when inhibiting responses to happy faces—errors that were accompanied by heightened amygdala activation and reduced ventromedial PFC recruitment. These findings reflect the adolescent brain's amplified emotional reactivity and limited regulatory capacity.

Self-Report Measure of Self-Regulation: Subjective Insights into Self-Regulation

Self-report measures offer a unique vantage point into adolescents' internal experiences and perceived capacities for self-regulation, complementing objective data obtained from neurocognitive and neuroimaging paradigms. Instruments such as the Self-Regulatory Inventory (SRI) have been central in assessing both short-term and long-term aspects of self-regulation. Short-term self-regulation involves managing immediate emotions and impulses, while long-term self-regulation refers to planning, commitment, and persistence toward future goals. Together, they reflect how adolescents adapt their behavior across different timeframes and motivational contexts (Moilanen, 2007). In the present study, adolescents completed the SRI to provide insight into how they perceived their own ability to regulate emotions, behaviors, and goals. These self-perceptions were then examined in relation to subsequent behavioral outcomes,

including self-reported substance use, providing a subjective lens on risk that may not be evident through task-based measures alone.

Despite their utility, self-report measures are subject to notable limitations. Studies have shown modest correlations between self-reported and neurocognitive indicators of self-regulation, suggesting they tap distinct constructs (Dang et al., 2020). While tasks like the Emotional Go/No-Go provide objective indices of inhibitory control under experimentally controlled conditions, self-reports reflect subjective perceptions that can be influenced by social desirability, introspective inaccuracy, or cultural narratives—such as stereotypes portraying adolescents as impulsive (Steinberg et al., 2009). This divergence has important implications: adolescents may perceive themselves as well-regulated, yet show reduced control in emotionally salient contexts that engage immature neural systems like the prefrontal cortex and ventral striatum (Hare et al., 2008). As a result, researchers caution against using self-report measures in isolation, advocating instead for multimodal approaches that capture both perceived and enacted regulation thus reflecting the complex and multifaceted nature of adolescent behavior (Demidenko et al., 2019; Zald & Treadway, 2017).

The Present Study

The literature reviewed above highlights three key components of self-regulation: neural mechanisms of reward processing and control, behavioral manifestations of inhibitory control, and subjective experiences of self-regulation. While these components have often been studied in isolation, questions remain about how they interact across development and contribute to meaningful outcomes such as substance use. Although the dual systems and opponent process frameworks are well supported, existing methods typically offer static or indirect snapshots of

regulation. rtfMRI-nf offers a dynamic method for measuring volitional modulation of brain activity as it unfolds, providing a more temporally sensitive window into reward-related self-regulation. The present study leverages this method to examine whether NAcc modulation during rtfMRI-nf reveals meaningful developmental differences and enhances prediction of substance use beyond self-report and neurocognitive measures.

This study aims to address the following research questions:

1. Does real-time fMRI neurofeedback of the NAcc reveal meaningful developmental differences in reward-related self-regulation, as posited by dual systems of brain development, between adolescents and young adults beyond those captured by self-report or neurocognitive tasks?

2. Can self-regulation measures across self-report, neurocognitive, and neural domains predict individuals' likelihood of belonging to the adolescent or young adult group, with neural indices providing predictive utility beyond self-report and neurocognitive measures?

3. Within the adolescent group, can self-reported self-regulation, neurocognitive performance, and NAcc modulation predict substance use behaviors over time, with neural measures offering incremental predictive value over self-report and neurocognitive indicators.

Hypotheses:

1. Compared to young adults, adolescents will report lower self-regulation (SRI scores), perform worse on the Emotional Go/No-Go task, and show weaker volitional NAcc

modulation via rtfMRI-nf, reflecting developmental differences in reward-related self-regulation.

2. Self-regulation measures across self-report, neurocognitive, neural domains will significantly predict age group membership, with neural indices providing predictive value beyond self-report and neurocognitive measures.

3. Among adolescents, higher self-reported SRI scores, better Emotional Go/No-Go performance during No-Go trials, and a greater extent of volitional control over average NAcc activation will predict lower rates of substance use over a two-year follow-up period, with neural measures offering incremental predictive utility over self-report and neurocognitive indicators.

Methods

Participants

Participants were a community-recruited sample of two age groups from Southeast Michigan: adolescents aged 14–16 years and young adults aged 25–27 years. The initial sample was comprised of 152 participants (71 adolescents and 80 young adults). The final analytic sample comprised 131 participants, with 56 adolescents and 75 young adults. Participants were excluded from the analytic sample for one or more of the following reasons: scanning contraindications, incomplete or unusable data due to technical errors, failing to disclose medical conditions or substance use not reported during the screening process, poor imaging quality (e.g., significant distortion, excessive motion). Inclusion and exclusion criteria were also included to control for variables that could introduce bias or confound the results and ensured a healthy and representative sample for investigating developmental differences. These criteria ensure that all

participants were right-handed males and females aged 14–16 (adolescents) and 25–27 (young adults) who were physically and medically able to consent, had English as their first language, and reported low to moderate alcohol and other drug use within normative ranges for their age group. Participants were excluded if they had significant psychiatric or developmental disorders, medical or neurological conditions, recent centrally active medication use, a family history of psychosis, contraindications for MRI, IQ <70, or positive urine drug or pregnancy tests (if female). All participants provided informed consent, with minors providing assent, in accordance with approval from the University of Michigan Medical School Institutional Review Board.

Measures

Sociodemographic

Sociodemographic variables were analyzed to understand their potential influence on reward-related self-regulation and included age, race/ethnicity, sex, and parental education. Age was recorded in years, while race/ethnicity and sex were categorized based on participant self-report. In the present study, race was recoded as White (1) or not White (0). Sex was recoded as female (1) or male (2). Parental education was used as a proxy for socioeconomic status and recoded as 1 = some college or more or 0 = high school diploma or less. These variables were analyzed to understand their potential influence on reward-related self-regulation outcomes.

Self-Report Task: Self-Regulatory Inventory

Self-reported self-regulation was assessed using the Self-Regulatory Inventory (SRI), which consisted of questions adapted to be developmentally relevant to adolescents and young adults. These 36-item instruments measured self-control across behavioral, attentional, emotional, and cognitive domains (Moilanen, 2007). The measure includes subscales for short-

term and long-term self-regulation, reflecting both immediate impulse control and future-oriented planning.

For the purposes of this study, items from both subscales were combined to create a total score, which was calculated by summing responses across all items. This decision was based on preliminary analyses showing that the short-term and long-term self-regulation subscales were highly correlated ([$r(53) = 0.74$, $p < .001$]), suggesting substantial overlap in the constructs as measured in this sample. Collapsing across the subscales simplified interpretation and reduced redundancy, allowing us to model self-regulation as a unified construct consistent with our theoretical framework focused on overall reward-related self-regulation.

Neurocognitive Task: Emotional Go/No-Go

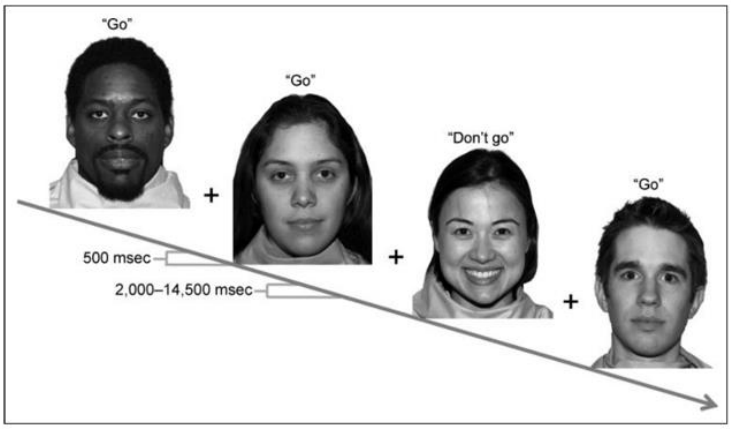
The Emotional Go/No-Go task was adapted from Hare et al. (2005, 2008) using stimuli from the NimStim set of facial expressions (Tottenham et al., 2009) and was presented using EPrime (Figure 1). Participants completed two conditions of the Emotional Go/No-Go task, designed to assess reward-related self-regulation. Happy faces represented rewarding stimuli. In the first condition, participants were instructed to respond to target stimuli (happy faces) and withhold responses for non-target stimuli (neutral faces). In the second condition, participants responded to target stimuli (neutral faces) and withheld responses for non-target stimuli (happy faces). Each stimulus was presented for 500ms, followed by a variable intertrial interval. Participants were instructed to respond quickly while minimizing errors.

