The relationship between adolescent physical activity, brain health, and academic achievement

by

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Authors Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

Abstract

Background: In addition to the numerous physical and mental health benefits attributable to regular physical activity, physical activity has more recently been hypothesized to improve academic performance via its beneficial impact on cognitive control and activation within the prefrontal cortex (PFC). Other lifestyle behaviours such as substance use, sleep hours and a high calorie, low nutrient diet are also thought to be associated with brain health and academic performance in youth.

Objective: The primary objective of this study is to examine the association between physical activity and academic performance in a sample of adolescents, and to examine the extent to which activity within the PFC and behavioural indices of inhibition may mediate this relationship. Secondary analyses investigate the potential mediation via brain health parameters on the relationship between lifestyle factors (i.e. substance use, fast-food consumption, average sleep hours) and academic performance.

Methods: Using a prospective observational study, a total of 67 participants underwent two study sessions scheduled approximately 5 days apart. The first 20-minute session included the completion of a questionnaire pertaining to demographic information, health behaviours and academic performance as well as two mental health scales. Participants subsequently completed the Multi-Source Interference Task while functional Near-Infrared Spectroscopy measures of PFC oxygenation was used to infer activation in this area. Fitbit Inspire watches were also distributed to participants in order to measure physical activity and sleep hours.

Results: Average active minutes were associated with greater % correct responses on the MSIT (β= .321, ρ= .019) as well as greater activation within the right dorsolateral PFC (β=.008 , *SE*= .004, ρ =.032), however there was no direct effect of physical activity on academic performance and no evidence of mediation through brain health parameters. The relationship between physical activity and task performance was moderated by

gender (ΔR^2= .077, F= 4.939 (1, 54), ρ =.031), such that females had greater MSIT performance than males. Both fast-food consumption and substance use were negatively associated with % correct responses (β= -.307, ρ= .023) and Math grades (β= -3.702, SE= 1.563, ρ= .022) respectively.

Conclusion: Overall, the results of this study indicate the importance of lifestyle behaviours on cognition and academic achievement in youth. There was evidence to support cognitive enhancements of physical activity, primarily for females, but these brain benefits did not translate into academic performance. These findings support prevention initiatives aimed enhancing cognition through physically activity, as well as those that aim to reduce the impact of fast-food consumption and substance use in adolescence.

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List of Abbreviations

PFC	Prefrontal cortex
OFC	Orbitofrontal cortex
dlPFC	Dorsolateral prefrontal cortex
dmPFC	Dorsomedial prefrontal cortex
MRI	Magnetic Resonance Imaging
fMRI	functional Magnetic Resonance Imaging
EEG	Electroencephalogram
MSIT	Multi Source Interference Task
fNIRS	functional Near-Infrared Spectroscopy
NIR	Near-Infrared
RT	Reaction time
SD	Standard deviation
L-dlPFC	Left dorsolateral prefrontal cortex
R-dlPFC	Right dorsolateral prefrontal cortex
L-mPFC	Left medial prefrontal cortex
R-mPFC	Right medial prefrontal cortex
OxyHb	Oxygenated hemoglobin
DeoxyHb	Deoxygenated hemoglobin
MET	Metabolic equivalent
BMI	Body Mass Index

CH	Channel

1 Introduction

1.1 Adolescent brain development

Adolescence marks a significant period of social, emotional and intellectual development. In addition, this age represents a transition from dependence to relative autonomy (1). Emerging independence surrounding lifestyle behaviours makes this a important period of consideration, as the initiation of many adverse health behaviours that continue into adulthood begin in adolescence (1). Co-occurring during this time are changes to the brain itself. Cross-sectional (2–4), longitudinal (5–7), and experimental (8) Magnetic Resonance Imaging (MRI) studies have demonstrated age-related linear increases in white matter density. Conversely, grey matter undergoes a non-linear inverted U-shape pattern of change, where density peaks at age 12 and then declines into adulthood (4,7). These changes in brain morphology are accompanied by age-dependent increases in neuronal signal transmission speed and efficiency through the enhanced myelination, production of new interconnections between neurons, as well as pruning of unnecessary connections (2,9,10). This pattern of neurodevelopment is particularly pronounced in the prefrontal cortex (PFC), a node important for decision-making and reward valuation, and one that has previously been implicated in a range of harmful and beneficial health behaviours (6,7). The next section will discuss the structure and role of the PFC in more detail.

1.2 Prefrontal cortex

The PFC is the cortical area that covers the anterior part of the frontal lobe. This region is extensively connected to sensory and motor systems, as well as a range of subcortical structures (11). Projections back to these systems allows for the PFC to exert “top-down” processing in relation to other regions based on internal goals (11). This high order cognitive control is essential for goal-directed behaviour and optimal decision making, as it allows for the inhibition of impulsive behaviours in addition to the selection of relevant actions based on intentions and contextual features of the environment (12).

Structurally, the PFC is understood to include the orbitofrontal cortex (OFC), as well as the medial and lateral PFC (11,13). Functionally, this region is most notably associated with executive functions, for which there are several sub-components. The OFC has been implicated in emotion regulation as well as decision-making for emotion and reward-related behaviours (14,15). The lateral PFC has a wide array of identified functions including short-term retention of information (i.e., working memory), task-switching, behaviour planning, as well as the related processes of inhibition, selective attention and goal selection (16). The dorsolateral PFC (dlPFC) association with inhibitory control has implications for the implementation of many types of discrete behaviors and decision making processes (17,18). Finally, the frontal poles and dorsomedial PFC (dmPFC) are implicated in social and emotional processing (19–21), and can therefore work in concert with the lateral PFC to govern socially relevant behaviors, which is of particular importance to adolescent development. Generally, the cognitive processes subsumed under the general term “executive functions” are grouped into three main categories: inhibition, working memory and task switching (22).

The identified functions of the PFC are especially pertinent for health-related decision making because this region is responsible for exerting goal directed control and behavioral regulation. Lack of maturation in the PFC has therefore been associated with impetuousness and the initiation of adverse health behaviours in youth (23). Prominent development in high order cognitive structures, underpin a transition from risky decision-making to greater stability as observed in adulthood (24). Consequently, understanding how structural and functional change in the PFC interact with health behaviours is an important line of inquiry in adolescence.

1.3 Functional development, health behaviours and academic performance

Along with the morphological changes, there is evidence to suggest that PFC activation also changes throughout development. Specifically, task-related activity in the PFC has been shown to increase with age with maturation peaking in early adulthood (25). Schroeter et al. examined the link between dlPFC engagement and inhibitory task performance in children and young adults using functional Near-Infrared Spectroscopy (fNIRS; 26). When compared to young adults, children demonstrated less activation in the lateral PFC (and particularly in the dlPFC) in response to the Stroop task (26). Age-related increases in dlPFC engagement during inhibitory task performance are also associated with improvements in task performance (26); together these results suggest superior engagement of the dlPFC in successful operation of inhibitory processes with increasing age. Adleman and colleagues corroborated these results, which also found age-related increases in activation in the lateral PFC (as measured by functional MRI; fMRI) into adulthood and in response to the same task (27). Other neuroimaging studies have found that activity in the medial PFC (mPFC) and OFC perform similarly throughout development (28–30). The increase in activity in these sub-regions may be demonstrating a transition from a diffuse to focused activation within the PFC caused by enhanced neural recruitment in this region, leading to a greater functional capacity throughout maturation (23,31).

When coupled with other psychosocial, emotional and physical changes, adolescence represents a critical time for identifying the neural correlates of burgeoning health behaviours. Furthermore, when considering that the various components of executive functioning are thought to enable high-order cognitive operations, and because academic achievement is thought to in-part rely on executive functioning, understanding how all three factors interact is of importance.

1.3.1 Prefrontal cortex and academic performance

Performance in school is thought to rely on executive functioning, as academic achievement requires a level of focused attention, discipline, planning and goal-directed behaviour. Longitudinal (32,33) as well as cross-sectional (34,35) studies have found reliable but modest associations between behavioural measures of executive functioning and academic variables; importantly some of these associations appear to be invariant across cultures, and important patterns exist among the sub-components of executive function and specific facets of academic achievement (36). In addition, Horowitz-Kraus et al. found that activation in the frontal and anterior cingulate cortical regions during a narrative comprehension task at the between the ages of 5-7 years old were positively correlated with college preparedness, as measured by performance on the standardized American College Test many years later (37). This evidence supports the notion that superior academic performance may partially may on executive function and PFC activation. Academic success is important for many important life prospects (including career attainment, income potential and social standing), and so it is advantageous to understand factors that contribute to achievement in youth.

1.3.2 Lifestyle behaviours, academic performance and the brain

Foundational research into normative adolescent brain development has informed further investigation into differences in activity reflecting both beneficial and adverse health behaviours. Protracted development in the PFC may be related to enhanced reward sensitivity, leading to increased sensation seeking and risky decision-making, which in turn contributes to poor health choices (38,39). Consequently, adverse health behaviours such as sleep restriction, a high calorie/low nutrient diet as well as substance use have all been shown to be negatively associated with executive functioning (40–42) and PFC activation (43–47) among adolescents.

Sleep is a critical factor that can influence overall health and daily lives, and sleep restrictions can detrimentally impact various cognitive processes. Many adolescents in Canada do not get the recommended 8-10 hours of sleep (48) so it is important to further understand how reduced sleep hours impact PFC activation and executive function. A recent meta-analysis found that sleep restriction has a significant and moderate negative causal effect on executive functions and cognition overall, as well as a small-to-moderate negative effect on inhibitory control and sustained attention specifically (49). Moreover, studies utilizing both fMRI and fNIRS have observed reductions in PFC activation and decreased connectivity between left anterior frontal and frontal areas as well as poorer performance on executive function tasks following induced sleep deprivation (43,44). Although the effects of sleep restriction are not homogenous across studies as there is high degree of variability between age ranges as well as measures of sleep, the observed cognitive effects of sleep restriction could be in part explained by reduced PFC activity (49).

A high calorie, low nutrient diet has also been shown to negatively impact performance on tasks measuring executive functions (50–52). In addition, one longitudinal study found that youth with a low level of executive functioning at baseline demonstrated a higher probability of regularly engaging in high calorie and low nutrition food consumption when assessed after three years, suggesting a potential reciprocal relationship (42). When assessing the neural pathways of eating behaviours, neuroimaging studies involving youth with overweight or obesity have helped to distinguish the role of the PFC in diet. In adolescent girls, a higher Body Mass Index (BMI) was correlated with greater impulsivity in response to inhibition tasks as well as reduced activation in the superior frontal gyrus, middle frontal gyrus, ventrolateral PFC, mPFC, and OFC (46). In addition, children with obesity have been shown to have reduced activation in the dlPFC in response to unhealthy food cues when compared to adults (53).

