Sleep and Self-Regulation:

A Longitudinal Analysis Across Adolescence

Mohammad S. Aqil

Department of Psychology, University of Michigan

Mentor: Dr. Daniel Keating

Co-Mentor: Dr. Edward Huntley

Author Note

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science with Honors in Biopsychology, Cognition, and Neuroscience from the University of Michigan in 2023

Abstract

This study aimed to investigate the relationship between sleep and self-regulation during adolescence, a critical period marked by significant changes in brain structure and function. Self-regulation is essential for individuals to achieve personal goals and maintain overall well-being. Essential aspects of self-regulation include response inhibition and sustained attention. A Parametric Go/No-Go task was utilized to analyze self-regulation and the Munich Chronotype Questionnaire to assess sleep quality via social jetlag and habitual sleep duration. A total of 1,487 participants were drawn from the Adolescent Health Risk Behavior (AHRB) study, which incorporated a longitudinal multi-wave design to evaluate adolescent risk behaviors and related psychosocial constructs. Results showed that longer habitual sleep duration was associated with faster and more consistent reaction times on the task, reflecting better self-regulatory information-processing. While few modest effects were present for social jetlag, no other strong relationships were found between sleep and self-regulation. Furthermore, sleep quality characteristics did not significantly impact performance on the parametric aspect of the task. Covariate effects were present, with factors such as parent level of education, race, and sex influencing various performance parameters on the task. The study's findings suggest that inadequate sleep duration during adolescence may result in a diminished capacity for self-regulatory information-processing. Further research is necessary to determine the practical implications of these findings. Therefore, at the current time, it is recommended that parents and educators prioritize promoting healthy sleep habits, specifically sufficient sleep duration, which encourages effective self-regulatory abilities in this pivotal developmental stage.

Keywords: sleep, self-regulation, go/no-go task, adolescence

Acknowledgments

I would like to express my gratitude to a number of individuals who have played crucial roles in my journey toward completing this honors thesis. First and foremost, I want to thank my mentor and Principal Investigator, Dr. Daniel Keating, for his thoughtful advice and unwavering encouragement throughout this process. I am grateful for the opportunities he has provided me to contribute to the AHRB study in a meaningful way. I also extend my heartfelt gratitude to Dr. Edward Huntley, my co-mentor and AHRB Study Coordinator, who has been an invaluable resource for me throughout the last four years of this journey. His guidance, patience, and support have been instrumental in helping me navigate this world of research. Furthermore, I am indebted to Dr. Josh Errickson, Dr. Bram Zandbelt, and Maggie Meyer for their assistance and direction related to the statistical analyses conducted in my thesis. Their expertise and feedback were critical in shaping my analysis and interpretation of the results. Additionally, I want to express my appreciation to Dr. Michael Demidenko, Dr. Alexander Weigard, and the rest of the faculty at AHRB for their insightful involvement during the review process. Their feedback has greatly improved the conceptualization of this thesis. Finally, I would like to acknowledge the love and support of my family and friends, as their never-ending encouragement has sustained me throughout this process, and I am grateful for their presence in my life.

Sleep and Self-Regulation: A Longitudinal Analysis Across Adolescence

Self-regulation refers to the process of controlling one's thoughts, emotions, and behaviors in order to reach personal goals and maintain well-being (Baumeister et al., 2006). This concept encompasses a range of processes that allow individuals to manage their impulses, adapt to changing environments, and pursue long-term goals. It is part of executive functioning, which can be divided into several components, including inhibition, working memory, and cognitive flexibility (Diamond, 2013; Miller & Cohen, 2001). Inhibition refers to the cognitive processes that are involved in controlling attention and inhibiting responses (Miyake et al., 2000). Whereas, working memory includes concurrent storage and manipulation of information (Baddeley & Hitch, 1994). Finally, cognitive flexibility refers to a plethora of different processes that involve the ability to change perspectives and think creatively (Davidson et al., 2016). All of these components contribute to the development of self-regulation in adolescence. This is a crucial development period due to the significant changes in brain structure and function that occur during this time (Blakemore & Choudhury, 2006).

Self-regulation and the Go/No-Go Task

This study focuses on self-regulation via response inhibition and sustained attention on a Parametric Go/No-Go (GNG) task. The GNG paradigm is a well-established and widely used tool in the field of neuroscience and psychology to assess response inhibition and sustained attention. The classical GNG task involves the presentation of two equally probable stimuli, where participants are instructed to respond to one (“go trial”) and refrain from responding to the other (“no-go trial”). The randomized presentation of stimuli maximizes uncertainty and engages multiple cognitive processes. The task also acts as a reliable measure of executive function in inhibitory processes (Thomas et al., 2016). The GNG task is commonly used in various settings, including clinical and experimental settings, to assess attentional control and inhibitory processes (Gillespie et al., 2022). The three primary measures obtained from the task are reaction time (RT), commission error (false alarms on no-go trials), and omission error (misses on go trials), which provide valuable insights into an individual's attentional control and response inhibition abilities. Other helpful measures include correct responses to go-trials (hits) and no-go trials (correct rejections).

Response inhibition is a crucial aspect of executive control, as it plays a pivotal role in the regulation of motor responses and goal-directed behavior (Diamond, 2012). Adolescence is a critical period for the development of response inhibition and related cognitive processes as young people navigate complex social and academic environments that require effective regulation of impulsive behavior (Crone & Dahl, 2012). Response inhibition is a complex concept that encompasses multiple processes, with the important ones being cancellation and withholding. Cancellation involves stopping a response that has already begun and is typically assessed through the use of the stop-signal task. In contrast, withholding involves preventing a prepared response that has not yet been initiated, and various tasks, such as the GNG task, Conners' continuous performance task, and the sustained attention to response task are used to measure this type of inhibition (Wright et al., 2014). This study will focus on the withholding aspect of response inhibition as evaluated by the GNG task. Response impulsivity and inhibition can be assessed via commission errors, which refer to the incorrect responses made to no-go trials on the GNG and similar tasks (Keilp et al., 2005; Patton et al., 1995; Spinella, 2004). By examining commission errors, one can gain a better understanding of the extent to which individuals are able to withhold inappropriate responses and the factors that influence the development of response inhibition in adolescence.

Sustained attention is another vital aspect of cognitive function that has been extensively researched, particularly in the context of adolescent development. Sustained attention is essential for academic and occupational success, and it has been shown to develop in adolescents during this critical period of brain development (McAvinue et al., 2012). This ability to maintain attention and avoid distractions is essential for academic achievement, especially in the areas of reading, writing, and numeracy (Lawrence et al., 2021). The GNG task can also provide insight into an individual's ability to sustain attention as omission errors, or the failure to respond to go stimuli, reflect attentional lapses during the task.

Signal Detection Theory

Other performance measures may also be derived from the GNG task besides error rates and RT parameters. The GNG task is closely related to signal detection theory (SDT). SDT is a psychological framework for understanding the decision-making process regarding the presence or absence of a stimulus in noisy environments (Green & Swets, 1966). In the GNG task, the two stimuli presented (go and no-go trials) can be viewed as signals. The participant's responses then represent their decisions about the presence or absence of these signals. SDT provides a way to quantify the participant's sensitivity to the stimuli (their ability to discriminate the signal from noise) using the d prime (d’) metric. In SDT, hits and false alarms are used to calculate d’, while misses and correct rejections also remain as essential measures of response accuracy (Green & Swets, 1966; Miller, 1996). The goal of SDT is to provide a mathematical framework for understanding the relationship between these four measures and to use this understanding to obtain a more comprehensive understanding of an individual's performance on the GNG task.

The d' metric has gained popularity in the literature on cognitive tasks such as the GNG task due to its ability to provide a standardized measure of signal detection sensitivity that is not influenced by response bias; response bias refers to a participant's tendency to respond in a certain way, regardless of the presence or absence of the signal (Stanislaw & Todorov, 1999). By utilizing d', one can evaluate sensitivity and response bias to obtain an accurate measure of participants' performance. This is why d' is a valuable metric that may enhance the understanding of cognitive processes that are involved in the GNG task. Furthermore, it may allow for a more thorough analysis of the influence that health-related issues, such as sleep deprivation, may have on an individual’s task performance.