The following variables were analyzed to evaluate reward-related inhibitory control: (1) hit rates for happy Go trials, (2) hit rates for neutral Go trials, (3) false alarm rates for happy No-Go trials, and (4) false alarm rates for neutral No-Go trials. Additionally, reaction times for hits

(happy and neutral Go trials) and reaction times for false alarms (happy and neutral No-Go trials) were included in the analyses.

Figure 1

Emotional Go/No-Go Task Design



Note. Participants were presented with facial stimuli for 500 ms, followed by an intertrial interval of 2,000–14,500 ms. In the task, "Go" trials required participants to respond to target stimuli (e.g., happy or neutral faces depending on the condition), while "Don't go" trials required participants to withhold their response to non-target stimuli (adapted from Hare et al. 2005).

Neuroimaging Task: Real-Time Functional Magnetic Resonance Imaging Neurofeedback

The rtfMRI-nf task was adapted from Greer et al. (2014) and is shown in Figure 2. During this task, participants were instructed to increase or decrease NAcc activity in feedback and no-feedback conditions. Prior to entering the scanner, participants were provided with psychoeducational information about NAcc function related to reward responsivity and instructed to generate five increase strategies (e.g., “Imagine an upcoming exciting event”) and five decrease strategies (e.g., “Imagine waiting in a long line”) to modify NAcc activity.

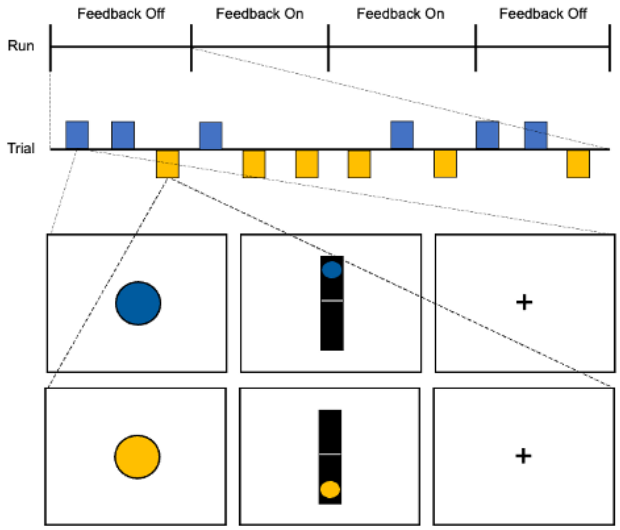
Once participants were in the scanner but before the rtfMRI-nf task, whole-brain anatomical structural scans were acquired, and bilateral NAcc regions of interest (ROIs) were specified in native space using reference maps from WFUPickAtlas and SPM12. The average signal from the NAcc ROIs provided real-time feedback through custom MATLAB software.

The rtfMRI-nf task consisted of four blocks (feedback off, feedback on, feedback on, feedback off), each with 12 pseudo-randomly ordered trials (increase trials represented by a blue ball, decrease trials represented by a yellow ball). Feedback blocks displayed a dynamic thermometer corresponding to NAcc activity, whereas feedback-off blocks displayed a static thermometer. Participants' NAcc activity was measured continually after the feedback cue for 8 seconds, followed by a variable rest interval (4–6 seconds). Post-task, participants completed a rating form to document the strategies used and their task experience, including motivation levels. Percent signal change in the NAcc was measured by averaging activity time courses by trial type and run number for each individual, providing a stable estimate of volitional modulation of NAcc activity while reducing noise from trial-level variability.

To control for placebo effects and motivation-related influences, we employed a bidirectional regulation control condition, where participants were instructed to both up-regulate and down-regulate NAcc activity. This within-person control design helps rule out non-specific effects, ensuring that observed changes in brain activity and behavior are due to neurofeedback rather than general arousal or task engagement. Bidirectional control is a widely recommended approach in neurofeedback studies as it minimizes expectancy biases and allows for physiological specificity (Sorger et al., 2019). By training participants to regulate in opposing directions, we can better determine whether neurofeedback effects are driven by true self-regulation rather than placebo or motivation-related factors.

Figure 2

Real-Time fMRI Neurofeedback Paradigm



Note. Runs are segmented into periods of feedback on and feedback off, during which participants are tasked with increasing or decreasing NAcc activity. Each trial consists of a cue presentation (e.g., a blue or yellow ball indicating task direction), feedback (thermometer visualization), and a fixation cross. Feedback-off periods do not display the thermometer, while feedback-on periods allow participants to see their performance in real-time (adapted from Greer et al., 2014).

Post Scan Rating Form

After completing the rtfMRI-nf task, participants completed a post-scan rating form outside of the scanner. This measure assessed participants' experiences and strategies used during the task. Specifically, participants were asked to rate their motivation to complete the task, their confidence in increasing and decreasing NAcc activity, and the difficulty of these tasks using a 5-point Likert scale (e.g., 1 = Very untrue, 5 = Very true). Additionally,

participants provided open-ended responses regarding the strategies they employed to increase or decrease their NAcc activity. Other questions included the clarity of task instructions and the visibility of visual feedback cues during the scan. Although not directly analyzed in this study, this measure was collected to document task engagement and strategy use, given the importance of individual variability in motivational and regulatory processes

Substance Use Questionnaire

To assess substance use, participants completed a detailed questionnaire which included items included items derived from the Monitoring the Future (MTF) study survey (Miech et al., 2025), a nationally recognized assessment of adolescent substance use behaviors. These questions assessed the frequency and quantity of use across a range of substances, including alcohol, tobacco products, marijuana, other illicit drugs (e.g., cocaine, LSD), and the misuse of prescription drugs. Follow-up assessments of substance use were administered every six months for two years to the adolescent sample. For the present study, substance use was coded as a binary variable: 1 = any substance use or 0 = no substance use).

Data Analysis

Prior to analysis, data were screened for accuracy, missing values, and outliers. Descriptive statistics were computed to provide an overview of the sample characteristics and key study variables. For continuous variables, means, standard deviations, and ranges were reported, while frequencies and percentages were used for categorical variables. To ensure clarity in the analysis, predictor and outcome variables have been explicitly distinguished here. Predictor variables include sociodemographic factors (e.g., age, sex, race/ethnicity, and parental education), SRI sum, neurocognitive performance metrics from the Emotional Go/No-Go task,

and average NAcc activation during the rtfMRI-nf task. Outcome variables were age group (adolescent vs. young adult) and in the adolescent group, longitudinally measured substance use.

To test the first hypothesis, mean comparisons between adolescents and young adults were conducted using independent samples t-tests. Effect sizes were calculated to quantify the magnitude of group differences, with Cohen's d reported. To test the second hypothesis, a hierarchical logistic regression was performed. Model performance was assessed using Model χ^2 to evaluate overall model fit, Nagelkerke's R^2 to assess explained variance, and odds ratios (ORs) to examine the relative predictive power of each model. Sociodemographics (Model 1: sex, race/ethnicity, and parental education), self-report (Model 2: sum SRI score), neurocognitive (Model 3: accuracy measures (hits, false alarm rates) and reaction times for both happy and neutral condition), and neuroimaging variables (Model 4 – Full Model: average percent signal change in NAcc activity for increase and decrease trials across runs) were entered sequentially. For research hypothesis 2, the outcome variable was group membership (1 = adolescent, 2 = young adult). For research hypothesis 3, the outcome measure was cannabis use at follow-up (1 = any use, 0 = no use).

Although multiple forms of substance use were assessed longitudinally (e.g., alcohol, prescription misuse), cannabis was selected as the focal outcome for follow-up analyses. This decision was based on both empirical and practical considerations. First, cannabis use demonstrated the greatest group differences in use between adolescents and young adults, suggesting stronger developmental relevance. Second, cannabis use exhibited the most robust associations with baseline self-regulation measures in subsequent predictive models. In contrast, alcohol and other substance use outcomes showed limited variability and yielded weak or non-significant effects in regression models, limiting their interpretive value.

All statistical analyses were performed using IBM SPSS Statistics Version 29.0.2.0. Statistical significance was set at $p < .05$, and corrections for multiple comparisons, such as the Bonferroni adjustment, were applied where appropriate to control for Type I error.

Results

Aim 1: Group Differences in Self-Regulation Between Adolescents and Young Adults

Sociodemographic Characteristics

As shown in Table 1, no significant differences were observed in sex distribution between groups, $t(128) = -0.85$, $p = 0.40$. The adolescent group had a significantly higher percentage of White versus non-White participants relative to the young adult group, $t(128) = 3.19$, $p = .002$, $d = 0.55$. The adolescent group had a higher percentage of parents with a high school education or greater, though this difference did not reach statistical significance, $t(129) = 1.86$, $p = 0.07$, $d = 0.31$.