There is evidence that substance use and substance use disorders can also be detrimental to brain regions implicated in executive functioning among adolescents. Executive functioning has been shown to be weaker in habitual users of cocaine, amphetamines, cannabis, tobacco and alcohol (54). In addition, youth with a history of alcohol and cannabis use demonstrate less activation in the inferior frontal cortex, but enhanced mPFC response when completing a working memory task (45). Moreover, the effects of substance use can potentially persist into early adulthood. When followed for a period of ten years, young adults with a history of alcohol use disorder or a substance use disorder demonstrated poorer performance on verbal and visual learning and memory tasks as well as reduced executive functioning compared to non-users (41). Although the correlational nature of the above data does not preclude the possibility that poor executive control contributes to the development of higher levels of substance use, and taken with the findings from the longitudinal study, this evidence is at least suggestive of an association in need of further exploration, particularly using prospective study designs.

Sleep restriction, a poor diet and substance use have all been shown to detrimentally impact academic performance in adolescents (45,55,56). Because each of these lifestyle behaviours have been shown to have a negative relationship with indicators of executive function (e.g., task performance and cortical network engagement), it is plausible to believe that the relationship between each factor and academic achievement may be mediated (in part) through the brain.

In contrast to the apparent adverse effects of the above mentioned health behaviours, both acute and regular physical activity have been shown to enhance some parameters of PFC function and improve task performance on cognitive tasks that tap executive control (57–59). Understanding how physical activity impacts cognition in could help to strengthen executive functions in youth. Moreover, cognitive enhancement via physical activity may help to bolster academic achievement. The relationship between physical activity, the brain and academic performance will be explored in the following section.

1.3.3 Physical Activity, Academic Performance and the Brain

Participation in regular physical activity has many physical and mental health benefits, including enhanced cardiorespiratory fitness, a decreased risk of type 2 diabetes, reduced risk for premature mortality, as well as improved mood and reduced depressive symptoms (60–64). Physical activity regimes have also been shown to improve the functional and cognitive capacity of older adults (65–67). The latter effects appear especially important for brain regions supporting executive control and memory (57,66,68–70). These brain health benefits of physical activity may be present throughout the lifespan, and yet, especially important for adolescents whom must rely on such functions in the academic sphere (57,58,71–73).

While the precise pathway through which physical activity influences brain health remains unclear, it is generally thought to increase the production of growth factors critical for synaptic plasticity, angiogenesis and the development of new neuronal architecture, and changes in cerebrovascular dynamics (57). In adolescents, systematic reviews and meta-analyses on the effects of physical activity on executive functions have found net positive effects (74–78) with acute aerobic exercise and in the moderate to vigorous range producing the strongest benefits (76–78).

There is also evidence to support a relationship between greater levels of physical activity and adaptive brain activation during cognitive task performance. A recent study investigating the effects of acute physical activity on the cognitive function of older adults found significantly greater activation in the right and left dlPFC post-exercise session during an interference task (67). Although there are very few studies that investigate this topic in children or adolescents, it appears that there is a reliable difference between higher- and lower-fit children. Higher-fit children have been shown to exhibit superior performance on executive performance tasks as well as increased activity in the fronto-parietal regions of the brain (68,79,80). Given the rapid neural development in adolescence, the perceived cognitive benefits of physical activity, both in terms of performance on executive function tasks and through enhanced brain activation, during this critical period may be especially important for the progression of a healthy neurocognitive structure and function into adulthood.

Furthermore, the cognitive benefits of exercise could positively impact academic achievement. This "brain benefit" hypothesis postulates that the cognitive enhancements within the PFC could translate into improved academic performance because achievement in school in part relies on strong executive functions. Currently, the wealth of evidence in support of the relationship between physical activity and academic achievement suggests a null to weak association between the two variables. Systematic and meta-analytic reviews of the literature have shown variable results ranging from null to small positive effects of physical activity interventions (both acute and long-term) on academic performance (74,78,81–85). However, among the studies reviewed there is a large degree of heterogeneity in intervention components assessed, a high degree of variability in the quality of the study designs, and a limited number of studies with sufficient power (74,82,84). More problematic is the inability to achieve blinding (single or double) when assessing physical activity interventions. This also applies to studies involving exercise effects on the brain, which can lead to expectancy effects and therefore an over-estimation of brain health benefit (in both cognitive testing and functional imaging). In addition, very few randomized trials exist examining the brain health benefits of exercise in children, and the few that exist have mixed results (68,86). It is possible that over-estimations cloud the true effect of physical activity on the brain, and that the cognitive enhancements of physical activity are not potent enough to influence academic achievement in adolescents. Therefore, further investigations into the mediating role of the brain are warranted.

Longitudinal studies provide an alternative method of investigation, as they do not require blinding and allow for longer durations of investigation. However, the results of previous longitudinal analyses examining the relationship between physical activity and academic achievement in adolescence have also been variable. Several studies have found small to moderate associations (87–91), and some have found null associations (92). The sample sizes have been limited in some cases and the absolute effect sizes have been relatively small. For this reason, larger sample sizes are required in order to better examine the association between the two variables.

In contrast to the “brain benefit” hypothesis, the removal of physical activity from school curriculums decades ago across North America was often rationalized based on an assumption that physical activity programming competes for time with academic subjects. This perspective posited a negative effect of physical activity on academic performance based on time competition between the two. The “brain-benefit” and “time-competition” perspectives pertaining to physical activity and academic performance suggest a significant relationship, but in opposite directions. It could be that the variation in results from the current body of literature on the topic stems from competition between the two hypotheses. However, if both hypotheses exist, the stronger of the two will determine the net effects (net benefit or net cost). Further research must be done in order to distinguish between the brain benefit and time competition hypotheses.

The following section will describe a preliminary analysis of physical activity and academic performance using a large sample of adolescents. This study aimed to elucidate whether or not a relationship between physical activity and academic performance exists when utilizing a large representative sample of adolescents.

1.4 Physical Activity and academic achievement in a population-based sample

An investigation into the relationship between physical activity and academic performance was undertaken utilizing the COMPASS study longitudinal dataset of 9,898 students (93). Self-reported measures of both physical activity and academic performance were collected through the COMPASS student questionnaire during waves 2 to 4 (2013-2016). In terms of academic performance, most recent English and Math grades were the outcome of interest and were treated as a continuous variable. Three measures of physical activity (minutes of MVPA, meeting the national physical activity guidelines and sport participation) formed the predictors. Daily minutes of both moderate and vigorous physical activity were combined to create a continuous measure of moderate to vigorous physical activity (MVPA). In addition, a binary measure of whether or not the student met the minimum Canadian physical activity requirements (60 minutes of MVPA per day) was included. Finally, the response to three binary items measuring different facets of sport participation were used.

In this data, the relationship between baseline average daily MVPA and academics performance was statistically significant, but negative in direction and near zero in both raw and covariate adjusted models (93). Similar to MVPA, meeting the national guidelines at baseline was significantly but negatively associated with greater academic achievement at follow-up and in covariate adjusted models. Again, this effect was near zero in magnitude. In contrast, small positive effect was observed with relation to varsity sport participation, but this effect may have been due to other factors besides brain benefits (e.g., social environment, formal or informal academic assistance; 92).

It is possible that the use of self-reported activity and academic achievement data among adolescents was not optimal, as both self-report measure may be subject to social desirability and recall bias. The use of accelerometers as a more objective measure of physical activity, and the inclusion of the actual grades received in English and Math could have reduced bias. Furthermore, this longitudinal investigation did not employ a neuroimaging protocol in order to evaluate the role of the brain in this relationship. Given the results of this study, it still remains unclear to what extent the cognitive enhancements of physical activity are contributing to academic performance.

1.5 Study rational

This thesis will examine the relationship between lifestyle behaviours and academic performance while exploring cognitive interference task performance and fNIRS measures of brain activity as mediational mechanisms. Two primary hypotheses exist: the "brain benefit hypothesis" postulates that a positive relationship between physical activity may be mediated through the brain health benefits of physical activity. In contrast, the "time-competition" hypothesis posits that physical activity detracts from academic pursuits through a competition for time producing a negative association. While this topic has been previously explored, the brain benefit hypothesis has not been adequately tested in adolescents.

While the above preliminary analysis involving COMPASS suggested a null or slight negative association between the two variables, the use of self-reported measurements was a significant limitation. For example, the two items combined to measure moderate and vigorous activity both were found have unacceptably low reliability (moderate physical activity: *ICC*=.22; vigorous physical activity: *ICC*=.18; MVPA: *ICC*=.25) when compared to a research grade accelerometer (Actigraph; 93). There were also no measures of cognitive or brain activity related mediators. Furthermore, the results were not sufficient in order to favour one of the two hypotheses. It is possible that both are actually correct and that they are mutually opposing forces resulting in a near-null overall association over time.

The emergence of new portable brain imaging technologies—particularly fNIRS—may prove to be more logistically feasible for many types of research studies involving the brain and development and when field settings are required for data collection. This technology is comparable to fMRI in that it measures blood oxygenation parameters for inferring neuronal activity within brain regions (95). Although it has inferior spatial resolution to fMRI, it has better spatial resolution than Electroencephalograms (EEG; 96,97). fNIRS also is less subject to motion artifacts than both EEG and fMRI (96,97) and its portability allows for it to be deployed in field settings more flexibly than any other brain imaging option currently available. Therefore, this technology provides an opportunity to investigate brain activity in a sample of adolescents in a field setting (e.g., on-site in school-based settings where adolescents are recruited).

Further, given the association between many other lifestyle behaviors and brain health parameters, the current study provided an opportunity to examine other behavioral predictors of brain health and academic achievement, including diet, substance use and sleep.

1.6 Purpose and hypotheses

The primary purpose of this thesis is to investigate the relationship between accelerometer assessed physical activity and academic performance, as mediated through brain health parameters. The latter will be assessed by interference task performance and brain activation patterns assessed by fNIRS. Secondary analyses will attempt to elucidate whether the relationships between other lifestyle behaviours (sleep hours, substance use and eating behaviours primarily) and academic performance are similarly mediated through these same brain health parameters. This study will attempt to build off of the preliminary analysis on the topic described above and will utilize accelerometery and a brain imaging protocol in order to assess the potential cognitive benefits of physical activity.

The hypotheses are as follows:

1. Higher levels of accelerometer-assessed physical activity will predict superior performance on a cognitive interference task.

2. Higher levels of accelerometer-assessed physical activity will predict greater task-related activation in the lateral PFC during the task, specifically during interference trials (i.e., a pattern of adaptive engagement).
3. Physical activity will predict academic achievement, and this effect will be mediated by functional activation of the PFC during the cognitive interference task.
4. Fewer sleep hours, frequent fast-food consumption and frequent substance use will all be associated with decreased task-related PFC function in the lateral and medial areas, as well as poorer cognitive task performance.
5. Fewer sleep hours, frequent fast-food consumption and frequent substance use will all be associated with poorer academic performance.