Sleep in Adolescence

Studies have found that sleep plays a crucial role in adolescent cognitive health, enhancing executive functioning and behavioral regulation (Tarokh et al., 2016). However, factors such as academic pressure, social obligations, and increased technology use, make adolescents at risk for decreased sleep quality (Owens et al., 2010). It has been estimated that up to 70% of adolescents in the U.S. sleep less than eight hours a night (Zee et al., 2014), which falls short of the recommended 8-10 hours (Paruthi et al., 2016). Sleep deficiency has been associated with imbalances between affective and cognitive control systems in adolescents. This may lead to difficulties in regulating behavior, emotions, and attention (Telzer et al., 2013). As sleep-related interventions have the potential to improve sleep quality, sleep may function as a modifiable factor in adolescent cognitive functioning, which emphasizes the need for future research in this area. Therefore, it is crucial to investigate the relationship between sleep and response inhibition in adolescents to understand better and prevent negative cognitive and behavioral outcomes.

Sleep and Self-regulation

Moreover, research has indicated that adolescents are at a heightened risk for various negative cognitive health consequences, including impulsivity. This can be attributed, in part, to developmental delays in their brain's cognitive control pathways (Somerville et al., 2010). Additionally, the onset of puberty can lead to sleep deprivation, which has also been linked to these outcomes (Hagenauer 2009). Impulsivity has been linked with many important behavioral outcomes in adolescence. Impaired response inhibition, being a leading cause for impulsivity (Olmstead, 2006), has been found to be a predictor of alcoholism and illicit drug use in adolescents who are at risk for these types of disorders (Meyers et al., 2018; Nigg et al., 2006). The strong associations between impulsivity, response inhibition, and related constructs in the crucial developmental period of adolescence indicate the need for further research into the role of sleep in these relationships.

To date, the amount of research that has been conducted utilizing GNG tasks to evaluate associations between sleep and self-regulation is sparse. These studies found mixed associations between sleep and GNG task performance, potentially due to study design limitations, such as insufficient task difficulty (Tashjian et al., 2017; Sagaspe et al., 2012; Schapkin et al., 2006). The specific type of parametric GNG task used in this study allows for a unique opportunity to evaluate the role of sleep in response inhibition via multiple difficulty levels (Durston et al., 2002; van Belle et al., 2014). No longitudinal studies were found to have been conducted focusing on response inhibition (specifically withholding) and sleep in adolescence using this type of GNG task. However, other forms of response inhibition (cancellation) have been studied using the SST and sleep in longitudinal adolescent samples (Wong et al., 2010).

This study aims to provide a deeper understanding of the role of sleep in self-regulation during adolescence, as evaluated by the GNG task. It was hypothesized that (1) individuals with higher sleep quality, as indicated by longer sleep duration and smaller social jetlag, will exhibit better overall accuracy on the task. Additionally, (2) both commission and omission error rates will decrease as sleep quality increases, leading to better overall accuracy on the task. Lastly, it was expected that (3) the impact of task difficulty on performance would be greater for individuals with worse sleep quality, with more challenging levels of the task having a more negative impact on their performance compared to those with higher sleep quality. These hypotheses were tested by evaluating the sleep quality of individuals, analyzing the participants' performance on the parametric GNG task, and controlling for potentially confounding variables such as parent level of education, race, sex, and differences in task administration.

Methods

Participants were from the Adolescent Health Risk Behavior (AHRB) study, a longitudinal study designed to characterize behavioral and cognitive correlates of adolescents' health risk behavior trajectories. The first wave of the AHRB study consisted of a nonprobability sample of 10th and 12th-grade students recruited from nine public school districts across eight Southeastern Michigan counties, using a quota sampling approach to increase socioeconomic, racial, and ethnic diversity. Throughout the course of the study, the participants' ages ranged from 14 to 22 years old, and their educational levels varied from 10 to 16 years. Of 2,278 who provided parental consent, 2,017 (88.5%) participated in the first wave (non-participation was primarily due to absence on the day of in-school assessments). Furthermore, of these participants, a total of N = 1,487 completed the GNG task and met performance criteria which will be discussed later.

Table 1

Sample Characteristics of Waves 1-3

	W1	**W2**	**W3**
	(*N* = 1487)	(*N* = 799)	(*N* = 785)
	M (SD)	*M (SD)*	*M (SD)*
Age (years)	16.7 (1.1) 14-19	18.3 (1.2)	19.3 (1.2) 17-22
Years of Education	11.02 (1.0) 10-12	12.5 (1.2)	13.6 (1.3) 11-16
	N (%)	*N* (%)	*N* (%)
Female	851 (55.2)	481 (60.2)	476 (60.6)
Race			
White Non-Hispanic	866 (56.1)	500 (62.6)	480 (61.1)
Black Non-Hispanic	338 (21.9)	146 (18.3)	152 (19.4)
Hispanic	112 (7.3)	41 (5.1)	51 (6.5)
Other	227 (14.7)	112 (14)	102 (13)
Parent Level of Education			
High School or Less	349 (24.2)	132 (19.6)	118 (17.7)
Some College	416 (28.9)	174 (25.8)	165 (24.7)
College	429 (29.8)	219 (32.4)	232 (34.8)
Beyond College	247 (17.1)	150 (22.2)	152 (22.8)

Note. Demographic characteristics of participants for each wave.

Procedure

Survey procedures were designed to protect students' privacy by allowing confidential and voluntary participation and were approved by the University of Michigan Institutional Review Board. Parental consent and adolescent assent for participation were actively obtained. Eligible participants were initially contacted by mail and provided with a study brochure and an informed consent document that could be signed and returned to the student's school. A total of 5,009 eligible participants took a consent form home that required active parental consent to participate, and 2,278 (45.8%) students returned the parental consent forms to their schools. Most of those simply did not return the forms; parents rarely declined participation.

In Wave 1 (W1; March 2015 - February 2016; N = 1,487), data were collected in schools during class periods or an elective (excluding one school, collected after the school day due to scheduling constraints) via self-report surveys administered using computer-assisted self-interviewing (Illume version: 5.1.1.18300). Surveys assessed engagement in risk behavior and a range of related psychosocial constructs. Cognitive tasks were administered in a second school session within one week of the first session, with task order randomly assigned to participants. Upon completion, participants were compensated with $50 for their time. Two web-based computer-assisted self-interview questionnaires were conducted in follow-up assessments, Wave 2 (W2; February 2017 – October 2017; N = 799) and Wave 3 (W3; February 2018 – October 2018; 250 N = 785). Furthermore, 56% of the original sample (1,130 individuals) completed at least one of these follow-up assessments. The response rate for each follow-up was 45%, similar to the nationally recognized Monitoring the Future panel survey (Patrick et al., 2018). Table 1 provides the demographic characteristics of the sample at each wave. The limitations section will address the impact of attrition and the change in the mode of administration.

Munich Chronotype Questionnaire

The Munich Chronotype Questionnaire (MCTQ) is a self-administered questionnaire that evaluates an individual's preferred circadian rhythm, also known as their chronotype, as well as the misalignment between their internal biological clock and their external environment, referred to as social jetlag. Developed by Roenneberg et al. (2003), the MCTQ consists of 19 questions assessing various aspects of sleep and wakefulness. Participants are asked to indicate their typical bedtime and waking time on both weekdays and weekends, as well as their preferred bedtime and waking time. They also rate their sleep quality and the ease with which they fall asleep and wake up. The MCTQ is widely used in sleep research to assess an individual's chronotype and to evaluate social jetlag. The two sleep characteristics of focus for this study were habitual sleep duration and social jetlag. Social jetlag is calculated as the difference between the midpoint of sleep on weekends and weekdays, whereas habitual sleep duration is a weighted average of sleep time on weekdays and weekends. Understanding an individual's sleep patterns and social jetlag can provide valuable insights into the impact of sleep and wakefulness on self-regulation in adolescents.

Parametric GNG task

Of the 2,017 participants who enrolled in the study, N = 1,487 (74%) were able to complete the GNG to a sufficient standard. Unsatisfactory completion was due to time constraints in the classroom setting. In this task, there are five runs that last 3 minutes and 56 seconds each. Each run contained 57 trials, with 75% of the total trials as go trials, resulting in 70 total no-go trials across all runs. The stimulus duration was 500 ms and the interstimulus interval was 3500 ms (total trial length 4000 ms). Furthermore, “foil trials" (no-go trials after two or four go trials) were also included to prevent subjects from learning the pattern. The parametric variation in this task is that the number of preceding go trials is varied by including one, three, or five go trials before a no-go trial, representing increasing levels of task difficulty and allowing analysis of the effects of preceding context on response inhibition. At least 20 of each type of trial is present per subject. The order of presentation for the different types of no-go trials was pseudorandomized (Durston et al., 2002; van Belle et al., 2014). Individuals with less than 200 available trials or less than 55% overall accuracy were flagged as invalid profiles and removed from the analysis. These decisions were based on maintaining consistency with similar literature (Weigard et al., 2019).