Self-Report Self-Regulation

Adolescents reported slightly lower sum scores on the SRI compared to young adults, with this difference approaching statistical significance, $t(129) = -1.89$, $p = 0.06$, $d = -0.33$.

Neurocognitive Performance: Emotional Go/No-G

Adolescents exhibited significantly higher false alarm rates to both happy-face No-Go trials and neutral face No-Go trials compared to young adults, $t(123) = 3.79$ and 4.78, $p < .001$. Hit rates and reaction times did not differ significantly between groups for either condition ($p =$ ns).

Neuroimaging: Nucleus Accumbens Modulation

During Run 2 (first neurofeedback run) increase trials, young adults demonstrated significantly greater average NAcc activation than adolescents $t(129) = -2.00$, $p = 0.048$, $d = -0.35$. Similarly, in Run 3 (second neurofeedback run) increase trials, young adults again showed greater average NAcc activation compared to adolescents, $t(129) = -2.18$, $p = 0.03$, $d = -0.39$. Conversely, adolescents showed significantly greater activation during Run 3 decrease trials, $t(129) = 2.26$, $p = 0.03$, $d = 0.43$. There were no other significant differences in average NAcc modulation across runs or trials between adolescent and young adult groups.

Table 1

Group Comparison of Adolescents and Young Adults

Variable	Adolescent (*n*=56)	Young Adult (*n*=75)	t
	*M (SD) o*r %	*M (SD) or* %	
Sociodemographic Characteristics (%)			
Male Sex	42.0	49.0	-0.85
White	80.0	54.7	3.19**
Parent Education	96.4	88.0	1.86
Self-Report: Self-Regulatory Inventory (SRI)			
Sum SRI	130.46 (15.90)	135.41 (13.94)	-1.89
Neurocognitive: Emotional Go/No-Go			
Happy Face Go, Neutral Face No Go			
Happy Face Hit (%)	99.04	97.98	0.66
Happy Face False Alarm (%)	21.61	11.43	3.79***
Happy Face Hit RT (M)	375.68 (38.66)	363.91 (34.58)	1.79
Happy Face False Alarm RT (M)	331.68 (56.79)	327.12 (79.01)	0.35
Neutral Face Go, Happy Face No Go			
Neutral Face Hit (%)	96.42	98.47	-1.35
Neutral Face False Alarm (%)	30.84	17.91	4.78***
Neutral Face Hit RT (M)	381.37 (38.32)	381.59 (37.44)	-0.03
Neutral Face False Alarm RT (M)	342.47 (55.72)	340.47 (42.57)	0.23
Neuroimaging: Real-Time fMRI Neurofeedback (rtfMRI-nf) (M)			
Avg Run 1 NoFB Increase Trials	0.29 (.22)	0.26 (.20)	0.86
Avg Run 1 NoFB Decrease Trials	0.19 (.24)	0.14 (.18)	1.48
Avg Run 2 FB Increase Trials	0.22 (.23)	0.31 (.24)	-2.00*
Avg Run 2 FB Decrease Trials	0.20 (.19)	0.14 (.18)	1.93
Avg Run 3 FB Increase Trials	0.17 (.22)	0.25 (.22)	-2.18*
Avg Run 3 FB Decrease Trials	0.21 (.29)	0.11 (.18)	2.26*
Avg Run 4 NoFB Increase Trials	0.14 (.24)	0.18 (.20)	-1.20
Avg Run 4 NoFB Decrease Trials	0.13 (.23)	0.11 (.20)	0.51
Self-Report: Substance Use Questionnaire (%)			
Substance Use FU 1	9.8	-	-
Substance Use FU 2	33.3	-	-
Substance Use FU 3	23.7	-	-
Substance Use FU 4	28.6	-	-
Overall Substance Use FU 1-4	39.6	-	-

*$p < .05$. **$p < .01$. ***$p < .001$

Note. $N = 131$. M = mean; SD = standard deviation; parent education: 1 = Some college or more or 0 = High school diploma or less; race/ethnicity: 1 = White or 0 = Non-White. Substance use was dichotomized as 1 = yes (substances use reported) or 0 = no (no substance use reported), encompassing all substances assessed in the questionnaire, including alcohol, cannabis, nicotine, illegal drugs, and prescription misuse.

Aim 2: Predicting Age Group Membership Using Self-Regulation Measures

To assess whether self-regulation measures predicted being in the adolescent versus young adult group, a series of hierarchical logistic regression models were estimated using sociodemographics (Model 1), self-report (Model 2), neurocognitive (Model 3), and neuroimaging variables (Model 4 – Full Model). Predictors were chosen based on a combination of theoretical relevance and observed bivariate correlations. Correlations between all variables included in regression analyses are provided in Supplementary Appendix Table A.

In Model 1, White participants were more likely to be adolescents than young adults. Model 2 added self-reported self-regulation (Sum SRI), which did not significantly differentiate group status (Table 2). Model 3 added neurocognitive performance on the Emotional Go/No-Go task, revealing that higher false alarm rates to neutral face Go trials significantly predicted being in the adolescent group. Finally, Model 4 added average NAcc activation during Run 2 increase trials of the rtfMRI-nf task. Higher average NAcc activation was a significant predictor of being in the young adult vs. adolescent group, even after accounting for Model 1-3 predictors. The final model (Model 4) achieved the strongest fit overall (Nagelkerke $R^2 = 0.35$, Model $\chi^2 = 37.64$, $p < .001$).

Table 2

Hierarchical Multivariable Logistic Regression Model Predicting Adolescent vs. Young Adult Group Membership

	Model 1	Model 2	Model 3	Model 4
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
Sociodemographic Characteristic				
White	-1.13** (0.14, 0.73)	-1.20** (0.13, 0.69)	-1.23** (0.12, 0.73)	-1.33** (0.10, 0.67)
Self-Report: Self-Regulatory Inventory (SRI)				
Sum SRI		0.02 (1.00, 1.05)	0.02 (1.00, 1.05)	0.01 (0.99, 1.04)
Neurocognitive: Emotional Go/No-Go				
Neutral Face Go False Alarms			-6.40*** (0.00, 0.04)	-7.03*** (0.00, 1.04)
Neuroimaging: NAcc Activation during rtfMRI-nf				
Run 2 Feedback Increase Trial				2.44* (1.58, 83.50)
Nagelkerke R^2	0.08	0.12	0.30	0.35
Model χ^2	8.05**	11.52**	30.94***	37.64***

*$p < .05$. **$p < .01$. ***$p < .001$

Note. OR = odds ratio; CI = 95% confidence intervals. Sociodemographic group: White vs. Non-White; NAcc = nucleus accumbens; rtfMRI-nf = real-time functional magnetic resonance imaging neurofeedback.

To evaluate the robustness of our findings, additional models (not tabled) tested alternate configurations of predictors. Across these models, NAcc activation during Run 3 increase trials continued to significantly predict group status (Appendix B), including when paired with happy-face Go false alarms (Appendix C). Average activation during Run 3 decrease trials was also examined but showed inconsistent predictive value. Reaction time variables were non-significant across all models and thus excluded from final models. Additional sociodemographic predictors such as sex (Appendix D) and parent education (Appendix E) provided modest contributions to model performance despite failing to reach statistical significance. Across models, self-reported self-regulation (SRI sum scores) emerged as a significant predictor only in a limited subset of configurations—specifically, those with weaker overall fit and lower explanatory power. In contrast, in models that demonstrated stronger fit (i.e., higher Nagelkerke R^2 and significant model χ^2), SRI scores were consistently non-significant.

Aim 3: Predicting Adolescent Substance Use from Baseline Self-Regulation

Substance Use Descriptives Over Follow-Ups

A total of 53 adolescents completed at least one follow-up assessment (94.6% of the baseline analytic adolescent sample), and 29 adolescents (51.8%) completed all four follow-up assessments over the two-year period. Across the follow-up period, 21 adolescents (39.6%) reported use of at least one substance, eight individuals (15.1%) reported cannabis use, seven adolescents (13.2%) reported nicotine use, and 17 adolescents (32.1%) reported alcohol use. Table 3 presents descriptive comparisons between adolescents who reported any cannabis use across the four follow-up assessments and those who did not.

Sociodemographic characteristics. Group comparisons revealed no significant differences in race or parent education between cannabis users and non-users (p = ns). However, a significantly smaller proportion of cannabis users were male (13%) compared to non-users (47%), $t(51) = 2.34$, $p = 0.04$, $d = 0.70$.

Self-reported self-regulation. Adolescents who reported cannabis use had lower SRI sum scores compared to non-users, although this difference was not statistically significant, $t(51) = 1.36$, $p = 0.18$, $d = 0.52$.