2 Methods

2.1 Participants and setting

A sample of 67 adolescent high school students between the ages of 13-18, were recruited for this study. Participant age (13-18) was the sole inclusion criteria. Therefore, all students who produced a signed parental consent within the age range could participate. Given the nature of the recruitment venues (private schools), all participants were cognitively normal and free from movement disorders that might have impacted cognitive task performance or brain activation patterns.

One public and three private high schools located in Milton, London and Breslau served as recruitment sites for the study. Principals, teachers and/or key members of administration disseminated information and consent materials to the student body. Those students who wished to participate returned their signed consent forms to the administration helping to facilitate the study, or to the student researcher upon the first study session.

This study was approved by the University of Waterloo Research Ethics Committee and received clearance (ORE# 40674). Additional ethical clearance through the Milton District School board was attained prior to the commencement of the study.

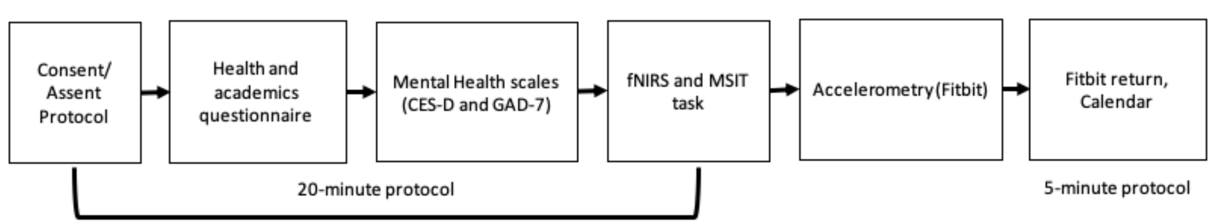
2.2 Procedure

The current study was a 5-day prospective observational study with two on-site data collection visits (Figure 1). During each visit, an open period was held during school hours where students could drop in and participate on their own time. This was necessary in order to ensure that data collection took place during free periods and did not impact class time, and that students could participate on-site with minimal inconvenience.

The data collection period was from December 2019 to March 2020. During the first session, students underwent an assent procedure upon presentation of their signed parental consent form. Next, three questionnaires were completed. The first consisted of 6 questions pertaining to demographic information (age and gender), eating behaviours, substance use and academic performance (Appendix 1). To measure academic performance, participants were asked to report their past years (2018-2019) English and Math grades in percentages. The final two questionnaires were mental health scales assessing the presence and frequency of anxiety and depression symptoms (See Appendix 3,4; 98,99). The results of the mental health scales were not included in the analysis but will be reported separately in a subsequent publication. Finally, students were fitted with the fNIRS headband while a cognitive interference task (Multi-Source Interference Task; MSIT; 99) was completed. In total, this first session took approximately 20 minutes per student. Upon completion of the cognitive task, students were given a Fitbit Inspire watch, oriented to its correct usage, and instructed to wear it consistently until the second data-collection period 5 days later.

The second period took place on the following Friday. During this session, students were asked to return their Fitbit and indicate any instances (day, time and duration) when the watch was removed during the period since the first session. This was accomplished using a weekly calendar (Appendix 2) and took approximately 5 minutes per student.

Figure 1. *Study protocol*



2.3 Demographics, health behaviours, and academics questionnaire

Self-reported demographics, eating behaviours, substance use, and academic achievement were assessed using this questionnaire (Appendix 1). Participants were asked to report their age and gender. In addition, students were asked “how many times have you eaten “fast-food” (eg. McDonalds, Burger King, etc.) in past week?” as a measure of calorically dense food consumption. Participants were also be asked “how many times have you experimented in the past month with substances (e.g., alcohol, cannabis, other)?”and responded using a scale ranging from 0,1-2, 3-5, 6+. To measure academic performance, students were asked “What was the final grade that you received last year (2018-2019) in Math class?” and “What was the final grade that you received last year (2018-2019) in English class?” Students were then able to indicate their English and Math grade in percentage.

2.4 Multi-Source Interference Task

Participants completed the MSIT as a measure of response inhibition (66,67). For this task, each trial consisted of three numbers that were horizontally aligned in the centre of a black computer screen in bold white 50pt font. Between trials a “+” sign was presented in the centre of the screen during a 1.75s inter-trial interval. The numbers corresponded to the “1, 2 and 3” numbered computer keys, and participants were instructed to indicate the unique number by pressing the corresponding key using their dominant hand (e.g., for the trial “112,” the correct response is 2).

Control and interference trials differed by the type of distractor used as well as the position of the target numbers in relation to their location on the keyboard. In control trials, the target number always matched their location on the keyboard, and the distractors were never used as targets (i.e., 0 is used in the other two positions; 3,4). During interference trials, the target number never matched its position on the keyboard and the distractors were also targets (e.g., 332 where the correct answer is “2”; 66,67). A 1.5 -

minute practice trial of 24 control trials followed by 24 interference trials initiated the task (100,101). Participants then completed 4 blocks of 24 control and interference trials for a total of 96 trials of each type. For the control blocks, the three possible stimuli each appeared 8 times, and for the interference blocks, each of the 24 possible stimuli appeared once (100,101). There was a fixed order of trials within each block, but blocks were counterbalanced between participants (i.e. either CICICICI or ICICICIC). A 30 second rest period with a fixation cross was included at the beginning of the first block and at the end of the last block (100,101).

During the initial orientation to the MSIT task, participants were asked to respond as quickly and accurately as possible in response to each number stimulus. Mean reaction time (RT) of correct responses, the % correct responses and the Standard Deviation (SD) for correct response latencies were measured. The MSIT has been validated for use in functional neuroimaging studies and has been shown to reliably activate the dorsal anterior midcingulate cortex, dlPFC and superior portions of parietal cortex (100). It is also appropriate for participants over 5 years of age and for those of different cultural backgrounds, and therefore ideal for adolescents and those of diverse ethnicities/cultural backgrounds (100).

2.5 Functional Near-Infrared Spectroscopy

fNIRS is an optical neuroimaging technique which non-invasively measures activation of the cortex using near-infrared (NIR) light (96,97). In order to measure regional activation, fNIRS takes advantage of two basic principles: The Hemodynamic Response and the modified Beer-Lambert Law. When a brain region is active or involved in completing a task, the metabolic needs of the neuron populations within the region increase (96). In order to support heightened metabolic demand, local arteriolar vasodilation increases leading to an upsurge in cerebral blood flow and changes in hemoglobin concentrations (96). This process, known as the Haemodynamic Response, produces an increases in oxygenated hemoglobin (OxyHb) as well as a (slightly time lagged) relative decrease in deoxygenated hemoglobin (DeoxyHb; 96). Because hemoglobin is the main chromophore that absorbs NIR light and does so differently when oxygenated (>800nm) versus deoxygenated (<800nm), fNIRS can utilize the spectroscopic features of hemoglobin in order to infer regional brain activation (96).

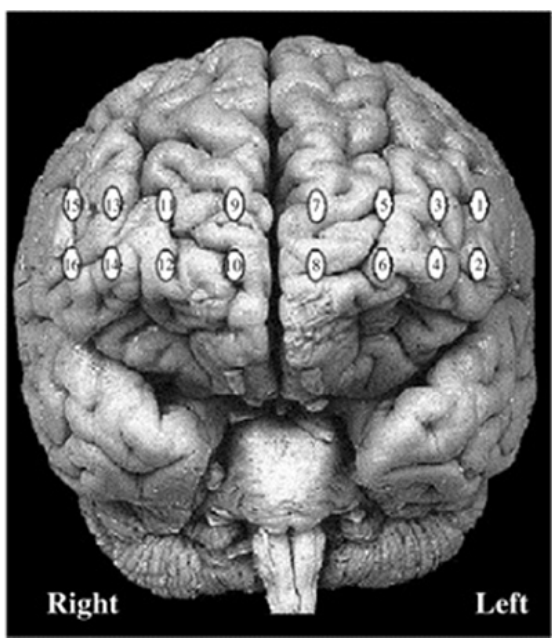
The second principle dictates how fNIRS emitted NIR light can account for light attenuation via other biological layers (scalp, skull, cerebrospinal fluid) in order to estimate oxygenation changes in the cortex. The Beer-Lambert law predicts both the absorption and attenuation of light based on the material that the light is travelling through (96,97). Being that NIR is partially scattered during its trajectory into the cortex, fNIRS can utilizes sources of NIR light and detectors placed a distance away from each other in order to collect the backscattered light and measure changes in light attenuation that is typical of oxygenated and deoxygenated hemoglobin in the cortex (96,97). Therefore, by utilizing two wavelengths of NIR light corresponding to the spectra of oxy- and deoxy-hemoglobin, fNIRS can measure the light attenuation in order to quantify oxygenation of the cortex without interference from other tissues.

While some studies have looked at the resting state functional connectivity (102,103), pairing fNIRS with a cognitive task that produces activation in a target brain region can identify changes in activity relative to a baseline. Such task-related functional activity can then be compared across a sample in order to identify differences in activation relative to other variables. For this study, a fNRIS headband was worn while the MSIT task is completed, in order to measure task related activation. The critical metric was the change in OxyHb between MSIT control and interference trials in each target area from 2 seconds to 8 seconds and relative to baseline. Task-related hemodynamic responses in cortical regions correlate well with similar responses assessed via fMRI (95).

The continuous wave fNIR devices 203C unit was used for this study. This device consists of a headband embedded with 4 LED light sources and 10 detectors joined to create 16 channels (See Figure 2). Two additional short channels are placed within a closer distance (2.5 cm) in order to capture oxygenation in the scalp (104). Participants were fitted with the fNIRS headband and instructed to minimize head movement during measurement. A short baseline measurement (20 seconds) preceded task-related measurements. Four regions of interests (ROI) were identified, corresponding to conceptually important subregions of the prefrontal cortex: the left dlPFC (L-dlPFC), right dlPFC (R-dlPFC), left mPFC (L-mPFC) and right mPFC (R-mPFC) . Channels 3,4 and 6 make up the L-dlPFC; 13,14 and 15 the R-dlPFC; 7,8 the L-mPFC and 9,10 the R-mPFC.

Raw light intensities in the 730 nm (for DeoxyHB) and 850 nm (for OxyHb) wavelengths were recorded using the COBI Studio software and were first visually inspected in order to reject the optodes that did not have adequate contact with the scalp. Using the modified Beer-Lambert law, raw light intensities were then converted into OxyHb and DeoxyHb concentrations (105). A band-pass filter at .005-.1 Hz was subsequently applied to the OxyHb signals in order to reduce physiological noise and artifacts that may have been present (i.e. heartbeat, respiration).