Analyses

A thorough statistical analysis was performed to investigate the associations between sleep characteristics and a range of performance measures in the GNG. A mixed-effects linear regression model approach was employed to account for individual and group-level factors in the analysis. The model dependent variables included (1) d', (2) overall accuracy, (3) commission error, (4) omission error, (5) parametric variation, (6) mean RT, and (7) RT variability, each selected to provide a nuanced understanding of the relationship between sleep and task performance. Models 6 and 7 focused on the participants' RT on hits only. The predictors incorporated in the analysis were habitual sleep duration, social jetlag, mode of administration, age (as a proxy for wave), sex, race, and parent level of education, chosen based on their potential relevance to the relationship and controlled for their potential confounding effects. These predictors were the same for each model except for the parametric variation model (5); which utilized commission errors as the dependent variable, included the three levels of the task as predictors, and analyzed interactions between the levels and sleep characteristics. The margins command was used to analyze the effects of these predictors, examine interactions in the parametric variation model, and visualize interesting findings. This enabled a more in-depth understanding of the mechanisms by which sleep characteristics might influence task performance and self-regulation.

Given the multiple models conducted in this study, a correction for multiple comparison errors was performed using the Benjamini-Hochberg (BH) correction method to control the false discovery rate (Benjamini & Hochberg, 1995). This correction was applied separately to the self-regulatory models (1-5) and information-processing models (6 and 7), as RT does not directly evaluate self-regulatory behavior on the task. This approach ensured the validity of the results and reduced the risk of type I errors. It is important to note that although this method provides corrected *p*-values, these are not displayed; all *p*-values referred to in this study are original, uncorrected *p*-values, whereas significance post-correction is explicitly stated or indicated by bolded coefficients within tables.

Results

Summary Data

Table 2

Summary of Sleep and GNG Task Performance

	M (SD)
Sleep Duration (hr)	7.47 (1.28)
Social Jetlag (hr)	2.46 (1.39)
d-prime (d')	0.00 (1.87)
Overall Accuracy (%)	86.34 (8.34)
Commission Errors (%)	10.38 (5.15)
Omission Errors (%)	3.30 (5.69)
Mean RT (ms)	434.09 (71.67)
RT Variability (ms)	124.41 (97.59)

Note. Sleep characteristics and task performance parameters across all waves.

Sleep Characteristics

Altogether, 2,789 MCTQ surveys were completed throughout W1-3; non-completion was either due to opting out of the survey completely or providing insufficient data. Overall sleep characteristics data for all waves showed that, on average, participants had a habitual sleep duration of 7 hours and 28 minutes (range: 1 hour and 18 minutes to 12 hours and 50 minutes) and an average social jetlag of 2 hours and 27 minutes (range: 0 to 10 hours and 30 minutes misalignment).

Task Performance

A total of 2,854 GNG tasks met sufficient criteria to be included in the analyses. Self-regulatory processes were evaluated by d', overall accuracy, omission error, and commission error. Whereas information-processing was evaluated using mean RT and RT variability. Table 2 provides the means and standard deviations for the self-regulatory and information-processing parameters across all waves. Participants had a wide range of performance on the task, with individuals ranging from the cutoff of 55% overall accuracy to having no errors on the task (100%). Both types of errors were committed by participants. However, commission errors had a higher mean rate of occurrence, with participants ranging from having no commission errors to a 24.75% commission rate on no-go trials. Although omission errors were less common, participants demonstrated a wide range of omission errors, with some committing no omission errors and others having up to a 39% omission rate on go-trials. Regarding information-processing, the mean RTs ranged from 112 to 1257 ms, with a corresponding RT variability range of 34 to 838 ms. These findings indicate significant inter-individual variability in both average RT and RT variability.

Correlations

Table 3

Correlation Matrix of Sleep and GNG Task Performance

	1	2	3	4	5	6	7	8
(1) Sleep Duration	1.000							
(2) Social Jetlag	-.221***	1.000						
(3) Overall Accuracy	.030	-.039*	1.000					
(4) Commission Errors	-.036	.078***	-.741***	1.000				
(5) Omission Errors	-.012	-.013	-.794***	.180***	1.000			
(6) Hit RT	-.037*	-.023	-.185***	-.102***	.363***	1.000		
(7) SD Hit RT	-.041*	.006	-.657***	.367***	.630***	.604***	1.000	
(8) D prime	.036	-.063***	.933***	-.933***	-.522***	-.045***	-.549***	1.000

Note. * $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$, two-tailed.

In order to examine relationships between variables, a correlation matrix was constructed. Table 3 indicates that many variables were significantly correlated with one another. Firstly, social jetlag was negatively associated with habitual sleep duration in this sample. Overall accuracy and commission errors were weakly correlated with social jetlag but not habitual sleep duration. Omission errors were not correlated with either sleep characteristic. As expected, both errors of commission and omission had a strong negative correlation with overall accuracy. Furthermore, commission errors and omission errors were slightly correlated with one another. RT and RT variability were correlated with habitual sleep duration, overall accuracy, commission errors, and omission errors. A positive correlation was also found between RT and RT variability. Lastly, d' was correlated with all variables except habitual sleep duration; strong correlations were found with overall accuracy, commission errors, omission errors, and RT variability.

Sleep and Task Performance

Regression model results will be discussed by predictors, beginning with the effect of sleep characteristics on task performance, then by analyzing the task's parametric aspect, and lastly, by investigating the effects of covariates on task performance. These same results are displayed by task performance outcome in Appendix A.

Table 4

Significant Relationships Between Sleep and GNG Task Performance

	d'	Overall Accuracy	Commission Errors	Omission Errors	Mean RT	RT Variability
Sleep Duration					-	-
Social Jetlag	-*	-*	+*			

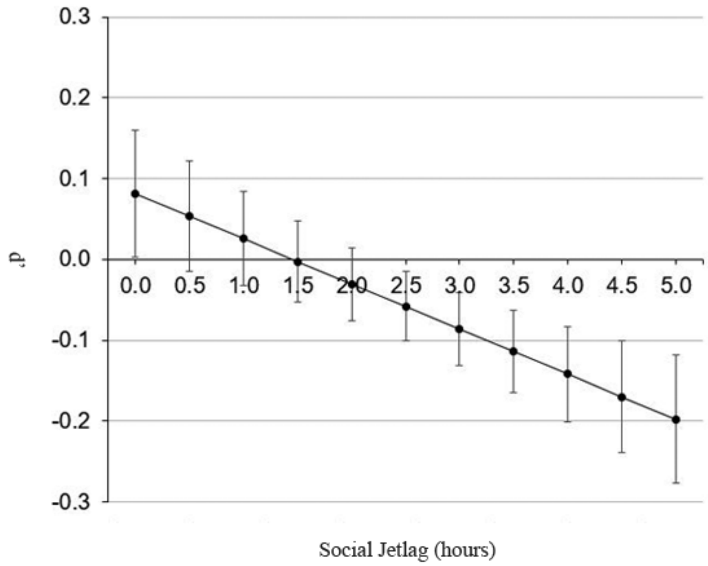
Note. + indicates a positive effect, - indicates a negative effect, and * indicates that the effect was no longer significant after the BH correction.

Social Jetlag

Moderate effects indicated that higher social jetlag predicted worse overall accuracy (b = -0.25, SE = 0.12, p = .04) through more commission errors (b = 0.15, SE = 0.07, p = .05). However, it failed to predict omission errors (b = 0.12, SE = 0.08, p = .16). These effects were no longer significant after the BH correction was applied. A moderate effect indicated that greater social jetlag led to lower response sensitivity, as indicated by d' (see Figure 1; *b* = -0.06, *SE* = 0.03, *p* = .04). This effect was also no longer significant after the BH correction. Lastly, effects for social jetlag not on mean RT or RT variability were not found.