Neurocognitive performance. No significant differences were observed between cannabis users and non-users on any emotional Go/No-Go metrics (p = ns).

Neural modulation. Adolescents who reported cannabis use at follow-up showed significantly lower average NAcc activation during Run 2 increase trials compared to non-users, $t(51) = 2.21$, $p = 0.03$, $d = 0.85$ (Figure 3).

Table 3

Group Comparison of Cannabis Use vs. Non-Use

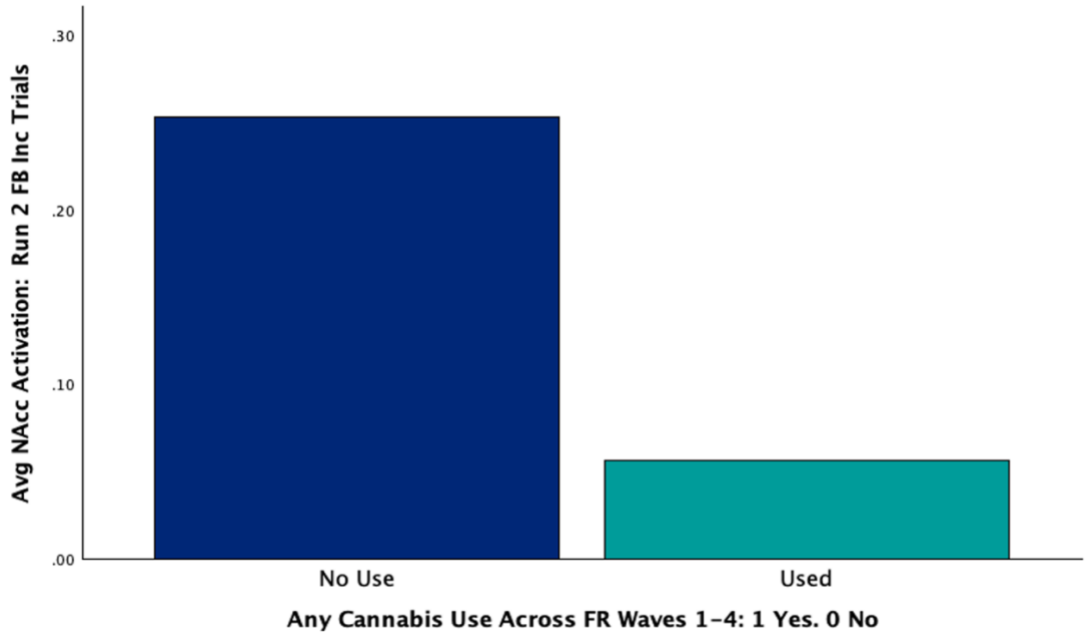
Variable	Any Cannabis Use (n = 8)	No Use (n = 45)	t
	M (SD) or %	*M (SD) or* %	
Sociodemographic Characteristics (%)			
Male Sex	13.00	47.00	2.34*
White	75.00	82.22	0.47
Parent Education	100.00	97.78	-0.42
Self-Report: Self-Regulatory Inventory			
Sum SRI	123.13 (17.80)	131.36 (15.48)	1.36
Neurocognitive: Emotional Go/No-Go			
Happy Face Go, Neutral Face No Go			
False Alarm (%)	19.71	22.38	0.43
Hit RT (M)	381.30 (44.31)	374.55 (38.83)	-0.44
False Alarm RT (M)	327.64 (55.98)	333.37 (57.49)	0.26
Happy Face No Go, Neutral Face Go			
False Alarm (%)	25.96	31.29	0.83
Hit RT (M)	386.22 (36.42)	380.50 (40.18)	-0.38
False Alarm RT (M)	361.69 (90.44)	338.00 (50.72)	-1.02
Neuroimaging: Avg. NAcc Activation During rtfMRI-nf (M)			
Run 1 NoFB Increase Trials	0.25 (.16)	0.31 (.23)	0.63
Run 1 NoFB Decrease Trials	0.09 (.33)	0.22 (.23)	1.35
Run 2 FB Increase Trials	0.06 (.31)	0.25 (.22)	2.21*
Run 2 FB Decrease Trials	0.23 (.10)	0.20 (.21)	-0.44
Run 3 FB Increase Trials	0.12 (.17)	0.17 (.23)	0.67
Run 3 FB Decrease Trials	0.25 (.23)	0.20 (.31)	-0.45
Run 4 NoFB Increase Trials	0.06 (.38)	0.15 (.22)	0.95
Run 4 NoFB Decrease Trials	0.23 (.17)	0.10 (.24)	-1.49

*$p < .05$

Note. *M*=mean; *SD*=standard deviation; parent education: 1 = Some college or more or 0 = High school diploma or less; race/ethnicity =1 = White or 0 = Non-White. Cannabis use was dichotomized as 1 = yes (they used) or 0 = no (they did not).

Figure 3

Average Nucleus Accumbens Activation During Feedback-Based Reward Upregulation by Cannabis Use



Hierarchical Logistic Regression Predicting Cannabis Use

A series of hierarchical logistic regression models were tested using sociodemographic (Model 1), self-report (Model 2), neurocognitive (Model 3), and neuroimaging predictors (Model 4 – Full Model). Each model evaluated a single predictor per domain in stepwise blocks, and variable selection was guided by both theoretical relevance and observed bivariate associations (see Supplementary Table A). Although initial models followed a full four-step structure, exploratory comparisons revealed that removing self-report (SRI sum scores) from the model improved both significance and fit—making it possible to identify a neural predictor as the first significant contributor to cannabis use risk.

As mentioned above and shown in Table 4, the final model included sex (Model 1), neutral face Go hit reaction time from the Emotional Go/No-Go task (Model 2), and average NAcc activation during Run 2 increase trials of the rtfMRI task (Model 3). Lower average NAcc activation during Run 2 increase trials significantly predicted cannabis use at follow-up and the model achieved a significant overall fit. While females were more likely than males to report cannabis use at follow-up, this effect did not reach significance across models. Neurocognitive performance—specifically, neutral face Go hit reaction time—did not contribute meaningfully to prediction in this configuration ($p = 0.65$).

Table 4

Hierarchical Multivariable Logistic Regression Models Predicting Cannabis Use

	Model 1	Model 2	Model 3
	OR (95% CI)	OR (95% CI)	OR (95% CI)
Sociodemographic Characteristic			
Male Sex	-1.76 (0.02, 1.51)	-1.76 (0.02, 1.52)	-2.00 (0.01, 1.41)
Neurocognitive: Emotional Go/No-Go			
Neutral Face Go Hit RT		0.00 (0.98, 1.02)	0.01 (0.99, 1.03)
Neuroimaging: NAcc Activation during rtfMRI-nf			
Run 2 FB Inc Trial			-3.62* (0.00, 0.86)
Nagelkerke R^2	0.11	0.12	0.26
Model χ^2	3.49	3.62	8.36*

*$p < .05$.

Note. OR = odds ratio; CI = 95% confidence intervals. Sociodemographic group: Male vs. Female; NAcc = nucleus accumbens; rtfMRI-nf = real-time functional magnetic resonance imaging neurofeedback.

Additional models (not shown) tested alternative predictor combinations. When paired with self-regulation indices like SRI scores (Appendix F) and Go/No-Go false alarms (Appendix G), average NAcc activation during Run 2 increase trials remained the most robust contributor, consistently trending toward significance. No other self-regulation measure—neurocognitive or self-report—was significantly associated with cannabis use. Sociodemographic factors added little predictive value; only sex contributed modestly to model fit, without reaching significance.

Discussion

The present study examined developmental differences in reward-related self-regulation using self-report, neurocognitive, and neural measures. By moving beyond static assessments and integrating rtfMRI-nf, we sought to offer a more sensitive perspective on how self-regulatory capacity evolves from adolescence to young adulthood and how these differences relate to risk for substance use. Our findings highlight the contribution of dynamic neural indices, alongside traditional measures, in advancing our understanding of self-regulation during this critical developmental window. Key findings indicated that greater volitional NAcc activation during neurofeedback increase trials significantly distinguished young adults from adolescents, above and beyond self-report and neurocognitive indices. Among adolescents, weaker upregulation of the NAcc was associated with subsequent cannabis use, highlighting neural modulation as a potential risk marker not captured by traditional measures.