Figure 2. *Brain regions corresponding to the 16 fNIRS channels.*



2.6 Accelerometry

At the conclusion of the first 20-minute session, each participant was given a wearable Fitbit Inspire watch to wear until the second session on the following Friday. Each Fitbit watch was embedded with an triaxial accelerometery sensor that measured linear acceleration along three orthogonal axes (X, Y and Z) and can detect movement including gravity (106). The accelerometry sensor was used to determine step counts, active minutes and sleep hours. Step counts were determined solely using the accelerometer sensors. The Fitbit watches employed an estimate of metabolic equivalents (MET) to distinguish active minutes and exercise intensity (107). A MET over 3 was used to denote activity, and proprietary algorithm was then used to classify active minutes into "lightly active, fairly active and very active" (107,108). Combination of "fairly light" and "very active" minutes per day defined the physical activity variable of interest. Sleep hours were inferred by (lack of) movement identified by the accelerometery sensor; one hour of sleep was inferred when minimal movement occurred for more than one hour continuously using a proprietary scoring interpretative algorithm (109,110). The Fitbit watches also estimated the number of calories burned per day using the basal metabolic rate (BMR). BMR is rate at which calories are burned at rest to maintain vital functions, and was calculated using the activity data as well as physical characteristics that are entered in the Fitbit account upon initialization (i.e. height, weight, sex and age; 95).

Students were instructed to wear the Fitbit consistently Monday to Friday, day and night. Each Fitbit Inspire watch was linked to a Fitbit account so that physical activity and sleep data could be accessed remotely and recorded. The Fitbits were synced using the Fitbit app once during the first and last sessions. During the final session, students were asked to drop in and return their Fitbit watch and specify whether or not the watch was removed during the week using a weekly calendar (Appendix 10). The weekly calendar completed by each participant was consulted to assess periods of non-wear in terms of both activity and sleep hours. Those who were lost to follow-up were excluded from the analysis.

Similar wrist worn Fitbit devices have been found to be a reliable measure of observed step counts and energy expenditure, as the within-participant correlation for this relationship was .77–.85 (111). The Fitbit Flex was also found to be highly correlated with a research grade accelerometer (Actigraph) when used outside of the laboratory (*r*=.5-1.0; 112).

2.7 Statistical analysis

All statistical analyses were conducted using SPSS. Descriptive statistics were calculated for all continuous and categorical variables. The Explore subcommand in SPSS was used to generate Boxplots and distributional statistics; together these were employed to assess skewness and kurtosis for each individual variable, and to any extreme outliers that may be present. If the skewness statistic was between $\pm$2.0 than a normal distribution was inferred.

One extreme outlier was removed from the fast-food consumption variable and three extreme outliers were removed from the % correct MSIT responses variable. English grades, the percentage of correct MSIT responses, the mean MSIT RT and MSIT SD, were subjected to winsorization. These variables were chosen as the initial boxplots had a significant skewness (outside $\pm$2.0) and were not normally distributed. Winsorization is a statistical process by which extreme values below the 5th percentile and above the 95th percentile are replaced by the 5th and 95th percentile values respectively. This helped to reduce the effect of extreme outliers and maintain the rank ordering of data points, while also maintaining the overall sample size.

To calculate the fNIRS indicators of oxygenation in each ROI the mean change in OxyHb was calculated for the interference and control blocks of the MSIT separately and for each channel. These mean values of oxygenation were then transformed into Z scores and the mean of the Z scores were calculated for all channels making up each ROI. All ROI aggregates were then subjected to winsorization.

Hierarchical linear regression models were employed in order to examine the relationship between each lifestyle behavior (i.e., physical activity, sleep hours, fast-food consumption frequency and substance use frequency) and MSIT performance (% correct responses) while controlling for age. The PROCESS macro was utilized to run moderated regression analyses in order to examine the moderating effect of gender and BMI on the above models (i.e., all lifestyle factors and MSIT % correct responses; 113). Multiple mediation models were then utilized to assess the potential mediating effect of the brain health parameters (MSIT indicators, fNIRS ROI oxygenation) while controlling for the % correct responses. Final conditional process models assessed whether the above multiple mediation models differed based on gender, age or BMI. An estimate of BMI was calculated by the Fitbit watches upon the first day of wear, and relied on physical characteristics (year of birth, height, weight, sex) supplied by the participants.

2.8 Sample size determination

Because this study has no comparators and no previous attempt has been made to utilize fNIRS in an off-site location in order to study associations between lifestyle factors, brain health parameters and academic performance, no prior effect size could be used to estimate the minimum sample size required for this study. Therefore, an effect size estimate of moderate magnitude (r=.40) was used to conduct the sample size calculations. Using this value and when keeping statistical power at .80 and alpha at .05, a two-tailed hypothesis yields a minimum sample size of 47 participants. Our realized sample size was 67, and all analyses exceeded the critical value of 47 even following data loss and/or elimination.

3 Results

Initial predictive models were fitted using multi-level modelling of within-person effects pertaining to trials within blocks and blocks within task. Modelling these nested effects did not significantly improve model fit, and so the primary analyses presented below utilized data averaged across trials and blocks of the same type. This enabled the use of multiple mediation models, using an ordinary least squares regression approach, which forms the primary analytic approach in the sections below. Given the focus of the study on executive control and evaluative processes, our functional imaging analyses were primarily focussed on oxygenated hemoglobin levels in interference blocks. During signal processing, each individual task trial was divided into a 2 second baseline and 8 second sampling epoch, and so OxyHB levels described below represent average changes (increases normally) in OxyHB from each of these local baselines during each individual task trial.

Initial analyses show lifestyle behaviors as predictors of interference task performance (% correct MSIT responses). These are followed by multiple mediation models testing simultaneous mediational effects of a given target behavior (e.g., activity, sleep, etc.) on an academic performance outcome (e.g., Math grades or English grades) through all brain primary health parameters (e.g., MSIT reaction mean reaction times; MSIT reaction time variability; fNIRS parameters), while controlling for MSIT task performance. Subsequent conditional processed models explored the extent to which the multiple mediation models were moderated by age, gender and BMI. fNIRS channels were combined into neuroanatomically relevant ROIs, corresponding to the L-dlPFC, R-dlPFC, L-mPFC, and R-mPFC. All multiple mediation and conditional process models focussed on these four regions of interest.

3.1 Lifestyle predictors of interference task performance

Means and standard deviations (SD), as well as N and % for categorical variables, for all sample characteristics and primary study variables are presented in Table 1. The majority of students were aged 16-17 (61.2%) and Male (59.7%).

Table 1. *Mean and SDs for the study characteristics*

Variable	N	%
Gender		
Female	26	38.8
Male	40	59.7
Age		
13	2	3.0
14	13	19.4
15	6	9.0
16	15	22.4
17	26	38.8
18	5	7.5
Substance use (times in past month		
0 times	46	68.7
1-2 times	10	14.9
3-5 times	1	1.5
6+ times	10	14.9
Variable	**Mean**	**SD**
Fast-food consumption (times in past week)	1.909	1.444
Grades (%)		
English	80.91	9.569
Math	79.30	12.076
Average sleep hours	7.162	1.046

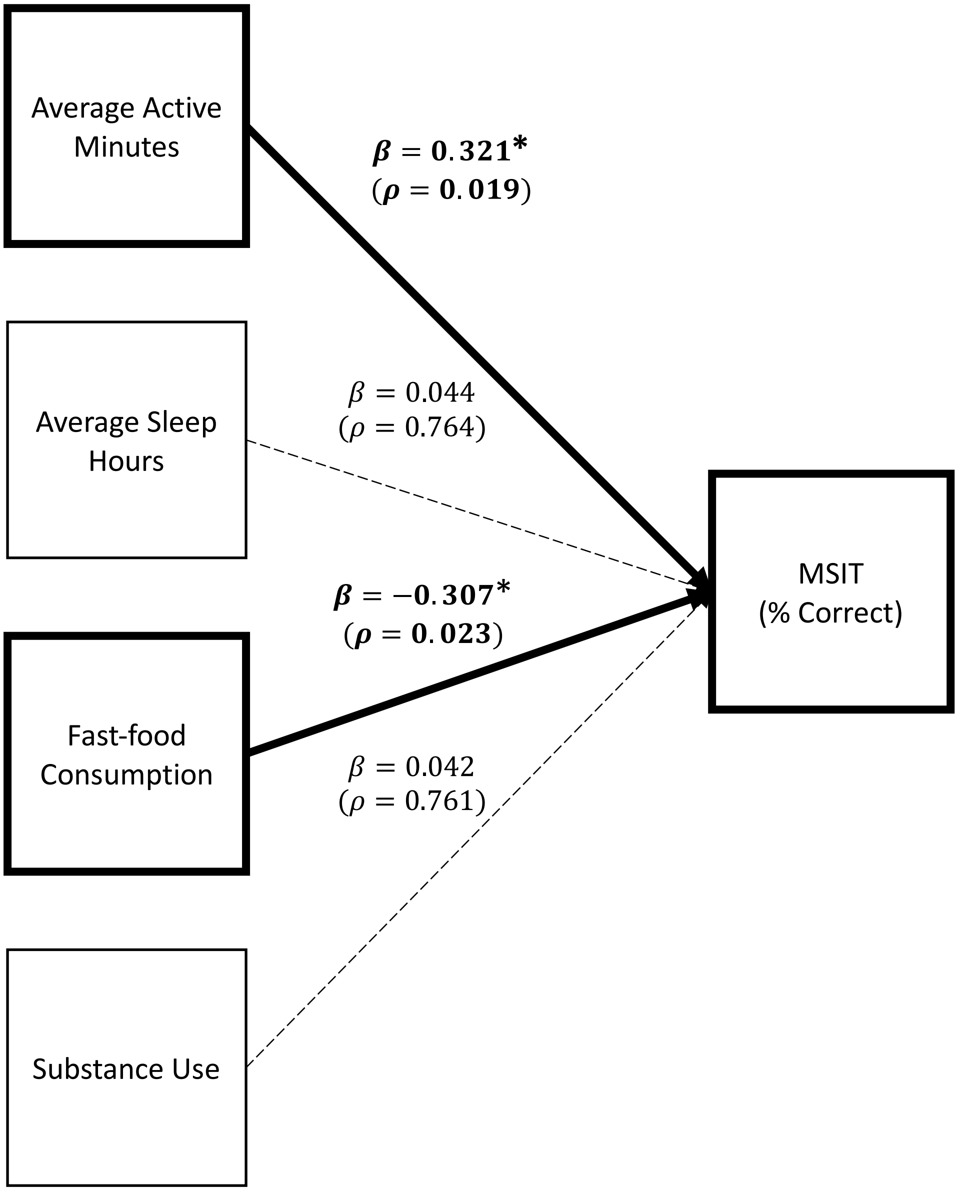
Average steps counts	8914.279	3451.436
Average active minutes	32.391	28.456
MSIT % correct responses	0.883	0.056
fNRIS regions of interest (μmolar)		
L-dlPFC OxyHb	-0.030	0.659
R-dlPFC OxyHb	-0.004	0.735
L-dmPFC OxyHb	-0.061	0.660
R-dmPFC OxyHb	-0.041	0.623

OxyHb response (i.e., OxyHB increases from local baseline) in the prefrontal cortex during the MSIT task is presented in Figure 3; oxygenation is presented in each left (CH 1-8) and right (CH 9-16) hemisphere by individual channel. Results showed a pattern of relative increase in OxyHb in interference versus control blocks in channels corresponding to the L-dlPFC ROI; likewise, stronger relative increases in OxyHb were evident in control more so than interference blocks in the channels corresponding to the R-dlPFC ROI (e.g., CH13; Figure 3). This is the expected pattern of activation for an interference task demanding of cognitive control and provides validation that the MSIT task was engaging of important nodes in the executive control network during interference blocks. Cortical activation during interference tasks is often highly lateralized, with anticorrelation of left- and right-sided effects, as per the pattern observed here. Such lateralized effects are of unknown origin in a definitive sense however, they could be related to the proportion of left- or right-handed individuals in a given sample. Some studies exclude left-handed individuals (a step that was not taken here), which may artificially create an opposite lateralization effect compared to what we observed in this data.