Figure 1

Margins Plot of d' and Social Jetlag



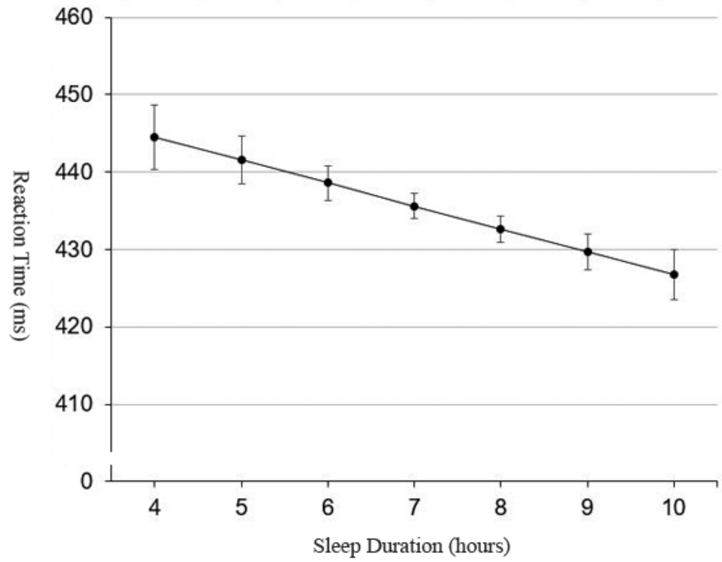
Note. This figure represents response sensitivity as evaluated by d' at varying degrees of social jetlag.

Habitual Sleep Duration

Habitual sleep duration was not found to predict changes in overall accuracy (*b* = 0.09, *SE* = 0.12, *p* = .45), omission errors (*b* = -0.07, *SE* = 0.09, *p* = .40), or commission errors (*b* = -0.02, *SE* = 0.08, *p* = .81). However, habitual sleep duration did predict changes in the information-processing models mean RT and RT variability; increased habitual sleep duration led to faster (see Figure 2; *b* = -2.97, *SE* = 1.1, *p* = .01) and less variable RTs (see Figure 3; *b* = -3.56, *SE* = 1.46, *p* = .02). These are the only sleep effects on task performance that were maintained post BH correction. When comparing Level 1 to Level 3, a moderate effect indicated that commission errors increased on Level 3 regardless of habitual sleep duration (*b* = 0.04, *SE* = 0.02, *p* = .04); this effect failed to meet criteria for significance after the BH correction.

Figure 2

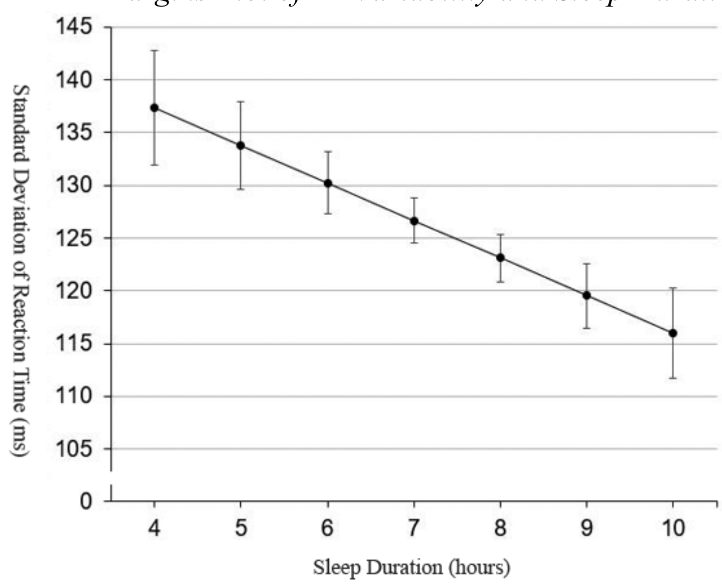
Margins Plot of RT and Sleep Duration



Note. This figure represents RTs on correct go trials at various amounts of sleep duration.

Figure 3

Margins Plot of RT Variability and Sleep Duration



Note. This figure represents RT variability (represented by the standard deviation of RTs) on correct go trials at various amounts of sleep duration.

Parametric Variation

When accounting for the parametric variation in the model, social jetlag again indicated a modest effect predicting more commission errors (b = 0.06, SE = 0.03, p = .03). The effect failed to reach statistical significance following the BH correction. While the effect of social jetlag on commission errors did not reach statistical significance following the BH correction, it is worth noting that the uncorrected results suggest a modest effect. Future research may investigate whether larger sample sizes or different statistical methods might reveal a stronger association between social jetlag and cognitive performance. Furthermore, the level of difficulty only has a significant effect on commission errors for Level 2 compared to the reference Level 1 (b = 0.04, SE = 0.02, p = .04); the difficulty of Level 3 did not have a significant effect on commission errors when compared to commission errors on Level 1.

The parametric variation model included interactions between the levels of difficulty and sleep characteristics to analyze if habitual sleep duration or social jetlag had an effect on how participants performed on each level. While a main effect of habitual sleep duration on commission errors is not present, a modest interaction between habitual sleep duration and the most complex level of the task was observed. Prior to the BH correction, this interaction indicates that in Level 3, commission errors increase regardless of the participants' habitual sleep duration (i.e., sleep duration does not compensate for the difficulty in this level). After the correction was applied, this interaction was no longer statistically significant. The margins for interaction between sleep duration and Levels 1 and 2 suggest that participants made fewer errors at those levels as their habitual sleep duration increased, which is the expected result. In summary, once the correction is applied, no significant interactions are observed between habitual sleep duration or social jetlag and the different levels of the task.

Covariates

Table 5

Significant Relationships Between Covariates and GNG Task Performance

	d'	Overall Accuracy	Commission Errors	Omission Errors	Mean RT	RT Variability
Parent Level of Education	+	-	-	-*	-*	-
Race	-*	-		+	+	+
Age						+
Female					+	
Web Administration		-		+		+

Note. + indicates a positive effect, - indicates a negative effect, and * indicates that the effect was no longer significant after the BH correction. All race effects occurred for Black non-Hispanic adolescents.

Parent Level of Education

Parent level of education predicted changes in many parameters across most models, and these effects were largely maintained post BH correction. Firstly, higher parent level of education led to larger d' in all groups when compared to the reference “high school or less” group (“some college” b = 0.30, SE = 0.12, p = .01; “college” b = 0.45, SE = 0.12, p = .00; “beyond college” b = 0.57, SE = 0.14, p = .00). Similarly, higher parent level of education led to better overall accuracy rates in all groups (“some college” b = 1.18, SE = 0.53, p = .03; “college” b = 1.92, SE = 0.52, p = .00; “beyond college” b = 2.31, SE = 59, p = .00). Parent level of education also initially predicted fewer omission errors in the “college” (b = -0.81, SE = 0.33, p = .01) and “beyond college” (b = -0.81, SE = 0.37, p = .03) group; however, these effects were removed by the BH correction. Higher parent level of education predicted fewer commission errors in all groups (“some college” b = -0.81, SE = 0.33, p = .02; “college” b = -1.15, SE = 0.33, p = .00; “beyond college” b = -1.51, SE = 0.38, p = .00). This effect for parent level of education on commission errors was reduced, yet maintained when the model accounted for the parametric variation of the task ("some college" b = -0.27, SE = 0.11, p = .02; "college" b = -0.38, SE = 0.11, p = .00; "beyond college" b = -0.50, SE = 0.13, p = .00). After the BH correction was applied, all effects for "some college" on self-regulatory metrics were rendered non-significant. The information-processing models were also impacted by the parent's level of education. For the mean RT model, a modest effect for the "college" group having lower mean RTs (b = -9.35, SE = 4.37, p = .03) was removed by the BH correction. Reduced RT variability was associated with the "college" (b = -14.85, SE = 5.74, p = .01) and "beyond college" groups (b = -12.69, SE = 6.50, p = .05).

Race

When referenced to White non-Hispanics, Black non-Hispanics had worse overall accuracy (b = -2.25, SE = 0.49., p = .00) by committing more omission errors (b = 2.39, SE = 0.31, p = .00) on the task. No effect for race was found for commission errors, even when accounting for the parametric nature of the task. A weak effect initially indicated that Black non-Hispanics showed decreased response sensitivity or d' (b = -0.25, SE = 0.11, p = .03); however, it was deemed insignificant by the BH correction. Mean RT and RT variability were also predicted by aspects of race in that Black non-Hispanics had higher RTs (b = 10.84, SE = 4.13, p = .01) and RT variability (b = 40.12, SE = 5.43, p = .00).