Developmental Differences in Self-Regulation

Among all modalities, neural differences measured through rtfMRI-nf were the most robust markers of age-related variation. Young adults demonstrated significantly greater average NAcc activation during reward upregulation trials in the rtfMRI-nf task, suggesting more effective recruitment of the reward-control pathway and likely reflecting more mature

frontostriatal connectivity (Casey & Jones, 2010). In contrast, adolescents showed significantly greater NAcc activation during Run 3 decrease trials, consistent with a weaker capacity to downregulate reward-related brain activity. Rather than successfully disengaging from motivational processing, adolescents appeared to maintain or even increase NAcc activation during downregulation, suggesting difficulty exerting volitional control over the reward system when instructed to suppress it. Such findings reflect the dual systems model, suggesting vulnerability begins to decline after mid-adolescence, when both sensation seeking and impulsivity lessen, and regulatory systems strengthen. Our findings reflect this pattern: adolescents showed difficulty downregulating reward-related activity, consistent with this imbalance, whereas young adults' more effective NAcc modulation during upregulation indicates a period of refinement and maturation within reward-control.

Importantly, these patterns support more nuanced frameworks of reward dysfunction. Traditional interpretations often describe the reward system as either hyper-responsive (overactive) or hypo-responsive (underactive), but emerging models—such as those proposed by Zald and Treadway (2017)—highlight that these patterns can vary depending on context. For instance, individuals may show heightened activation in anticipation of immediate rewards but blunted responses when rewards are delayed, effortful, or require regulation. In this study, adolescents showed reduced NAcc activation during reward upregulation trials but elevated activation during downregulation trials. This divergent pattern suggests not a global sensitivity issue, but rather difficulty in modulating reward responses flexibly depending on task demands. Such inflexibility may reflect a broader immaturity in the regulatory calibration of the reward system, with implications for impulsive behavior and risk-taking during adolescence.

Complementing these neural findings, neurocognitive performance also showed significant group differences. Adolescents had significantly higher false alarm rates than young adults for both happy- and neutral-face No-Go trials, indicating a generalized inhibitory control deficit. This extends prior work by Casey and Jones (2010), who found that adolescents struggle particularly to inhibit responses to appetitive cues due to heightened striatal sensitivity. Our results suggest that this difficulty may not be limited to emotionally rewarding stimuli alone, but reflects a broader immaturity in response inhibition. Although both groups showed comparable engagement, as indicated by similar reaction times and hit rates, young adults consistently demonstrated stronger suppression of prepotent responses, highlighting more mature regulatory control. This may translate into real-world challenges, such as difficulty pausing before reacting in emotionally charged or peer-influenced situations.

Finally, self-report data revealed subtler age-related trends. Adolescents scored slightly lower than young adults on the SRI, with this difference trending towards statistical significance. While not a strong differentiator in this sample, this trend is consistent with prior research suggesting gradual improvements in perceived self-regulatory ability with age and cognitive maturation (Memmott-Elison et al., 2020). The limited effect size may reflect developmental variability in introspective accuracy, particularly in younger populations, as well as the influence of social desirability bias, and internalized stereotypes about adolescence (Steinberg et al., 2009; Hare et al., 2008). These findings suggest that while adolescents may be in the early stages of developing self-regulatory insight, subjective ratings may be less sensitive than behavioral or neural indicators.

Collectively, these results underscore the importance of using a multimodal approach when studying developmental self-regulation and the value of neural indices of reward-related

self-regulation. While adolescents may report only modest differences in their regulatory abilities, neurocognitive and neural data reveal significant and objective developmental distinctions. These findings contribute to a growing understanding of how different modalities capture unique aspects of emerging self-regulatory capacity during the transition from adolescence to adulthood.

Predicting Group Membership

Although all regulatory modalities captured age-related variation at the group level, the most robust and consistent self-regulatory predictors of developmental status emerged from neurocognitive and neural domains. Specifically, diminished NAcc activation during reward upregulation was strongly associated with adolescent status, highlighting impaired reward modulation as a key marker of regulatory immaturity. Importantly, neural measures—particularly NAcc activation during reward upregulation—accounted for unique variance in group membership over and above both neurocognitive performance and self-report scores. This suggests that rt-fMRI neurofeedback data offers distinct and added value in identifying developmental differences in self-regulation that are not captured by traditional measures alone.

Neurocognitive data also consistently contributed to group classification. Increased false alarms to neutral cues were among the strongest behavioral predictors of adolescent membership. This suggests that difficulty with inhibitory control in emotionally ambiguous contexts may be particularly sensitive to the developmental stage. While inhibitory control across both affective conditions reflects developmental maturity, performance under neutral conditions may better differentiate age-related variation in cognitive control.

In contrast, self-report measures provided limited predictive utility. Tools such as the SRI captured only modest age-related differences and did not significantly contribute to

distinguishing adolescents from young adults when other variables were considered. This aligns with prior research indicating that introspective measures often fall short in detecting developmental variation in self-regulatory capacity, likely due to self-perception biases or social desirability effects (Steinberg et al., 2009).

Finally, among demographic variables, race/ethnicity consistently predicted group membership more strongly than sex or parent education. This pattern underscores the importance of considering sociocultural context in neurodevelopmental research. While our study did not directly investigate the mechanisms underlying these differences, the finding suggests that structural and cultural factors such as access to resources, chronic stress, or culturally shaped norms may influence developmental trajectories of self-regulation. For example, adolescents from higher socioeconomic backgrounds tend to demonstrate greater future orientation, suggesting that contextual supports like economic stability may facilitate the development of long-term goal setting and regulatory control (Steinberg et al., 2009). Future research should explicitly examine how sociocultural experiences interact with neurobiological development to shape regulatory outcomes.

Predicting Cannabis Use in Adolescence

The longitudinal findings from this study offer compelling evidence that neural indices of reward-related self-regulation—specifically, NAcc activation during reward upregulation—serve as early markers of vulnerability to cannabis use in adolescents. In essence, adolescents who failed to increase NAcc activation in response to reward cues during neurofeedback were more likely to report cannabis use over the next two years. Importantly, Casey and Jones (2010) emphasize that while adolescence is broadly marked by heightened risk-taking tendencies, individual differences in neural development—particularly in top-down regulatory control—may

help to explain why some youth are more prone to substance use and addiction than others. Their work highlights that impaired prefrontal regulation, apparent even prior to drug exposure, may set the stage for long-term vulnerability to alcohol and substance abuse, further supporting the notion that early neural markers can identify high-risk individuals before behavioral patterns are established.

This raises a critical insight—being able to modulate reward system activity may serve as a protective factor, whereas failure to do so might reflect disrupted motivational engagement with goal-directed reward cues, a critical component of reinforcement learning (Dickerson & Adcock, 2021). Adolescents who cannot effectively engage reward circuitry in response to goal-directed cues may find non-drug incentives less motivating, potentially increasing reliance on external, high-salience rewards like substances. At the same time, difficulty downregulating reward responses suggests difficulty disengaging from salient reward cues. This difficulty may mirror the disrupted cost-benefit decision-making processes thought to underlie early substance use initiation (Zald & Treadway, 2017; Martz, 2020). Importantly, Casey and Jones (2010) emphasize that while adolescence is broadly marked by heightened risk-taking tendencies, individual differences in neural development—particularly in top-down regulatory control—may help to explain why some youth are more prone to substance use and addiction than others. Their work highlights that impaired prefrontal regulation, apparent even prior to drug exposure, may set the stage for long-term vulnerability to alcohol and substance abuse, further supporting the notion that early neural markers can identify high-risk individuals before behavioral patterns are established. This pattern may reflect impaired engagement in reinforcement learning processes, which are essential for adapting behavior based on reward outcomes and may contribute to increased vulnerability for cannabis use. In this sense, blunted responsivity could be

conceptualized as a marker of motivational disengagement or reduced incentive salience, rather than structural dysfunction per se. Thus, this study contributes to a growing body of evidence suggesting that it is not merely the presence or magnitude of reward responsivity that matters, but the capacity to flexibly engage and modulate this system in response to task demands.

These findings are consistent with prior work by Martz et al. (2016), which found that young adults who engaged in higher levels of cannabis use showed significantly blunted NAcc responses to monetary reward anticipation, even after accounting for prior and concurrent substance use. These findings could suggest that cannabis use may progressively dampen neural responsivity to non-drug rewards—a pattern consistent with the reward deficiency theory of addiction. From this perspective, the diminished NAcc activation observed at baseline in our adolescent sample may represent an early risk marker that, if compounded by subsequent use, leads to increasingly disrupted reward function over time.

Zald and Treadway (2017) further contextualize this disruption within a broader transdiagnostic framework, noting that dysregulation in reward circuitry—including both hypo- and hyper-responsivity—is implicated in a wide range of psychiatric conditions. From this perspective, adolescents who struggle to appropriately engage or modulate their reward systems may face heightened vulnerability not only to substance use, but to broader forms of psychopathology. Thus, difficulties with flexible reward modulation may represent an early, mechanistic marker of clinical risk, underscoring the real-world relevance of these neural indicators for identifying youth at risk before behavioral symptoms emerge.