Figure 3. *Increases in OxyHB levels for interference versus control blocks*

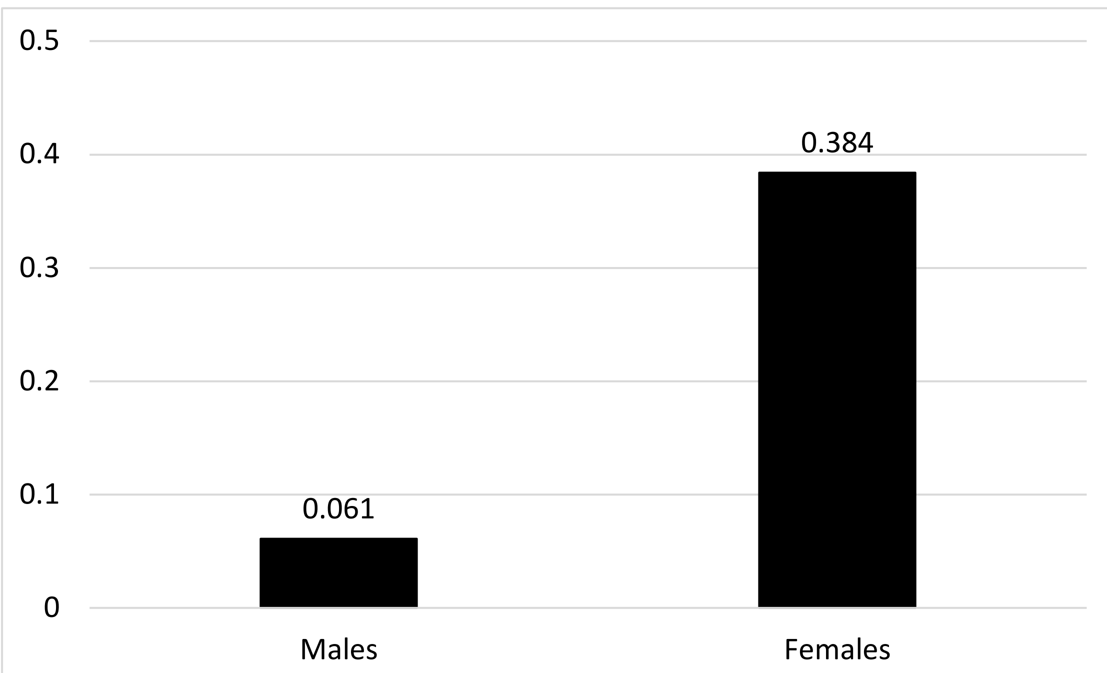
To examine the extent to which MSIT performance was predicted by each target lifestyle behavior, behavior-specific regressions were run using age as a covariate and each lifestyle behavior as a predictor. Findings are presented in Figure 4. Both fast-food consumption and accelerometer-assessed active minutes were significant predictors of MSIT performance. Specifically, more average daily minutes of accelerometer-assessed physical activity predicted greater % correct MSIT responses (β= .321, ρ= .019); likewise, less frequent fast-food consumption in the previous week predicted significantly greater % correct MSIT responses (β= -.307, ρ= .023). A reduced model predicting MSIT performance was created containing only average active minutes and fast-food consumption. This reduced model accounted for 24% of the variability in MSIT performance (ΔR^2= .244, ρ < .001). In the reduced model, higher average daily minutes of accelerometer-assessed physical activity predicted greater % correct MSIT responses (β=.382, ρ= .004). Likewise, less frequent fast-food consumption in the past week predicted significantly higher % correct MSIT responses (β= -.429, ρ= .001).

Figure 4. *Lifestyle behaviors predicting MSIT performance, controlling for age*



To determine whether the strength of association between each predictor and MIST performance differed for male and female participants, moderated regression analyses were performed separately for each target behavior. Gender was a significant moderator of the relationship between active minutes and MSIT performance (ΔR^2= .077, F= 4.939 (1, 54), ρ =.031), such that active minutes had a significant effect on MSIT performance for females (β = 1.018, SE= .412, ρ= .017) but not for males (β =.041, SE= .155, ρ=.793). The corresponding effect sizes were .061 for males and .384 for females (Figure 5). Gender was not a significant moderator of the relationship between fast-food consumption and MSIT performance (ΔR^2= .011, F=.699 (1, 59), ρ =.407). There was also no significant moderating effect of gender on the relationship between sleep (ΔR^2= .043, F= 2.194 (1, 47), ρ =.145) or substance use (ΔR^2= .000, F= .010 (1, 59), ρ = .919) and MSIT performance.

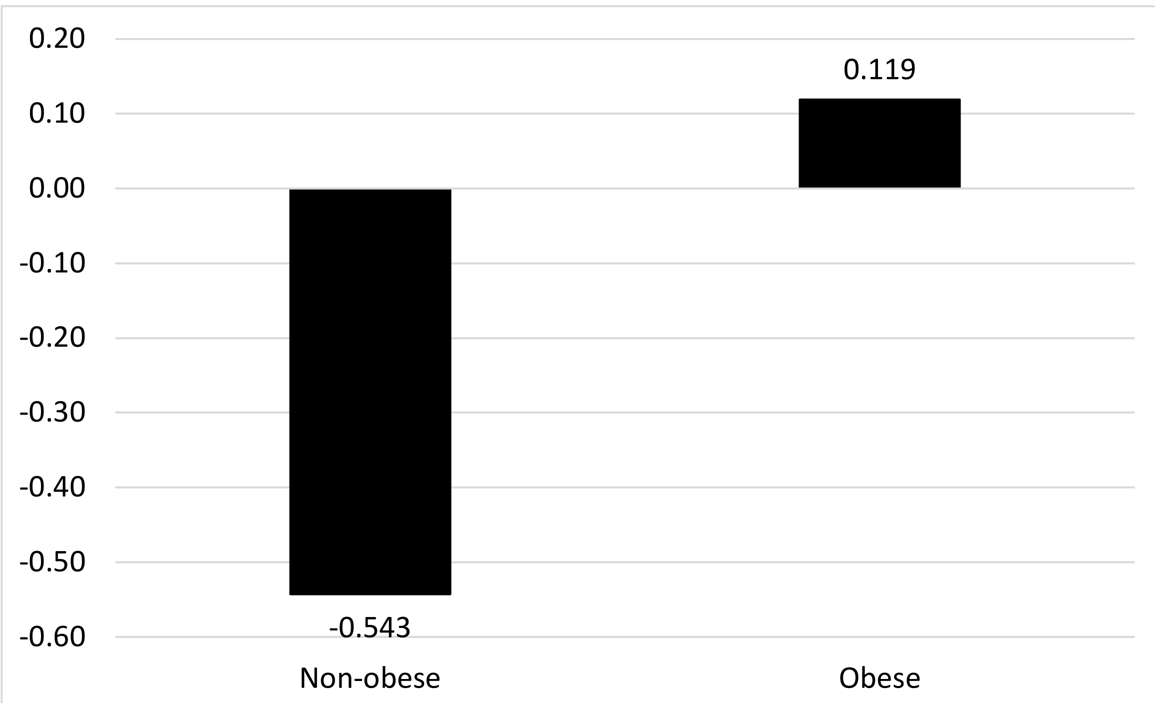
Figure 5. *Effect sizes for average active minutes predicting MSIT performance (% correct)*



Additional moderated regression analyses were performed to determine whether the strength of association between each predictor and MIST performance differed by body composition (quantified by BMI). BMI was calculated using percentile-based age and gender-specific cut-offs recommended by Centers for

Disease Control and Prevention for children and adolescents (114). Results indicated that BMI was indeed a significant moderator of the relationship between substance use and MSIT performance (ΔR^2= .127, *F*= 8.916 (1, 59), ρ =.004). The corresponding effect sizes were .119 for those for those whose BMI fell within the obese range and -.095 for non-obese (Figure 6). BMI was not a significant moderator of the relationship between active minutes (ΔR^2= .008, *F*= .492 (1, 55), ρ =.486), fast-food consumption (ΔR^2= .019, *F*= 1.171 (1, 58), ρ =.284), or average sleep hours (ΔR^2= .027, *F*= 1.384 (1, 48), ρ =.245) and MSIT performance.

Figure 6. *Effect sizes for substance use predicting MSIT performance (% correct)*



3.2 Multiple mediation models

In order to examine mediational processes predicting academic achievement from target lifestyle behaviors via candidate brain health mediators (MSIT parameters, fNIRS ROI), multiple mediation models were fitted using the PROCESS Macro in SPSS. This analysis was completed separately for each lifestyle behaviour (i.e., average sleep hours, average active minutes, fast-food consumption and substance use) and each academic outcome variable (i.e., English and Math grades), while controlling for % correct MSIT responses.