Age and Sex

Age only predicted RT variability and did not show a significant effect in any other model; older participants demonstrated more variability in their RTs (b = 4.20, SE = 1.64, p = .01). The implications of these results in developmental contexts will be discussed later. Sex only showed a significant effect in the model predicting mean RT, indicating that females had higher

RTs on hits compared to males ($b = 17.95$, $SE = 3.18$, $p = .00$). Both of these effects were maintained post BH correction.

Mode of Administration

Web administration in W2 and W3 led to worse overall accuracy ($b = -1.62$, $SE = 0.40$, $p = .00$) and more omission errors ($b = 1.76$, $SE = 0.28$, $p = .00$) compared to in-person administration in W1. However, web administration was found not to lead to increased commission errors ($b = -0.18$, $SE = 0.25$, $p = .47$), even when accounting for the parametric variation of the task ($b = -0.06$, $SE = 0.08$, $p = .47$). Furthermore, RT variability was also impacted by web administration in that the variability in RTs increased during web administration in W2 and W3 ($b = 26.52$, $SE = 4.69$, $p = .00$). The BH correction did not alter the significance of these effects on the self-regulatory or information-processing models.

Discussion

None of the hypotheses regarding overall accuracy, error rates, or difficulty levels on the task are strongly supported. While modest effects are present for social jetlag, these relationships were deemed insignificant after the BH correction (see Table 4). The present study finds more substantial evidence for an effect of sleep duration on self-regulatory information-processing in that decreased sleep duration led to slower RTs and more variability in RTs on the GNG task. Some studies have reported similar findings (Gosselin et al., 2019), whereas others did not observe an effect of sleep duration on RT (Tashjian et al., 2017; Vermeulen et al., 2016). The modest effects present for social jetlag on self-regulatory metrics and the strong effects of sleep duration on information-processing demonstrate the possibility that social jetlag and sleep duration play different roles in self-regulatory behavior. Social jetlag may directly influence self-regulation, whereas sleep duration is related to the processing speed of self-regulatory behavior. While not confirmed by this study, this indicates that further research into analyzing the effects of different components of sleep quality on self-regulation may be beneficial.

Importance of Sleep During Adolescence

The results of this study suggest that sleep duration is a significant factor influencing adolescent self-regulation. The significant relationship between sleep duration and both RT and variability in RT on the GNG task supports the idea that adequate sleep is crucial for optimal self-regulatory behavior (Dorrian et al., 2019). The finding that sleep duration significantly impacts RT indicates that adolescents who obtain adequate sleep may be better equipped to respond rapidly and accurately to stimuli, reflecting better self-regulatory capacity. Moreover, the significant association between sleep duration and variability in RT suggests that sleep may play a critical role in the consistency of self-regulatory behavior. It is important to note that while a significant relationship is observed through the GNG task, it is unsure how sleep duration may affect adolescents in practical, real-world contexts. Adolescents who experience insufficient sleep exhibit slower and more variable RTs, indicating reduced self-regulatory abilities, and therefore may have a higher risk for engaging in risky behaviors such as substance use, unsafe sexual practices, and reckless driving (Nigg et al., 2006). These results highlight the importance of promoting healthy adolescent sleep habits to facilitate optimal self-regulatory development. Parents and educators should focus on ensuring sufficient sleep duration to foster the development of effective self-regulatory skills in adolescents.

Future studies may better analyze the possible relationship between social jetlag and self-regulation by increasing task difficulty or utilizing different measures of self-regulation, as insufficient task difficulty has been a potential limitation for other studies as well (Schapkin et al., 2005). Another variation of this study may incorporate an experimental design similar to

Sagaspe and colleagues (2012) that utilizes sleep saturation and controlled sleep deprivation to better manipulate sleep quality; this may lead to larger, clearer effects on task performance compared to the results of the current study. Another interesting finding of this study is that age only affected RT variability and was unrelated to any other task performance metric. This suggests that self-regulation, as measured by the GNG task, did not change significantly across the adolescent age range in this sample, even though sleep quality seemingly improved (see Appendix B); only information-processing related to self-regulatory behavior varied due to age. It may be crucial to analyze this relationship with a sample that better represents adolescence, as the youngest participant in the AHRB sample was 14 years old, and adolescent development is noted to begin around age 10 (Sawyer et al., 2018). Since self-regulation may develop earlier in adolescence, it is possible that this trajectory was not observed in this study.

Demographic Characteristics and Self-regulation in Adolescents

The results indicate that demographic factors, including parent education level, race, and sex, significantly influence adolescent self-regulation. Higher parent education levels, as a marker of socioeconomic status (SES), were strongly linked to increased response sensitivity, better overall accuracy, fewer commission errors, and reduced RT variability. These results align with previous research indicating the vital role SES plays in cognitive development and academic achievement among adolescents (Hair et al., 2015; Li et al., 2022). Adolescents from higher SES families may have greater access to resources and opportunities that promote cognitive development, such as quality education, enrichment activities, and healthcare. Therefore, interventions aimed at enhancing self-regulation in adolescents should also address disparities in SES to ensure that all adolescents have access to the resources required for optimal cognitive development.

In addition, race was linked to self-regulation in this study, with Black non-Hispanic adolescents performing worse on the task than White non-Hispanics, exhibiting more omission errors and having slower RTs and greater RT variability. These findings are consistent with previous studies indicating that racial inequalities in sleep quality or SES may impede psychosocial adjustment during adolescence (El-Sheikh et al., 2022; Guglielmo et al., 2018). To improve self-regulation in affected populations, it is essential to address these disparities by implementing interventions. These interventions should aim to increase access to quality education, enrichment activities, and healthcare, as well as address systemic issues such as poverty, racism, and discrimination.

Finally, the findings show that there are sex differences in self-regulatory information-processing speed during adolescence, with females having slower mean RTs than males. These sex differences may have significant implications for the development of effective self-regulatory skills during adolescence. Further research is needed to better understand the nature of sex differences in self-regulation and how they affect the development of self-regulatory skills in adolescents. Overall, these results highlight the importance of considering demographic factors, including SES, race, and sex, when planning interventions to enhance adolescent self-regulation.

Strengths, Limitations, and Future Research

Validity of Task

Due to the GNG paradigm's long history in this field of research, many variations of these tasks have been created and used in studies. The lack of standardization in this paradigm gives rise to issues relating to the reliability and validity of variant tasks. Some studies have attempted to provide reliability and validation for certain types of GNG tasks (Kuntsi et al., 2005; Langenecker et al., 2007; Thomas et al., 2016). However, a recent analysis conducted under AHRB indicated that the GNG task used in this study may not be a valid indicator of self-regulation for this sample (Demidenko et al., 2019). This finding suggests that changes in performance on the GNG task cannot be directly linked with changes in self-regulation, which may explain the lack of direct effects found between sleep characteristics and task performance metrics in this study. According to this study, a possible explanation for the lack of validity of the task is that variations in cognitive task self-regulation may be more commonly observed in the context of problem behaviors, such as in clinical populations and substance use disorders. However, the group of adolescents in the AHRB sample may not exhibit these problem behaviors frequently enough for these differences to be noticeable. Therefore, caution is warranted when interpreting the results of the present study, as the validity of the GNG task paradigm remains a topic of ongoing debate in the field.

Application of Findings in Practical Contexts

Even if one was to disregard issues pertaining to the task's validity, applying metrics derived from the GNG task in practical contexts related to adolescent risk behaviors is challenging and a limitation of the current study. While significant effects for covariates and sleep duration on various metrics related to task performance were present, many of these effects were small and difficult to apply to behavioral outcomes. For instance, it is difficult to predict how changes in milliseconds of RT or RT variability will map onto changes in risky behaviors such as drowsy driving or substance use. It is likely that minor changes in RT (see Figures 2 and 3) may be more important in the context of some risk behaviors than others. For instance, the impact of sleep duration on prolonging response time could be a critical factor to consider for drowsy driving, as even minor errors can have severe consequences. This same limitation applies to other metrics of the GNG task such as d’, overall accuracy, and commission errors; it can be challenging to correlate changes in cognitive task metrics to the corresponding impact on behavioral outcomes. This limitation leads to difficulties in providing impactful suggestions based on the findings. Since the scale of change in behavioral outcomes is unknown, suggesting significant changes in sleep habits may be impractical at this.