Notably, self-reported self-regulation and neurocognitive performance did not significantly predict cannabis use in this sample. Neither SRI scores nor Emotional Go/No-Go metrics (e.g., false alarms or reaction times) contributed meaningfully to predictive models.

These null effects reinforce longstanding concerns about the limited correspondence between self-report, neurocognitive, and neural measures (Dang et al., 2020; Demidenko et al., 2019). Self-report tools may fail to capture the kinds of implicit, motivational deficits implicated in early risk behavior, particularly given adolescents' susceptibility to social desirability and misestimation of their regulatory abilities (Hare et al., 2008; Steinberg et al., 2009). Similarly, while inhibitory control tasks like the Emotional Go/No-Go remain valuable for assessing age-related changes in neurocognitive performance, they may be less sensitive to emerging substance use patterns in relatively low-risk samples. These findings underscore the potential of real-time fMRI-based measures of reward engagement as early indicators of substance use vulnerability.

Implications and Advantages of a Multimodal Approach

Although reward-related self-regulation spans neural, cognitive, and self-report domains, these components are often studied in isolation, limiting insight into how these systems interact during development. This study addressed that gap by adopting a multimodal framework and longitudinal design to assess self-regulatory function across adolescence and early adulthood—a period marked by heightened reward sensitivity and still-maturing control systems (Galvan et al., 2006; Memmott-Elison et al., 2020). Across modalities, discrepancies emerged that underscore why relying on a single source of data can obscure critical insights into developmental processes. For example, although adolescents and young adults reported similar levels of self-regulation on the SRI, these subjective impressions did not align with observed differences in neural activation or inhibitory performance. This mirrors previous findings that self-report measures often fail to capture underlying cognitive and affective processes involved in real-time self-regulation (Dang et al., 2020; Demidenko et al., 2019). These dissociations suggest that introspective assessments

are limited by factors such as social desirability, inaccurate self-appraisal, or culturally shaped self-perceptions (Steinberg et al., 2009).

In contrast, neural measures—particularly NAcc modulation during reward-based upregulation—emerged as robust predictors of both developmental status and longitudinal cannabis use. These findings emphasize the value of rtfMRI-nf as a tool to capture volitional control over affective brain circuits implicated in risk behavior (Greer et al., 2014; Martz et al., 2020). Unlike static measures of brain function or generalized neurocognitive tasks, rtfMRI-nf provides a dynamic index of how well individuals can engage or disengage the reward system in response to goal-directed cues.

Importantly, group differences and predictions in NAcc activation were most pronounced during neurofeedback runs, highlighting the added value of rtfMRI-nf beyond self-report and neurocognitive measures. The presence of feedback, compared to non-feedback conditions, enhanced the ability to detect individual differences in regulatory capacity, capturing additional variation over and above self-report or neurocognitive tasks alone. This has important implications for identifying latent vulnerabilities that may not yet manifest behaviorally but hold predictive power for future substance use or other maladaptive outcomes (Zhao, 2021; Dickerson & Adcock, 2021). These findings are especially relevant in light of neurodevelopmental models emphasizing the maturational imbalance between early-developing subcortical reward systems and slower-developing prefrontal control regions. As Steinberg et al. (2009) demonstrate, adolescents—particularly between ages 13 and 16—show a stronger preference for immediate over delayed rewards, even in the absence of impulsivity per se. This bias aligns with peak NAcc reactivity and reflects a neurobiological tendency to prioritize short-term goals, which may not always be apparent in behavior or self-report. By directly assessing adolescents' ability to

modulate this system, rtfMRI-nf provides a powerful window into how this imbalance functions at the neural level, offering a more precise and mechanistic understanding of self-regulatory development.

This multimodal strategy not only enriches theoretical models of adolescent risk but also informs early detection and intervention. For instance, the high specificity of neurofeedback effects in adolescents (Linden et al., 2021) and the promising associations between volitional brain control and real-world behavior suggest that rtfMRI-nf based tools could complement or even precede traditional interventions (Martz et al., 2020). While variability in task design, instruction, and outcome measures continues to challenge standardization (Hampson & Linden, 2021), rtfMRI-nf remains a powerful tool—providing anatomically precise, real-time access to subcortical processes like those in the NAcc, which are difficult to assess using surface-based methods or traditional neurocognitive tasks (Linden et al., 2021). Its ability to capture volitional control over neural activation not only complements self-report and neurocognitive measures but also holds promise for translational applications in domains such as reward sensitivity and emotion regulation (Dickerson & Adcock, 2021; Martz et al., 2020; Zald & Treadway, 2017). Its translational potential is underscored by early findings linking feedback-based modulation to changes in behavior and emotional functioning (Thibault et al., 2016; Zhao, 2021).

Importantly, the benefits of self-regulation extend beyond the scope of substance use vulnerability. There is consistent evidence that adolescents who demonstrate strong self-regulatory skills tend to fare better across a range of developmental outcomes, including academic achievement, prosocial behavior, and lower rates of emotional and behavioral problems (Memmott-Elison et al., 2020). By identifying neural and behavioral indicators that

precede or underlie these outcomes, multimodal approaches can enhance our capacity to recognize at-risk youth and implement earlier, more tailored interventions.

Limitations

This study offers valuable insights into neural self-regulation across adolescence, yet several limitations merit consideration. First, while the sample size was adequate for initial comparisons, attrition—particularly due to COVID-related disruptions during the fourth substance use follow-up—introduced missing data. This limits the power to detect late-emerging substance use and may have biased longitudinal estimates. While categorizing cannabis use into a binary "any" versus "no use" variable increased statistical power within a relatively small sample, this approach does not capture important distinctions in the frequency, intensity, or problematic pattern of use. As a result, it may conflate meaningful differences between experimental and more persistent use, potentially obscuring more nuanced associations with self-regulatory functioning.

Second, the generalizability of findings is constrained by sample composition. The adolescent group was more racially homogeneous and had higher parental education levels than the young adult group. Although covariates such as race/ethnicity were statistically controlled, developmental patterns of self-regulation and substance use may differ across sociocultural contexts (Demidenko et al., 2019; Somerville et al., 2010). Additionally, we cannot rule out that observed group differences in reward modulation reflect confounding factors like hormonal development, differences in neurotransmitter profiles, or other effects of puberty, which were not directly assessed (Casey & Jones, 2010; Schreuders et al., 2018; Somerville et al., 2010; Steinberg, 2008).

Third, interpretive challenges exist in neurofeedback paradigms—especially for downregulation trials. Due to dense dopaminergic innervation in the NAcc, successful regulation may paradoxically trigger phasic dopamine bursts as a "goal achieved" signal, increasing BOLD activity and masking true downregulation (Dickerson & Adcock, 2021; Hampson & Linden, 2021). This paradox complicates interpretation of neural suppression trials and raises the need for caution in interpretation when BOLD signals do not decline.

Fourth, while the rtfMRI-nf paradigm is promising, its utility was assessed using only a single-session design. Research suggests that modulation capabilities often improve across multiple sessions, and short exposure may underestimate learning capacity (Goebel, 2021; Martz et al., 2020). Furthermore, brief successful upregulation (e.g., seconds-long bursts of NAcc activity) may reflect phasic neurochemical constraints rather than sustained regulation failures (Greer et al., 2014).

Lastly, although neurocognitive tasks like the Emotional Go/No-Go provided behavioral indices of inhibitory control, such tasks often show limited ecological validity and poor predictive power for real-world risk behaviors (Demidenko et al., 2019). Likewise, self-report measures like the SRI, while useful for capturing introspective traits, may suffer from social desirability and low alignment with observed behavior (Dang et al., 2020). Together, these issues call for more holistic, multimodal validation of self-regulation constructs.

Future Directions

Building on these limitations, several avenues offer promising directions for future work. First, longitudinal designs should incorporate multi-session rtfMRI-nf protocols to evaluate whether neural modulation can be improved with practice—and whether such improvements track with behavioral outcomes over time (Goebel, 2021; Martz et al., 2020). In addition,

alternative imaging techniques, such as combined EEG-fMRI, could help disentangle fast dopamine-related events from sustained self-regulatory patterns and provide a richer temporal-spatial profile (Linden et al., 2021; Taylor & Martz, 2022).