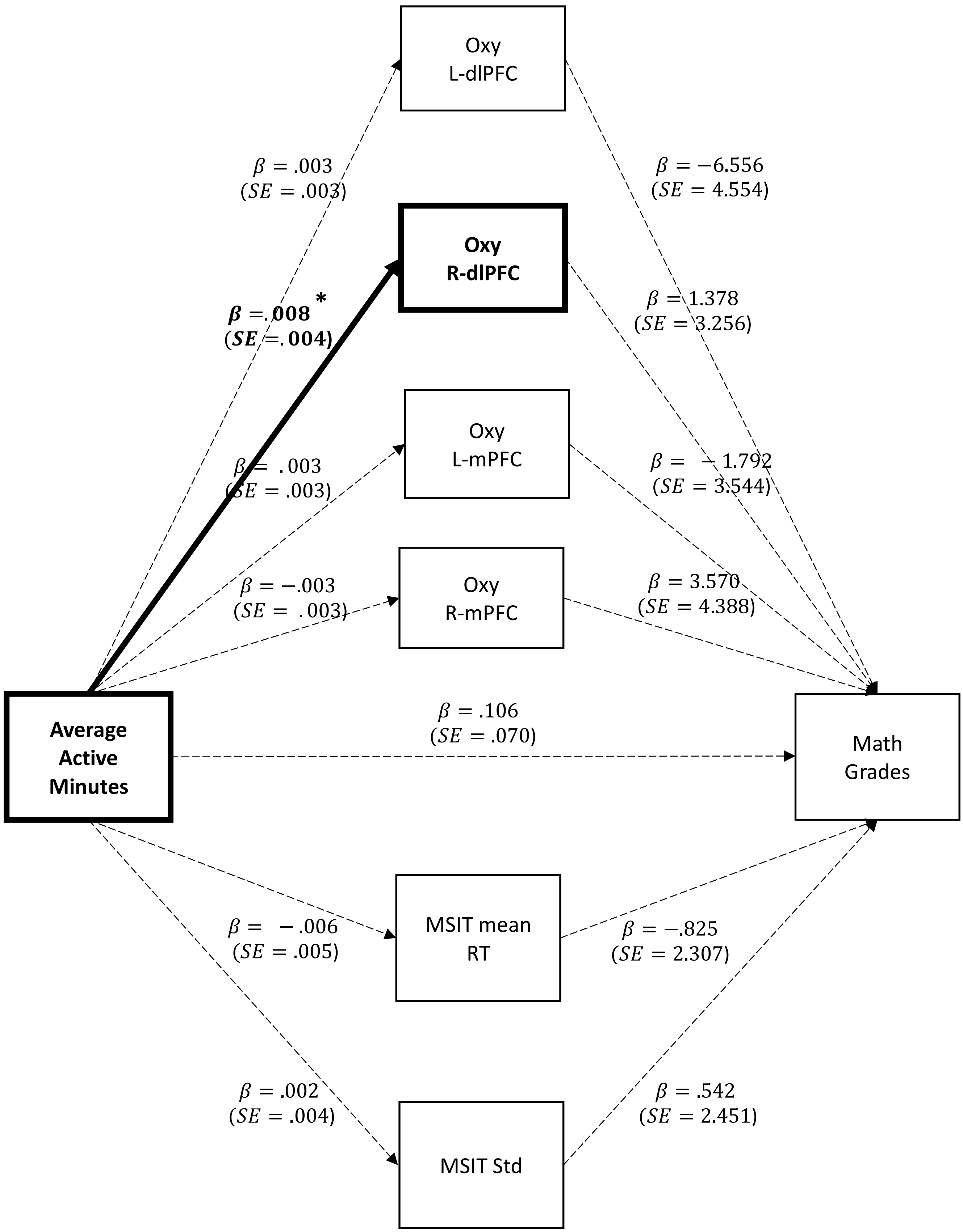
3.2.1 Math grades

3.2.1.1 Physical activity multiple mediation model

Figure 7 depicts the multiple mediation model predicting Math grades from average active minutes through brain health parameters. There was a significant effect of average active minutes on R-dlPFC OxyHb ($\beta = .008$, *SE*= .004, ρ =.032), but no effect of average active minutes on L-dlPFC OxyHb ($\beta = .003$, *SE*= .003, ρ = .295), L-mPFC OxyHb ($\beta = .003$, *SE*= .003, ρ =.401), or R-mPFC OxyHb ($\beta = -.003$, SE= .003, ρ= .266). There was also no direct effect of average active minutes on Math grades (β=.106, SE=.070, ρ= .139), and no effect of average active minutes on either the MSIT mean RT (β= −.006, SE=.005, ρ= .184), or on the MSIT SD ($\beta = .002, SE = .004, \rho = .676$). None of the brain health parameters were significant predictors of Math grades.

The indirect effect of average active minutes on Math grades through R-dlPFC OxyHb was not significant; the upper and lower bound for the 95% confidence interval for the indirect effect included zero (est.= .011 (*SE*= .025); CI_{LL} = -.039, CI_{UL} = .064), suggesting a null mediational effect. None of the other indirect effects involving brain health parameters were significant (Appendix 5).

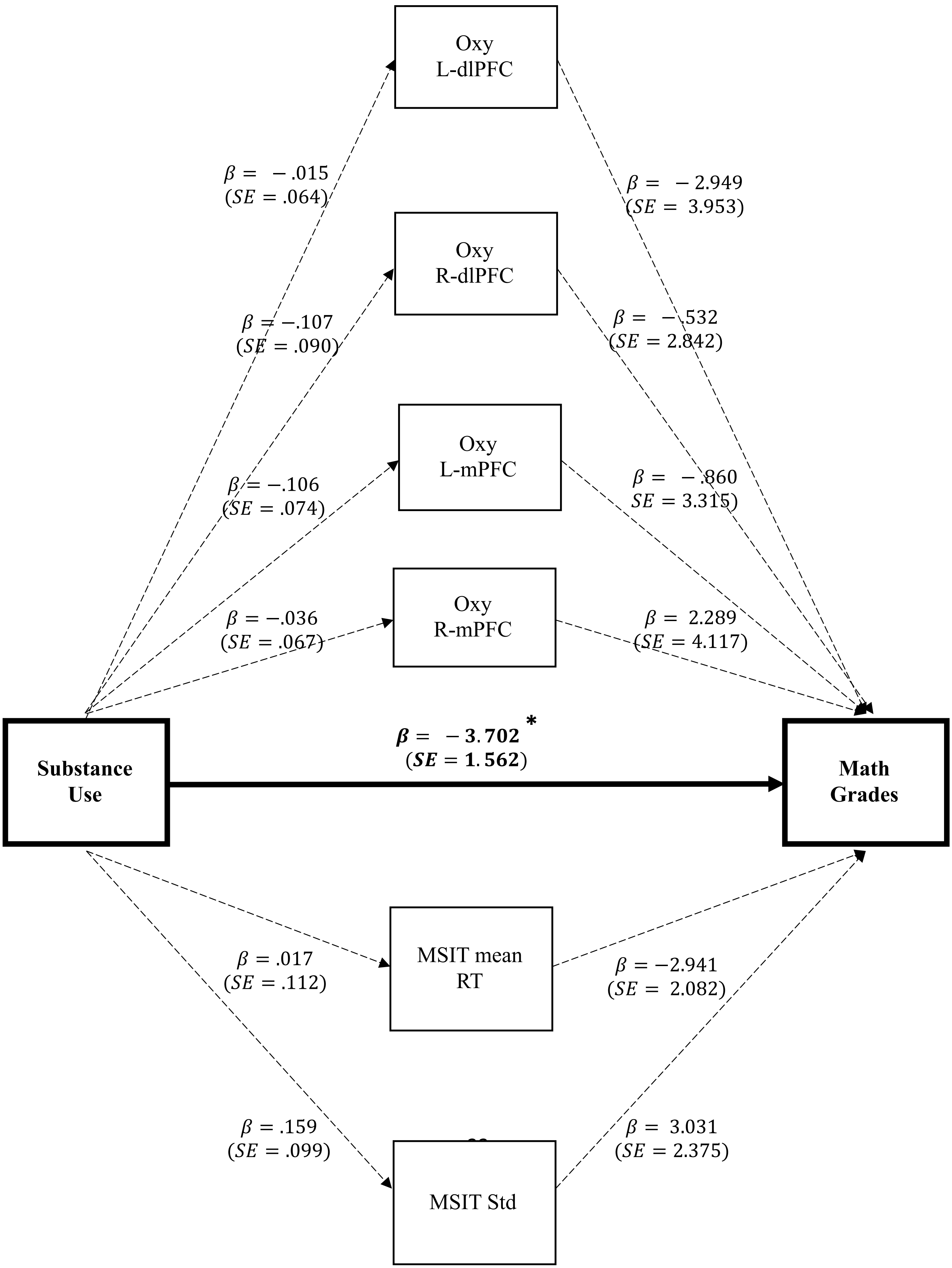
Figure 7. *Multiple mediation model predicting Math grades from accelerometer-assessed active minutes of physical activity through brain health parameters, controlling for MSIT % correct responses*



3.2.1.2 Substance use multiple mediation model

Figure 8 depicts the multiple mediation model predicting Math grades from substance use through brain health parameters. There was a significant direct effect of substance use on Math grades; specifically, more frequent substance use in the past month predicted significantly worse math grades (β= -3.702, SE= 1.563, ρ= .022). There was no effect of substance use on either the MSIT mean RT (β=.017, SE=.112, ρ= .883), or on the MSIT SD (β=.159, SE=.099, $\rho = .113$). There was also no significant effect of substance use on L-dlPFC OxyHb (β= −.015, SE=.064, ρ = .813), R-dlPFC OxyHb (β=−.107, SE=.090, ρ = .240), L-mPFC OxyHb (β=−.106, SE=.074, ρ = .176), or R-mPFC OxyHb (β=−.036, SE=.067, ρ= .630). None of the brain health parameters were significant predictors of Math grades, and none of the indirect effects involving brain health parameters were significant (Appendix 5).