Task Performance Metrics and Ex-Gaussian Analysis

The present study focuses solely on d’, overall accuracy, commission errors, omission errors, RT, and RT variability as measures of task performance. While this is a comprehensive set of metrics, advanced techniques may be utilized to provide deeper insight to performance on this task. One of these techniques may be to implement an ex-Gaussian analysis, which is a statistical method that may be applied to RT data in cognitive tasks, such as the GNG (van Belle et al., 2014; Lewis et al., 2017). This analysis attempts to compensate for the fact that for individuals that complete a cognitive task, the distribution of RTs is likely skewed due to long responses (Luce, 1986; van Zandt, 2000). This descriptive method contains three separate components: (1) a standard Gaussian distribution that relates to typical RTs, (2) an Exponential distribution that analyzes slower response times and outliers, and (3) a *tau* parameter that captures RT variability. These components allow for further analysis into RT mean, standard deviation, and variability. In regards to sleep, the *tau* parameter may provide valuable information regarding attentional lapses on the task (Leth-Steensen et al., 2000; Tarantino et al., 2013). It is important to note that although these advanced metrics may provide more nuanced insight into task performance, the limitation regarding interpreting how task performance changes translate to behavioral outcomes still needs to be addressed (Matzke & Wagenmakers, 2009).

Multiple Comparison Corrections

Statistical adjustments such as the Bonferroni or Benjamin-Hochberg corrections are widely used to reduce the risk of false positives in multiple comparisons (Chen et al., 2017). However, some of these corrections (most often the Bonferroni) have been criticized for being overly conservative and reducing statistical power (Holm, 1979; VanderWeele & Mathur, 2018). The decisions surrounding the use of these corrections are often arbitrary, with researchers choosing the specific correction method, significance threshold, and set of tests to apply the correction to based on convention or intuition rather than on a well-defined statistical rationale, although this is gradually changing (Lee & Lee, 2018). Despite these limitations and considerations, it is generally considered good practice to use some form of correction in multiple comparisons to reduce the risk of false positives. Although the Benjamini-Hochberg correction may have significantly reduced the power of this study, results were interpreted in light of the correction. Both the corrected and uncorrected findings were provided to paint a more transparent picture of the data.

Mode of Administration, Attrition, and Generalizability

As previously described in the Methods section, data for the first wave of the study were collected in schools during class periods or an elective via self-report surveys administered using computer-assisted self-interviewing, then subsequent follow-up assessments were conducted online (due to logistical constraints). This led to changes in performance on the GNG task and may raise concerns about the validity of this study's results. Analysis of covariates indicated that web-based administration of the GNG task led to worse overall accuracy and higher RT variability compared to in-person administration. However, web-based administration did not lead to an increase in commission errors. The present study attempted to account for the changing mode of administration by including it as a covariate in the analyses. Future studies replicating these findings should attempt to maintain a more well-controlled administration environment.

The mode of administration may also have impacted the sample's representativeness due to attrition, as some individuals may not have equal access to technology or may feel uncomfortable completing online assessments. Other factors may have also contributed to attrition between waves, which will be important to assess when building upon the current study. Future improvements to this study include the application of sample and attrition weights in the analysis. Application of sample weights may be particularly beneficial for the present study; sample weights are adjustment factors often used in survey data research that help account for differences between the current sample and the target population in terms of demographics, such as age, sex, and race (Pfeffermann, 1996). By reweighting the current data to match target population characteristics, sample weights can increase representativeness and improve the validity of the present study's findings. Applying these weights may also aid in correcting for implicit biases in the sampling method utilized in this study (Pew Research Center, 2018). Currently, the generalizability of the results of this study is limited to the current sample population, which consists of high schoolers and young adults originating in southeast Michigan. The implementation of statistical weights may allow for the findings to be extended to all U.S. adolescents, increasing the scope and relevance of the study.

References

Baddeley, A. D., & Hitch, G. J. (1994). Developments in the concept of working memory. *Neuropsychology*, 8(4), 485–493. https://doi.org/10.1037/0894-4105.8.4.485

Baumeister, R. F., Schmeichel, B. J., & Vohs, K. D. (2006). Self-regulation and the executive function: The self as controlling agent. In A. W. Kruglanski & E. T. Higgins (Eds.), *Social Psychology: Handbook of Basic Principles*, (pp. 516-539). Guilford Press. https://doi.org/10.1111/j.1467-9221.2008.00665.x

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society, Series B (Methodological)*, 57, 289-300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Blakemore, S. J., & Choudhury, S. (2006). Development of the adolescent brain: Implications for executive function and social cognition. *Journal of Child Psychology and Psychiatry,* 47(3-4), 296-312. https://doi.org/10.1111/j.1469-7610.2006.01611.x

Chen, S. Y., Feng, Z., & Yi, X. (2017). A general introduction to adjustment for multiple comparisons. *Journal of Thoracic Disease,* 9(6), 1725-1729. https://doi.org/10.21037/jtd.2017.05.34

Crone, E. A., & Dahl, R. E. (2012). Understanding adolescence as a period of social-affective engagement and goal flexibility. *Nature Reviews Neuroscience,* 13(9), 636-650. https://doi.org/10.1038/nrn3313

Davidson, M.C., Amso D., Anderson L. C., & Diamond A. (2006). Development of cognitive control and executive functions from 4–13 years: evidence from manipulations of memory, inhibition, and task switching. *Neuropsychologia,* 44, 2037–2078 https://doi.org/10.1016/j.neuropsychologia.2006.02.006

Demidenko, M. I., Huntley, E. D., Martz, M. E., & Keating, D. P. (2019). Adolescent health risk behaviors: Convergent, discriminant and predictive validity of self-report and cognitive measures. J*ournal of Youth and Adolescence,* 48(9), 1765-1783. https://doi.org/10.1007/s10964-019-01057-4

Dorrian, J., Centofanti, S., Smith, A., & McDermott, K. D. (2019). Self-regulation and social behavior during sleep deprivation. *Progress in Brain Research*, 246, 73-110. https://doi.org/10.1016/bs.pbr.2019.03.010

Durston, S., Thomas, K. M., Worden, M. S., Yang, Y., & Casey, B. J. (2002). The effect of preceding context on inhibition: An event-related fMRI study. *NeuroImage,* 16(2), 449-453. https://doi.org/10.1006/nimg.2002.1074

Diamond, A. (2012). Executive functions. *Annual Review of Psychology,* 64, 135-168. https://doi.org/10.1146/annurev-psych-113011-143750

El-Sheikh, M., Gillis, B. T., Saini, E. K., Erath, S. A., & Buckhalt, J. A. (2022). Sleep and disparities in child and adolescent development. *Child Development Perspectives,* 16, 200-207. https://doi.org/10.1111/cdep.12465

Gillespie, S. M., Lee, J., Williams, R., & Jones, A. (2022). Psychopathy and response inhibition: A meta-analysis of go/no-go and stop signal task performance. *Neuroscience & Biobehavioral Reviews,* 142, 104868. https://doi.org/10.1016/j.neubiorev.2022.104868

Green, D. M., & Swets, J. A. (1966). *Signal detection theory and psychophysics.* John Wiley & Sons. https://doi.org/

Guglielmo, D., Gazmararian, J. A., Chung, J., Rogers, A. E., & Hale, L. (2018). Racial/ethnic sleep disparities in US school-aged children and adolescents: A review of the literature. *Sleep Health,* 4(1), 68-80. https://doi.org/10.1016/j.sleh.2017.09.005

Hagenauer, M. H., Perryman, J. I., Lee, T. M., & Carskadon, M. A. (2009). Adolescent changes in the homeostatic and circadian regulation of sleep. *Developmental Neuroscience*, 31(4), 276-284. https://doi.org/10.1159/000216538

Hair, N. L., Hanson, J. L., Wolfe, B. L., & Pollak, S. D. (2015). Association of child poverty, brain development, and academic achievement. *JAMA Pediatrics*, 169(9), 822-829. https://doi.org/10.1001/jamapediatrics.2015.1475

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, 6(2), 65-70.