Second, examining functional connectivity during neurofeedback is a critical next step, particularly between the PFC and NAcc. Prior work highlights that successful neural modulation is not solely dependent on regional activation, but on the coordinated engagement of regulatory and reward-related brain systems (Greer et al., 2014; Schreuders et al., 2018). Assessing these pathways may offer deeper insight into the neural mechanisms underlying volitional control and better characterize the maturational imbalance thought to drive adolescent self-regulation difficulties.

Third, future designs should address task framing and motivational salience. If reward modulation feels cognitively effortful or lacks intrinsic motivation—especially for adolescents—task engagement may diminish, suppressing NAcc responsivity (Sawyers et al., 2024). Future designs should experiment with more naturalistic or gamified feedback environments to enhance emotional investment and improve learning outcomes (Hampson & Linden, 2021).

Third, neurofeedback paradigms remain under-standardized and the field must continue addressing methodological variability. rtfMRI-nf studies differ in targeted brain regions, feedback presentation, instructions, and session structure, which hinders cross-study comparisons. As efforts to standardize protocols and reporting evolve (Linden et al., 2021), future research should align with these recommendations while contributing empirical data to refine best practices. Standardization will be key to improving the field's reproducibility and clinical translatability.

Fourth, our findings underscore the relative strength of neural predictors over traditional neurocognitive or self-report metrics for identifying adolescents at risk for substance use. However, pinpointing which psychological traits (e.g., reward sensitivity, future orientation) best align with these neural markers remains a critical challenge (Demidenko et al., 2019). Future work should explore these dimensions to better map individual differences in self-regulation onto real-world outcomes like substance use. Notably, a higher proportion of cannabis users in our sample identified as female. This finding aligns with recent national data showing that marijuana use was slightly higher among adolescent females than males across multiple grade levels in 2024 (Miech et al., 2025). While the long-term stability of this pattern remains unclear, it warrants further investigation, as it may reflect shifting usage norms, contextual influences, or sex-specific mechanisms of self-regulation not fully captured by current models.

Finally, intervention development is a key translational target. rtfMRI-nf holds promise not only for measuring but also for enhancing reward-related self-regulation. For instance, targeting NAcc activity through repeated feedback could be incorporated into personalized interventions designed to strengthen volitional control over impulsive behaviors (Martz et al., 2020; Linden, 2021). While such approaches remain resource-intensive, Linden (2021) notes that if fMRI-based interventions were to significantly improve outcomes like substance abstinence, the downstream gains in productivity, healthcare cost savings, and quality of life could well justify their expense. Complementary strategies might focus on providing adolescents with safe, structured opportunities for risk-taking which could help channel sensation seeking in adaptive ways (Casey & Jones, 2010). Looking forward, if strong, replicable effects can be demonstrated, future efforts might explore more scalable formats—such as EEG-guided interventions or mobile applications that simulate feedback-like regulation without real-time imaging. However,

establishing robust neural-behavioral associations through fMRI remains a critical first step before adapting these techniques for more accessible and affordable use across diverse settings (Taylor & Martz, 2022).

In conclusion, this study examined developmental differences in reward-related self-regulation using a multimodal approach that integrated self-report, neurocognitive, and neuroimaging data. Neural indices—specifically NAcc modulation via rtfMRI-nf— not only complemented these other modalities but accounted for additional variance in both age group classification and longitudinal cannabis use. This suggests that neuroimaging may offer a more sensitive indicator of individual differences in self-regulatory capacity. This distinction is especially critical during adolescence, when motivational drives peak and regulatory systems are still maturing. While some dysregulation in reward-related self-regulation is normative, adolescents with reduced ability to volitionally regulate reward-related brain activity may be at an elevated risk for cannabis use. These findings carry important public health implications and may inform more individualized prevention and intervention programs aimed at strengthening reward-related self-regulation during this pivotal developmental window.

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Appendix A

Preliminary Correlations Used for Predictor Selection

Table A1

Adolescent Pearson Correlation

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1. White																									
2. Parent Edu	.27																								
3. Male	.24	.12																							
4. SRI Sum	-.16	-.20	.02																						
5. Run 1 Dec	.14	.03	.16	.20																					
6. Run 1 Inc	.17	.08	-.03	.13	.39**																				
7. Run 2 Dec	.07	-.02	-.02	.05	.46***	.60 ***																			
8. Run 2 Inc	.01**	-.09	.03	.15	.35**	.44***	.09																		
9. Run 3 Dec	.07	-.05	.10	.28*	.20	.30*	.49***	.18																	
10. Run 3 Inc	.08	-.12	-.08	-.20	.32*	.37*	.16	.35**	-.12																
11. Run 4 Dec	.01	-.02	-.14	.19	-.06	.27*	.18	.24	.19	.16															
12. Run 4 Inc	-.06	.01	-.08	.14	.29*	.33*	.09	.56***	.17	.44**	.18														
13. Hgo Hits	.18	.14	-.01	.00	-.01	-.01	-.02	-.03	-.03	-.14	-.08	-.03													
14. Hgo False Alarms	-.04	-.21	.08	.00	.36**	.26	.28*	.21	.06	.08	.01	.15	-.47***												
15. Hgo Hits RT	-.16	-.03	.10	.04	.19	-.05	-.10	.01	-.10	-.11	-.03	-.03	-.14	.14											
16. Hgo False Alarms RT	-.17	-.05	.15	-.11	-.19	-.07	-.34*	-.06	-.23	-.09	-.06	-.06	.04	-.01	.54***										
17. Ngo Hits	-.09	.43***	.02	.02	-.12	-.02	-.06	-.15	-.03	-.23	-.08	-.03	.06	-.10	-.01	.00									
18. Ngo False Alarms	-.05	-.31**	.24	.01	.41**	.19	.25	.30**	.14	.14	.02	.23	-.45**	.72***	.25	.05	-.55***								
19. Ngo Hits RT	-.08	.00	-.01	.11	.13	-.05	-.07	-.02	-.02	-.09	-.01	-.01	.04	-.20	.83***	.46 **	-.07	.02							
20. Ngo False Alarm RT	-.02	-.00	.15	-.07	.14	.04	.05	.04	.04	-.07	.03	-.09	.03	.01	.77***	.47***	-.16	.15	.78***						
21. Sub Use 1	-.00	.05	-.01	-.20	-.20	.03	.02	-.22	-.11	-.13	.21	-.15	.11	-.04	.16	.11	.04	-.10	.11	.38**					
22. Sub Use 2	.05*	.12	.00	-.02	-.21	-.20	-.05	-.09	.05	-.22	.16	-.26	-.05	.02	.03	-.05	.14	-.07	.02	.09	.43**				
23. Sub Use 3	-.21	-.30	-.27	.19	-.00	-.08	-.05	-.02	.08	-.18	.07	-.05	.07	-.01	.07	-.05	.15	-.12	.11	.01	.33	.40*			
24. Sub Use 4	-.16	-.27	-.19	.14	-.21	-.01	-.02	-.12	.17	-.19	.31	-.25	.12	.00	.06	.12	.16	-.20	.01	.07	.48**	.54 **	.71***		
25. Sub Use 1234	.10	-.17	-.06	.09	-.23	-.05	-.02	-.07	.09	-.22	.22	-.25	-.01	-.04	-.02	-.14	.13	-.13	.02	.03	.43**	.76 ***	.73***	.88***	

*p < .05, **p < .01, ***p < .001

Table A2

Young Adult Pearson Correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. White																				
2. Parent Edu	-.01																			
3. Male	-.17	-.13																		
4. SRI Sum	.27*	-.00	-.19																	
5. Run 1 Dec	-.03	.03	-.15	.16																
6. Run 1 Inc	.24*	-.01	.01	.09	.40***															
7. Run 2 Dec	-.18	-.12	.10	-.21	.33**	.23*														
8. Run 2 Inc	.17	-.11	.26*	.06	-.07	.34**	-.00													
9. Run 3 Dec	.03	-.19	.13	-.23*	.01	.01	.26*	.22												
10. Run 3 Inc	.14	-.12	-.05	.13	.25*	.53***	.20	.44***	-.16											
11. Run 4 Dec	.14	-.13	-.07	-.15	.08	-.09	.06	.03	.23	-.10										
12, Run 4 Inc	-.04	-.18	-.04	.17	.14	.24*	-.12	.13	.02	.15	-.33**									
13. Hgo Hits	.15	.33**	-.12	.02	-.07	.03	-.10	-.05	-.00	-.06	-.00	-.05								
14. Hgo False Alarms	-.10	-.22	.05	-.02	-.01	-.03	.09	.19	.03	.09	-.06	.06	-.77***							
15. Hgo Hits RT	-.22	-.01	.00	-.06	-.06	-.04	.07	-.04	.18	-.06	-.24*	.04	.16	-.17						
16. Hgo False Alarms RT	-.18	.09	-.05	.10	.40**	-.07	.08	-.18	-.05	-.22	-.03	-.08	-.06	.02	.37**					
17. Ngo Hits	.13	-.10	-.15	.20	.26*	.09	.06	-.06	.16	.07	.02	.08	-.03	-.03	-.08	-.07				
18. Ngo False Alarms	.02	.20	.08	-.12	-.21	-.04	.06	.14	.04	-.03	-.07	-.05	.04	.38**	.08	.09	-.49***			
19. Ngo Hits RT	-.21	-.06	-.00	-.07	-.10	-.14	.09	-.04	.26*	-.22	-.22	.10	-.01	-.03	.83***	.20	-.15	.11		
20. Ngo False Alarms RT	-.27*	.07	.30*	-.28*	-.13	-.12	.16	.07	.24*	-.23	-.14	-.05	-.02	-.02	.56***	.34**	-.34**	.28*	.57***	