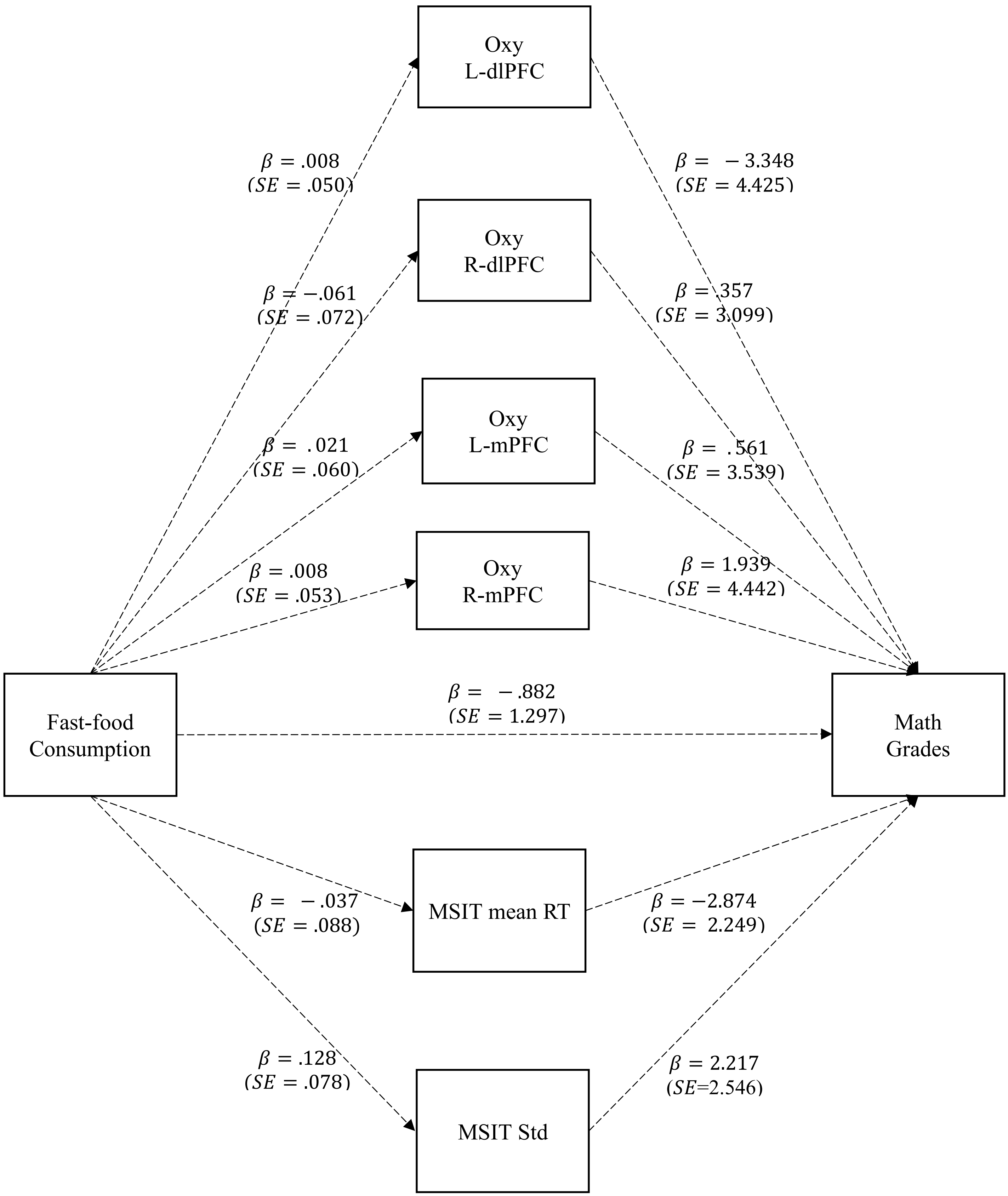
Figure 8. *Multiple mediation model predicting Math grades from self-reported substance use through brain health parameters, controlling for MSIT % correct responses*



3.2.1.3 Fast-food consumption multiple mediation model

Figure 9 depicts the multiple mediation model predicting Math grades from fast-food consumption through brain health parameters. There was no direct effect of fast-food consumption on Math grades (β= −.882, SE=1.297, ρ= .500), and no effect of fast-food consumption on either the MSIT mean RT (β= -.037, SE= .088, ρ= .679), or on the MSIT SD (β= .128, SE=.078, $\rho = .109$). There was also no significant effect of fast-food consumption on L-dlPFC OxyHb (β=.008, SE=.050, ρ = .874), R-dlPFC OxyHb (β= -.061, SE= .072, ρ = .406), L-mPFC OxyHb (β= .021, SE=.060, ρ = .731), or R-mPFC OxyHb (β=.008, SE=.053, ρ= .885). None of the brain health parameters were significant predictors of Math grades, and none of the indirect effects involving brain health parameters were significant (Appendix 5).

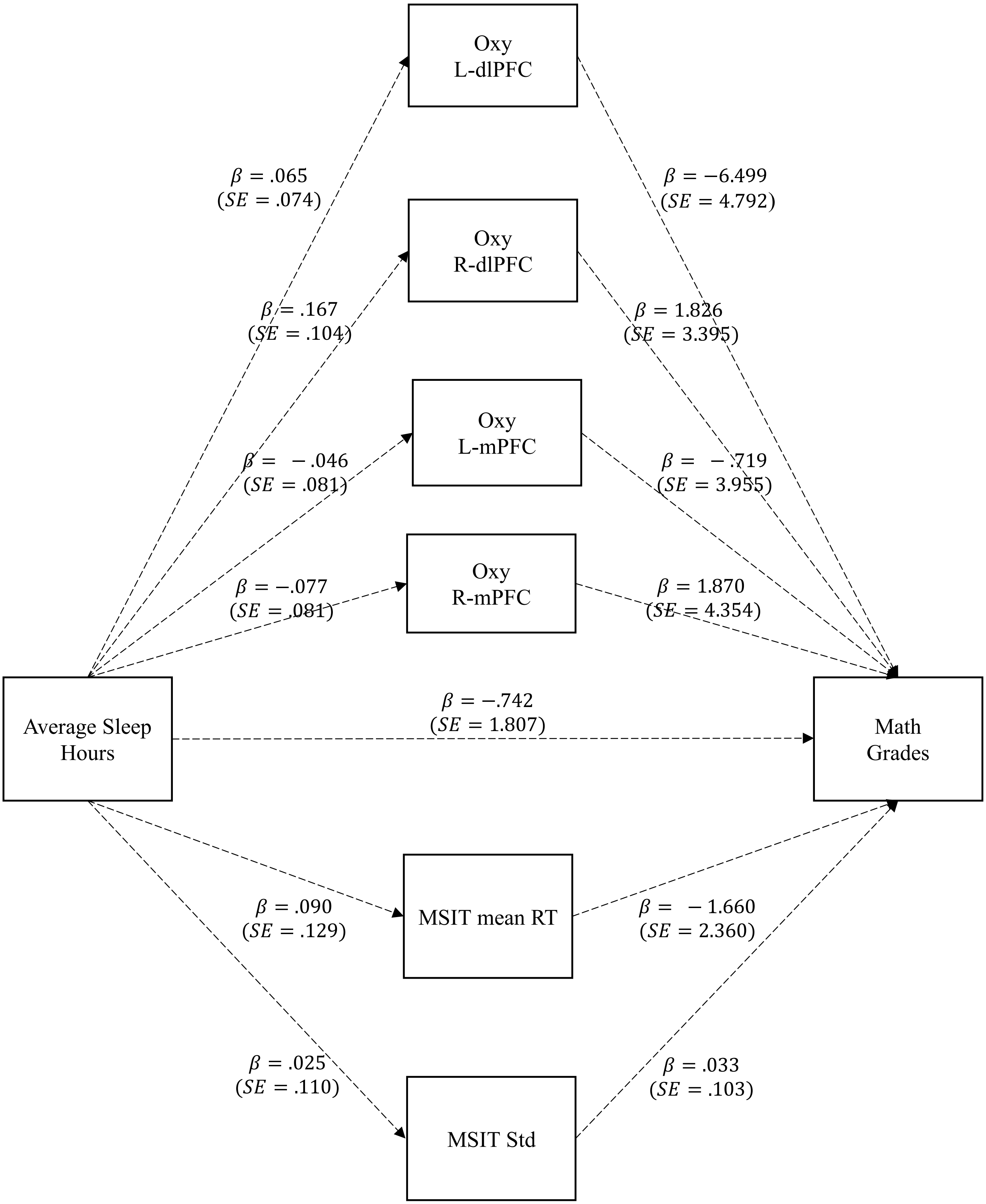
Figure 9. *Multiple mediation model predicting Math grades from self-reported fast-food consumption through brain health parameters, controlling for MSIT % correct responses.*



3.2.1.4 Average sleep hours multiple mediation model

Figure 10 depicts the multiple mediation model predicting Math grades from average sleep hours through brain health parameters. There was no direct effect of average sleep hours on Math grades (β=−.742, SE=1.807, ρ= .684), and no effect of average sleep hours on either the MSIT mean RT (β=.090, SE=.129, ρ= .488), or on the MSIT SD (β=.025, SE=.110, $\rho = .823$). There was also no significant effect of average sleep hours on L-dlPFC OxyHb (β=.065, SE=.074, ρ = .385), R-dlPFC OxyHb (β=.167, SE=.104, ρ = .114), L-mPFC OxyHb (β= −.046, SE=.081, ρ = .577), or R-mPFC OxyHb (β=−.077, SE=.081, ρ= .346). None of the brain health parameters were significant predictors of Math grades, and none of the indirect effects involving brain health parameters were significant (Appendix 5).

Figure 10. *Multiple mediation model predicting Math grades from accelerometer-assessed sleep hours through brain health parameters, controlling for MSIT % correct responses*