Keilp, J. G., Sackheim, H. A., & Mann, J. J. (2005). Correlates of trait impulsiveness in performance measures and neuropsychological tests. *Psychiatry Research,* 135, 191-201. https://doi.org/10.1016/j.psychres.2005.03.006

Kuntsi, J., Andreou, P., Ma, J., Börger, N. A., & van der Meere, J. J. (2005). Testing assumptions for endophenotype studies in ADHD: reliability and validity of tasks in a general population sample. *BMC Psychiatry*, 5, 40. https://doi.org/10.1186/1471-244X-5-40

Langenecker, S. A., Nielson, K. A., & Garavan, H. (2007). A task to manipulate attentional load, set-shifting, and inhibitory control: Convergent validity and test–retest reliability of the Parametric Go/No-Go Test. *Journal of Clinical and Experimental Neuropsychology*, 29(8), 842-53. https://doi.org/10.1080/13803390601147611

Lawrence, D., Houghton, S., Dawson, V., Sawyer, M., & Carroll, A. (2021). Trajectories of academic achievement for students with attention-deficit/hyperactivity disorder. Br J *Educational Psychology*, 91(2), 755-774. https://doi.org/10.1111/bjep.12392

Lee, S., & Lee, D. K. (2018). What is the proper way to apply the multiple comparison test? *Korean Journal of Anesthesiology*, 71(5), 353-360. https://doi.org/10.4097/kja.d.18.00242

Leth-Steensen, C., King Elbaz, Z., & Douglas, V. I. (2000). Mean response times, variability, and skew in the responding of ADHD children: A response time distributional approach. *Acta Psychologica*, 104(2), 167-90. https://doi.org/10.1016/s0001-6918(00)00019-6

Lewis, F. C., Reeve, R. A., Kelly, S. P., & Johnson, K. A. (2017). Sustained attention to a predictable, unengaging Go/No-Go task shows ongoing development between 6 and 11 years. *Attention, Perception, & Psychophysics*, 79(6), 1726-1741. https://doi.org/10.3758/s13414-017-1351-4

Li, M., Lindenmuth, M., Tarnai, K., Lee, J., King-Casas, B., Kim-Spoon, J., & Deater-Deckard, K. (2022). Development of cognitive control during adolescence: The integrative effects of family socioeconomic status and parenting behaviors. *Developmental Cognitive Neuroscience*, 57, 101139. https://doi.org/10.1016/j.dcn.2022.101139

Luce, R. D. (1986). *Response time: Their role in inferring elementary mental organisation.* Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195070019.001.0001

Matzke, D., & Wagenmakers, E. J. (2009). Psychological interpretation of the ex-Gaussian and shifted Wald parameters: A diffusion model analysis. *Psychonomic Bulletin & Review,* 16(5), 798-817. https://doi.org/10.3758/PBR.16.5.798

McAvinue, L. P., Habekost, T., Johnson, K. A., Kyllingsbæk, S., Vangkilde, S., Bundesen, C., & Robertson, I. H. (2012). Sustained attention, attentional selectivity, and attentional capacity across the lifespan. *Attention, Perception, and Psychophysics,* 74(8), 1570–1582. https://doi.org/10.3758/s13414-012-0352-6

Meyers, J., McCutcheon, V. V., Pandey, A. K., Kamarajan, C., Subbie, S., Chorlian, D., Salvatore, J., Pandey, G., Almasy, L., Anokhin, A., Bauer, L., Bender, A., Dick, D. M., Edenberg, H. J., Hesselbrock, V., Kramer, J., Kuperman, S., Agrawal, A., Bucholz, K., & Porjesz, B. (2019). Early sexual trauma exposure and neural response inhibition in adolescence and young adults: Trajectories of frontal theta oscillations during a Go/No-Go task. J*ournal of the American Academy of Child and Adolescent Psychiatry*, 58(2), 242-255.e2. https://doi.org/10.1016/j.jaac.2018.07.905

Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. Annual *Review of Neuroscience*, 24, 167-202. https://doi.org/10.1146/annurev.neuro.24.1.167

Miller, J. (1996). The sampling distribution of d'. *Perception & Psychophysics*, 58(1), 65-72. https://doi.org/10.3758/BF03205476

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. *Cognitive Psychology*, 41(1), 49-100. https://doi.org/10.1006/cogp.1999.0734

Nigg, J. T., Wong, M. M., Martel, M. M., Jester, J. M., Puttler, L. I., Glass, J. M., Adams, K. M., Fitzgerald, H. E., & Zucker, R. A. (2006). Poor response inhibition as a predictor of problem drinking and illicit drug use in adolescents at risk for alcoholism and other substance use disorders. *Journal of the American Academy of Child & Adolescent Psychiatry*, 45(4), 468-475. https://doi.org/10.1097/01.chi.0000199028.76452.a9

Olmstead, M. C. (2006). Animal models of drug addiction: Where do we go from here? *Quarterly Journal of Experimental Psychology*, 59(4), 625-653. https://doi.org/10.1080/17470210500356308

Owens, J. A., Belon, K., & Moss, P. (2010). Impact of delaying school start time on adolescent sleep, mood, and behavior. *Archives of Pediatrics & Adolescent Medicine*, 168(7), 610-616. https://doi.org/10.1001/archpediatrics.2010.96

Paruthi, S., Brooks, L. J., D'Ambrosio, C., Hall, W. A., Kotagal, S., Lloyd, R. M., Malow, B. A., Maski, K., Nichols, C., Quan, S. F., Rosen, C. L., Troester, M. M., & Wise, M. S. (2016). Consensus Statement of the American Academy of Sleep Medicine on the Recommended Amount of Sleep for Healthy Children: Methodology and Discussion. *Journal of Clinical Sleep Medicine*, 12(11), 1549-1561. https://doi.org/10.5664/jcsm.6288

Patrick, M. E., Couper, M. P., Laetz, V. B., Schulenberg, J. E., O'Malley, P. M., Johnston, L. D., & Miech, R. A. (2018). A sequential mixed-mode experiment in the U.S. National Monitoring the Future Study. *Journal of Survey Statistics and Methodology*, 6(1), 72-97. https://doi.org/10.1093/jssam/smx011

Patton J. H., Stanford M. S., & Barratt E. S. (1995). Factor structure of the Barratt impulsiveness scale. *Journal of Clinical Psychology*, 51, 768–774. https://doi.org/10.1002/1097-4679(199511)51:6<768::aid-jclp2270510607>3.0.co;2-1

Pew Research Center. (2018). *For weighting online opt-in samples, what matters most?* https://www.pewresearch.org/methods/wp-content/uploads/sites/10/2018/01/20 18.01.26_Weighting-Online-Opt-In-Samples.pdf

Pfeffermann, D. (1996). The use of sampling weights for survey data analysis. *Statistical Methods in Medical Research*, 5(3), 239-261. https://doi.org/10.1177/096228029600500303

Roenneberg, T., Wirz-Justice, A., & Merrow, M. (2003). Life between clocks: daily temporal patterns of human chronotypes. *Journal of Biological Rhythms*, 18(1), 80-90. https://doi.org/10.1177/0748730402239679

Sagaspe, P., Taillard, J., Amiéva, H., Beck, A., Rascol, O., Dartigues, J. F., Capelli, A., & Philip, P. (2012). Influence of age, circadian and homeostatic processes on inhibitory motor control: A Go/Nogo task study. *PloS One*, 7(6), e39410. https://doi.org/10.1371/journal.pone.0039410

Sawyer, S. M., Azzopardi, P. S., Wickremarathne, D., & Patton, G. C. (2018). The age of adolescence. *The Lancet Child & Adolescent Health*, 2(3), 223-228. https://doi.org/10.1016/S2352-4642(18)30022-1

Schapkin, S. A., Falkenstein, M., Marks, A., & Griefahn, B. (2006). After effects of noise-induced sleep disturbances on inhibitory functions. *Life Sciences*, 78(10), 1135-1142. https://doi.org/10.1016/j.lfs.2005.06.048

Somerville, L. H., Jones, R. M., & Casey, B. J. (2010). A time of change: Behavioral and neural correlates of adolescent sensitivity to appetitive and aversive environmental cues. *Brain and Cognition*, 72(1), 124-133. https://doi.org/10.1016/j.bandc.2009.07.003

Spinella, M. (2004). Neurobehavioral correlates of impulsivity: Evidence of prefrontal involvement. *International Journal of Neuroscience*, 114(3), 95-104. https://doi.org/10.1080/00207450490249347

Stanislaw, H., & Todorov, N. (1999). Calculation of signal detection theory measures. *Behavior Research Methods, Instruments, & Computers*, 31(1), 137-149. https://doi.org/10.3758/BF03207704

Tarantino, V., Cutini, S., Mogentale, C., & Bisiacchi, P. S. (2013). Time-on-task in children with ADHD: An ex-Gaussian analysis. *Journal of the International Neuropsychological Society: JINS*, 19(7), 820-828. https://doi.org/10.1017/S1355617713000623