*p < .05, **p < .01, ***p < .001

Appendix B

Alternative Neural Predictor Hierarchical Multivariable Logistic Regression Model Predicting Group Membership

	Model 1		Model 2		Model 3		Model 4	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Sociodemographic Characteristic								
White	-1.13**	(0.14, 0.73)	-1.20**	(0.13, 0.69)	-1.23**	(0.12, 0.73)	-1.39**	(0.10, 0.64)
Self-Report: Self-Regulatory Inventory								
Sum SRI			0.02	(1.00, 1.05)	0.02	(1.00, 1.05)	0.02	(0.99, 1.05)
Neurocognitive: Emotional Go/No-Go								
Neutral Face Go False Alarms					-6.40***	(0.00, 0.04)	-6.32***	(0.00, 0.05)
Neuroimaging: NAcc Activation								
Run 3 FB Inc Trial							2.31*	(1.37, 74.38)
Nagelkerke R^2	0.08		0.12		0.30		0.34	
Model χ^2	8.05**		11.52**		30.94***		36.20***	

*$p < .05$. **$p < .01$. ***$p < .001$

Note. OR = odds ratio; CI = 95% confidence intervals. Sociodemographic group: White vs. Non-White; NAcc = nucleus accumbens; rtfMRI-nf = real-time functional magnetic resonance imaging neurofeedback.

Appendix C

Alternative Neurocognitive Predictor Hierarchical Multivariable Logistic Regression Model Predicting Group Membership

	Model 1		Model 2		Model 3		Model 4	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Sociodemographic Characteristic								
White	-1.13**	(0.14, 0.73)	-1.20**	(0.13, 0.69)	-1.26**	(0.12, 0.69)	-1.43**	(0.10, 0.61)
Self-Report: Self-Regulatory Inventory								
Sum SRI			0.02	(1.00, 1.05)	0.02	(1.00, 1.05)	0.01	(1.00, 1.05)
Neurocognitive: Emotional Go/No-Go								
Happy Face Go False Alarms					-5.23**	(0.00, 0.14)	-5.20***	(0.00, 0.13)
Neuroimaging: NAcc Activation								
Run 3 FB Inc Trial							2.42*	(1.57, 81.02)
Nagelkerke R^2	0.08		0.12		0.25		0.30	
Model χ^2	8.05**		11.52**		25.21***		31.36***	

*$p < .05$. **$p < .01$. ***$p < .001$

Note. OR = odds ratio; CI = 95% confidence intervals. Sociodemographic group: White vs. Non-White; NAcc = nucleus accumbens; rtfMRI-nf = real-time functional magnetic resonance imaging neurofeedback.

Appendix D

Alternative Sociodemographic Predictor Hierarchical Multivariable Logistic Regression Models Predicting Group Membership

	Model 1		Model 2		Model 3		Model 4 (Full Model)	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Sociodemographic Characteristic								
Male Sex	0.32	(0.67, 2.81)	0.37	(0.70, 3.00)	0.68	(0.87, 4.51)	0.80	(0.95, 5.22)
Self-Report: Self-Regulatory Inventory								
Sum SRI			0.02	(1.00, 1.05)	0.02	(0.99, 1.05)	0.02	(0.99, 1.05)
Neurocognitive: Emotional Go/No-Go								
Neutral Face Go False Alarms					-6.76***	(0.00, 0.03)	-6.78***	(0.00, 0.03)
Neuroimaging: NAcc Activation								
Run 3 FB Inc Trial							2.13*	(1.14, 61.72)
Nagelkerke R^2	0.01		0.04		0.25		0.29	
Model χ^2	0.76		3.86		26.06***		30.57***	

*$p < .05$. **$p < .01$. ***$p < .001$

Note. OR = odds ratio; CI = 95% confidence intervals. Sociodemographic group: Male vs. Female; NAcc = nucleus accumbens; rtfMRI-nf = real-time functional magnetic resonance imaging neurofeedback.

Appendix E

Alternative Sociodemographic Predictor Hierarchical Multivariable Logistic Regression Model Predicting Group Membership

	Model 1		Model 2		Model 3		Model 4	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Sociodemographic Characteristic								
Parent Education	-1.23	(0.06, 1.44)	-1.20	(0.06, 1.49)	-1.36	(0.04, 1.74)	-1.15	(0.04, 2.39)
Self-Report: Self-Regulatory Inventory								
Sum SRI			0.02	(1.00, 1.05)	0.02	(0.99, 1.05)	0.01	(0.99, 1.04)
Neurocognitive: Emotional Go/No-Go								
Neutral Face Go False Alarms					-6.40***	(0.00, 0.04)	-6.92***	(0.00, 0.03)
Neuroimaging: NAcc Activation								
Run 2 FB Inc Trial							1.98*	(1.13, 46.32)
Nagelkerke R^2	0.03		0.06		0.26		0.30	
Model χ^2	2.76		5.63		27.15***		31.90***	

*$p < .05$. **$p < .01$. ***$p < .001$

Note. OR = odds ratio; CI = 95% confidence intervals. Sociodemographic group: High school diploma or less vs. Some college or more; NAcc = nucleus accumbens; rtfMRI-nf = real-time functional magnetic resonance imaging neurofeedback.

Appendix F

Additional Predictor Hierarchical Multivariable Logistic Regression Model Predicting Cannabis Use

	Model 1		Model 2		Model 3		Model 4	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Sociodemographic Characteristic								
Male Sex	-1.76	(0.02, 1.51)	-1.74	(0.02, 1.57)	-1.77	(0.02, 1.55)	-2.03	(0.01, 1.44)
Self-Report: Self-Regulatory Inventory								
Sum SRI			-0.03	(0.92, 1.02)	-0.34	(0.92, 1.02)	-0.27	(0.92, 1.03)
Neurocognitive: Emotional Go/No-Go								
Neutral Face Go Hit RT					0.01	(0.99, 1.03)	0.01	(0.99, 1.03)
Neuroimaging: NAcc Activation								
Run 2 FB Inc Trial							-3.33	(0.00, 1.27)
Nagelkerke R^2	0.11		0.16		0.17		0.28	
Model χ^2	3.49		5.13		5.45		9.26	

*$p < .05$. **$p < .01$. ***$p < .001$

Note. OR = odds ratio; CI = 95% confidence intervals. Sociodemographic group: Male vs. Female; NAcc = nucleus accumbens; rtfMRI-nf = real-time functional magnetic resonance imaging neurofeedback.

Appendix G

Alternative Neurocognitive Predictor Hierarchical Multivariable Logistic Regression Model Predicting Cannabis Use

	Model 1		Model 2		Model 3		Model 4	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Sociodemographic Characteristic								
Male Sex	-1.76	(0.02, 1.51)	-1.74	(0.02, 1.57)	-1.68	(0.02, 1.73)	-2.02	(0.01, 1.43)
Self-Report: Self-Regulatory Inventory								
Sum SRI			-0.32	(0.92, 1.02)	-0.32	(0.92, 1.02)	-0.28	(0.92, 1.03)
Neurocognitive: Emotional Go/No-Go								
Neutral Face Go False Alarms					-0.84	(0.00, 56.09)	0.79	(0.01, 795.64)
Neuroimaging: NAcc Activation								
Run 2 FB Inc Trial							-3.48	(0.00, 1.21)
Nagelkerke R^2	0.11		0.16		0.17		0.28	
Model χ^2	3.49		5.13		5.25		9.08	

*$p < .05$. **$p < .01$. ***$p < .001$

Note. OR = odds ratio; CI = 95% confidence intervals. Sociodemographic group: Male vs. Female; NAcc = nucleus accumbens; rtfMRI-nf = real-time functional magnetic resonance imaging neurofeedback.