Tarokh, L., Saletin, J. M., & Carskadon, M. A. (2016). Sleep in adolescence: Physiology, cognition and mental health. *Neuroscience & Biobehavioral Reviews*, 70, 182-188. https://doi.org/10.1016/j.neubiorev.2016.08.008

Tashjian, S. M., Goldenberg, D., & Galván, A. (2017). Neural connectivity moderates the association between sleep and impulsivity in adolescents. *Developmental Cognitive Neuroscience*, 27, 35-44. https://doi.org/10.1016/j.dcn.2017.07.006

Telzer, E. H., Fuligni, A. J., Lieberman, M. D., & Galván, A. (2013). The effects of poor quality sleep on brain function and risk taking in adolescence. *NeuroImage*, 71, 275-283. https://doi.org/10.1016/j.neuroimage.2013.01.025

Thomas, S., Rao, S. L., & Devi, B. I. (2016). Standardization of tests of attention and inhibition. *Indian Journal of Psychological Medicine*, 38(4), 320-325. https://doi.org/10.4103/0253-7176.185959

VanderWeele, T. J., & Mathur, M. B. (2019). Some desirable properties of the Bonferroni correction: Is the Bonferroni correction really so bad? *American Journal of Epidemiology*, 188(3), 617-618. https://doi.org/10.1093/aje/kwy250

van Belle, J., van Raalten, T., Bos, D. J., Zandbelt, B. B., Oranje, B., & Durston, S. (2014). Capturing the dynamics of response variability in the brain in ADHD. *NeuroImage: Clinical*, 7, 132-141. https://doi.org/10.1016/j.nicl.2014.11.014

van Zandt, T. (2000). How to fit a response time distribution. *Psychonomic Bulletin & Review*, 7(3), 424-465. https://doi.org/10.3758/BF03214357

Vermeulen, M. C., Astill, R. G., Benjamins, J. S., Swaab, H., Van Someren, E. J., & van der Heijden, K. B. (2016). Temperament moderates the association between sleep duration and cognitive performance in children. *Journal of Experimental Child Psychology*, 144, 184-198. https://doi.org/10.1016/j.jecp.2015.11.014

Weigard, A., Soules, M., Ferris, B., Zucker, R. A., Sripada, C., & Heitzeg, M. (2020). Cognitive modeling informs interpretation of Go/No-Go task-related neural activations and their links to externalizing psychopathology. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, 5(5), 530-541. https://doi.org/10.1016/j.bpsc.2019.11.013

Wong, M. M., Brower, K. J., Nigg, J. T., & Zucker, R. A. (2010). Childhood sleep problems, response inhibition, and alcohol and drug outcomes in adolescence and young adulthood. *Alcoholism: Clinical and Experimental Research*, 34(6), 1033-1044. https://doi.org/10.1111/j.1530-0277.2010.01178.x

Wright, L., Lipszyc, J., Dupuis, A., Thayapararajah, S. W., & Schachar, R. (2014). Response inhibition and psychopathology: A meta-analysis of go/no-go task performance. *Journal of Abnormal Psychology*, 123(2), 429-439. https://doi.org/10.1037/a0036295

Zee, P. C., Badr, M. S., Kushida, C. A., Mullington, J. M., Pack, A. I., Parthasarathy, S., Redline, S., Szymusiak, R. S., Walsh, J. K., & Watson, N. F. (2014). Strategic Opportunities in Sleep and Circadian Research: Report of the Joint Task Force of the Sleep Research Society and American Academy of Sleep Medicine. Sleep, 37(2), 219-227. https://doi.org/10.5665/sleep.3384

Appendix A

Regression coefficients and standard error estimates for all models

Mixed-effects linear regression analyses were conducted for all task performance parameters. Tables B1-3 indicate the coefficients, standard error, and level of significance for all effects in the regression models. Bolded coefficients indicate those effects which remained significant after the BH correction.

Table A1

Regression of Self-Regulatory Models (1-4)

	d'		Overall Accuracy		Commission Error		Omission Error	
	b	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Sleep Duration	0.01	0.03	0.09	0.13	-0.02	0.08	-0.07	0.09
Social Jetlag	-0.06*	0.03	-0.25*	0.12	0.15*	0.07	0.12	0.08
Mode								
In-Person (reference)								
Web	-0.16	0.09	**-1.62*** **	0.40	-0.18	0.25	**1.76*** **	0.28
Age	-0.05	0.03	-0.27	0.14	0.10	0.09	0.16	0.09
Sex								
Male (reference)								
Female	-0.03	0.09	-0.22	0.38	0.00	0.24	0.22	0.24
Race								
White Non-Hispanic (reference)								
Black Non-Hispanic	-0.25*	0.11	**-2.25*** **	0.49	-0.14	0.31	**2.39*** **	0.31
Hispanic	-0.06	0.18	-0.28	0.76	0.13	0.49	0.12	0.48
Other	-0.10	0.13	-0.69	0.55	0.08	0.35	0.60	0.35
Parent Level of Education								
High School or Less (reference)								
Some College	0.30*	0.12	1.18*	0.53	-0.81*	0.34	-0.41	0.33
College	**0.45*** **	0.12	**1.92*** **	0.52	**-1.15** **	0.33	-0.81*	0.33
Beyond College	**0.57*** **	0.14	**2.31*** **	0.59	**-1.51*** **	0.38	-0.81*	0.37

Note. Bolded values indicate effects that remained significant post BH correction.

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$ for uncorrected p-values.

Table A2

Regression of Processing Models (6&7)

	RT		RT Variability	
	b	*SE*	*b*	*SE*
Sleep Duration	**-2.97****	1.10	**-3.56***	1.46
Social Jetlag	-0.60	1.06	2.43	1.41
Mode				
In-Person (reference)				
Web	4.59	3.52	**26.52*****	4.69
Age	1.41	1.24	**4.20****	1.64
Sex				
Male (reference)				
Female	**17.95*****	3.18	7.20	4.18
Race				
White Non-Hispanic (reference)				
Black Non-Hispanic	**10.84****	4.13	**40.12*****	5.43
Hispanic	-0.34	6.43	2.07	8.45
Other	-0.68	4.66	8.59	6.12
Parent Level of Education				
High School or Less (reference)				
Some College	-4.23	4.46	-6.03	5.86
College	-9.35*	4.37	**-14.85****	5.74
Beyond College	-2.03	4.95	**-12.69***	6.50

Note. Bolded values indicate effects that remained significant post BH correction

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$ for uncorrected *p*-values.

Table A3

Regression of Parametric Variation Model (5)

	Commission Error	
	b	*SE*
Sleep Duration	-0.02	0.03
Social Jetlag	0.06*	0.03
Level		
1 (reference)		
2	**0.42****	0.16
3	0.22	0.16
Level Interaction Sleep Duration		
2	0.00	0.02
3	0.04*	0.02
Level Interaction Social Jetlag		
2	-0.02	0.02
3	-0.01	0.02
Mode		
In-Person (reference)		
Web	-0.06	0.08
Age	0.03	0.03
Sex		
Male (reference)		
Female	0.00	0.08
Race		
White Non-Hispanic (reference)		
Black Non-Hispanic	-0.05	0.10
Hispanic	0.04	0.16
Other	0.03	0.12
Parent Level of Education		
High School or Less (reference)		
Some College	-0.27*	0.11
College	**-0.38****	0.11
Beyond College	**-0.50*****	0.13

Note. Bolded values indicate effects that remained significant post BH correction;

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$ for uncorrected p-values.

Appendix B

Summary Data of Sleep and GNG Task by Wave

	W1	**W2**	**W3**
	M (SD)	*M (SD)*	*M (SD*
Sleep Duration (hr)	7.22 (1.19)	7.66 (1.29)	7.83 (1.34)
Social Jetlag (hr)	2.92 (1.34)	2.08 (1.28)	1.83 (1.26)
d-prime (d’)	-0.02 (1.85)	0.03 (1.84)	0.01 (1.92)
Overall Accuracy (%)	86.74 (7.69)	86.05 (8.75)	85.73 (9.19)
Commission Errors (%)	10.74 (5.31)	10.03 (4.92)	9.96 (4.98)
Omission Errors (%)	2.56 (4.70)	3.92 (6.44)	4.30 (6.58)
Mean Hit RT (s)	431.49 (60.90)	435.56 (73.69)	438.28 (89.19)
Hit RT Variability (s)	113.81 (82.68)	128.45 (100.77)	143.56 (119.07)

Note. Sleep characteristics and task performance for each wave. N differs by wave and variable.