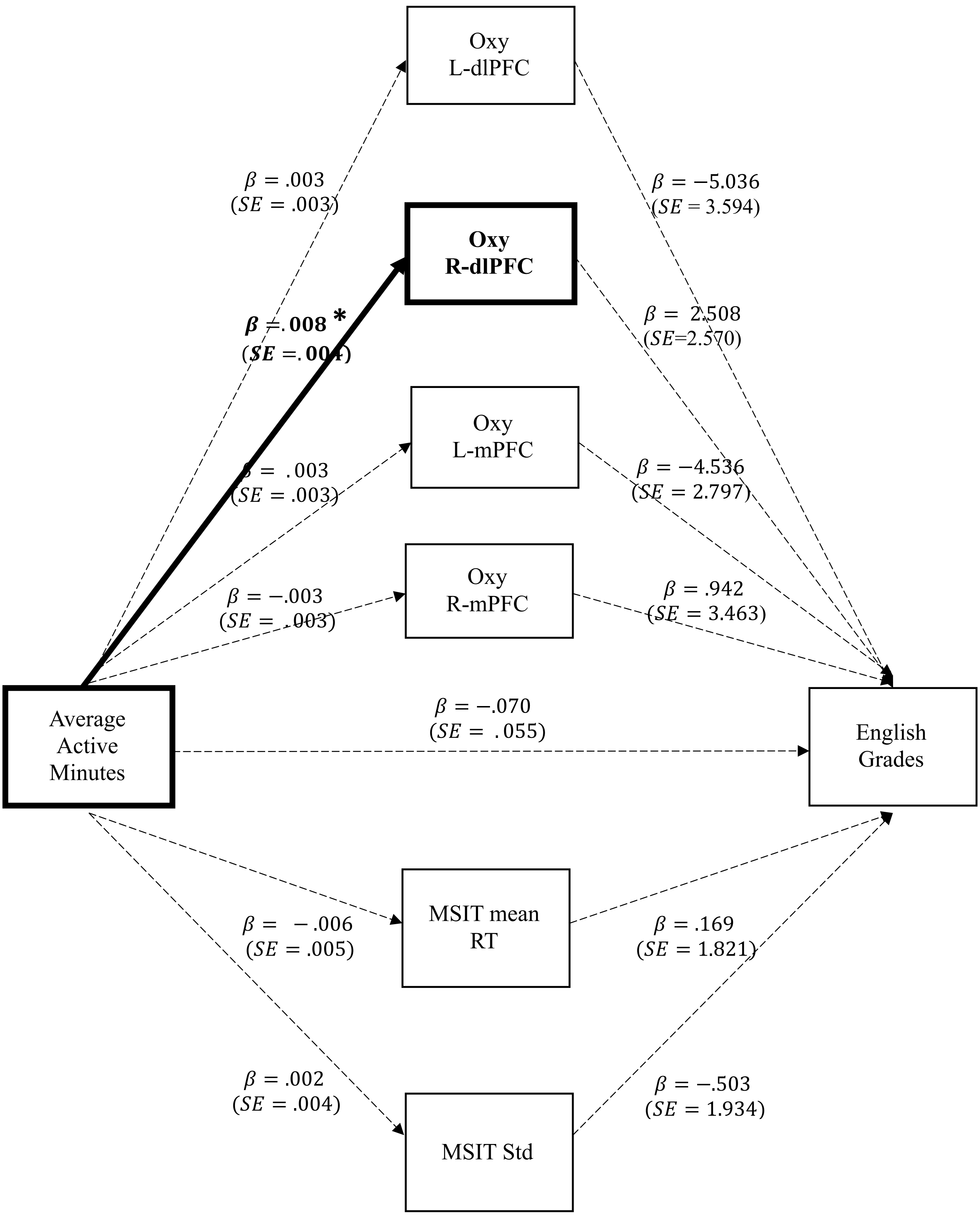
3.2.2 English grades

3.2.2.1 Physical activity multiple mediation model

The above multiple mediation models were repeated with English grades as the outcome variable. Figure 11 depicts the multiple mediation model predicting English grades from average active minutes through the brain health parameters. There was a significant effect of average active minutes on R-dlPFC OxyHb ($\beta = .008$, *SE*= .004, ρ =.032), but no effect of average active minutes on L-dlPFC OxyHb ($\beta = .003$, *SE*= .003, ρ = .295), L-mPFC OxyHb ($\beta = .003$, *SE*= .003, ρ =.401), or R-mPFC OxyHb ($\beta = -.003$, SE= .003, ρ= .266). There was also no direct effect of average active minutes on English grades (β=−.070, SE= .055, ρ= .659), and no effect of average active minutes on either the MSIT mean RT (β= −.006, SE=.005, ρ= .184), or on the MSIT SD ($\beta = .002, SE = .004, \rho = .676$). None of the brain health parameters were significant predictors of English grades.

The indirect effect of average active minutes on English grades through R-dlPFC OxyHb was not significant; the upper and lower bound for the 95% confidence interval for the indirect effect included zero (est.= .020 (*SE*= .027); CI_{LL} = -.023, CI_{UL} = .081), suggesting a null mediational effect. None of the other indirect effects involving brain health parameters were significant (Appendix 6).

Figure 11. *Multiple mediation model predicting English grades from accelerometer-assessed active minutes of physical activity through brain health parameters, controlling for MSIT % correct responses*



3.2.2.2 Remaining multiple mediation models

None of the direct or indirect effects predicting English grades were significant (Appendix 6). Figures 12 through 14 show the path coefficients for substance use, fast-food consumption and average sleep hours.

Figure 12. *Multiple mediation model predicting English grades from self-reported substance use through brain health parameters, controlling for MSIT % correct responses*

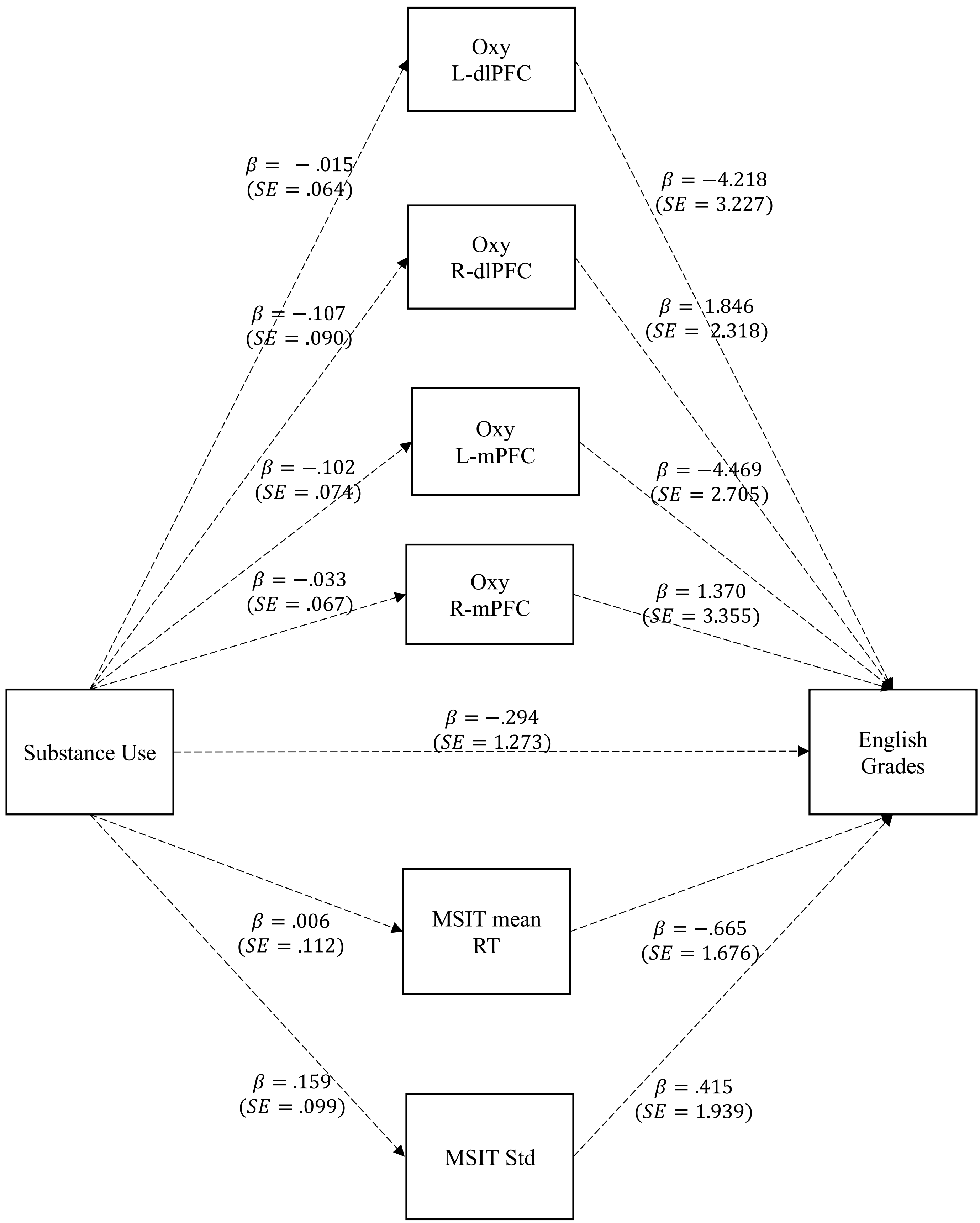


Figure 13. *Multiple mediation model predicting Math grades from self-reported fast-food consumption through brain health parameters, controlling for MSIT % correct responses*

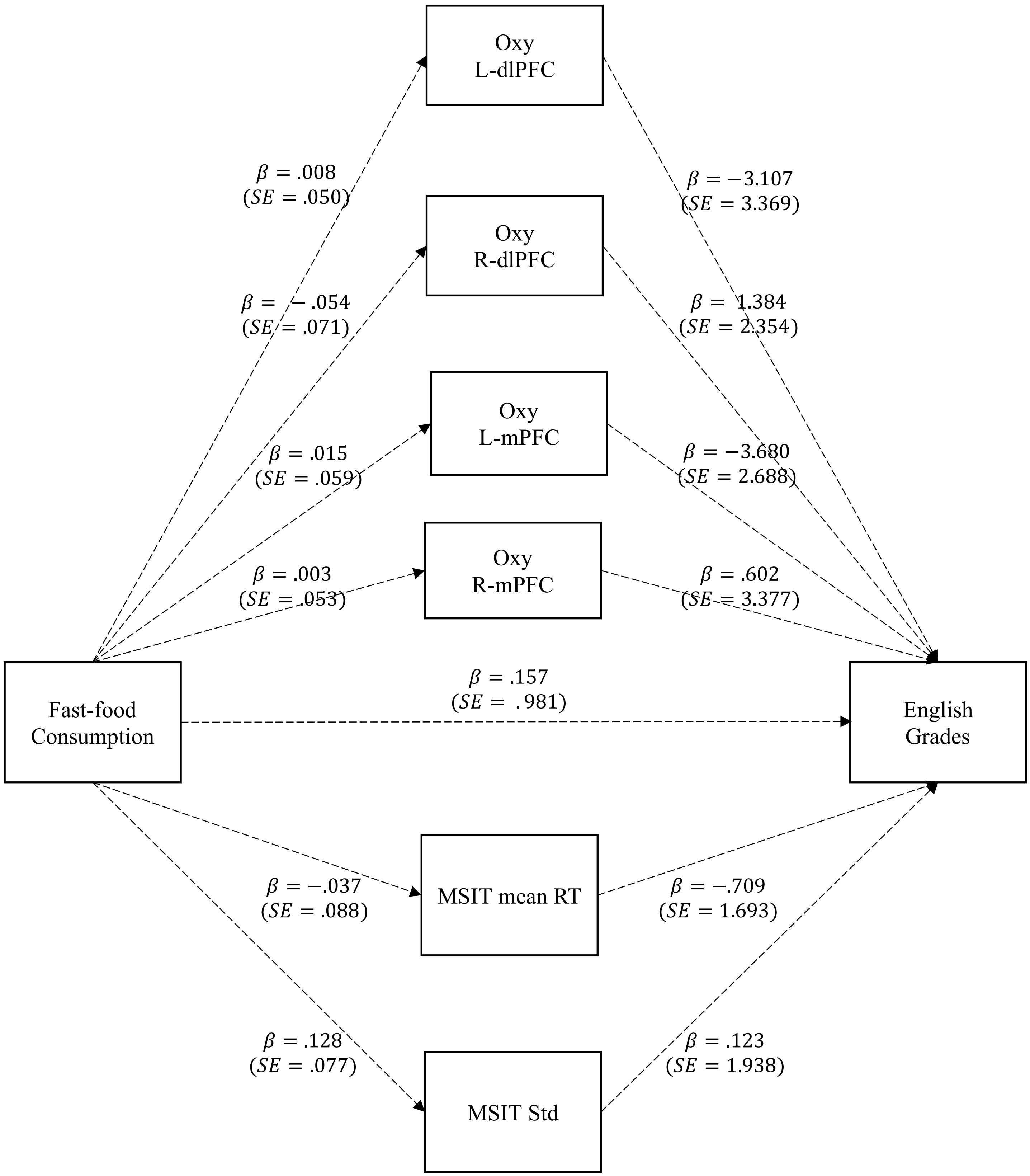
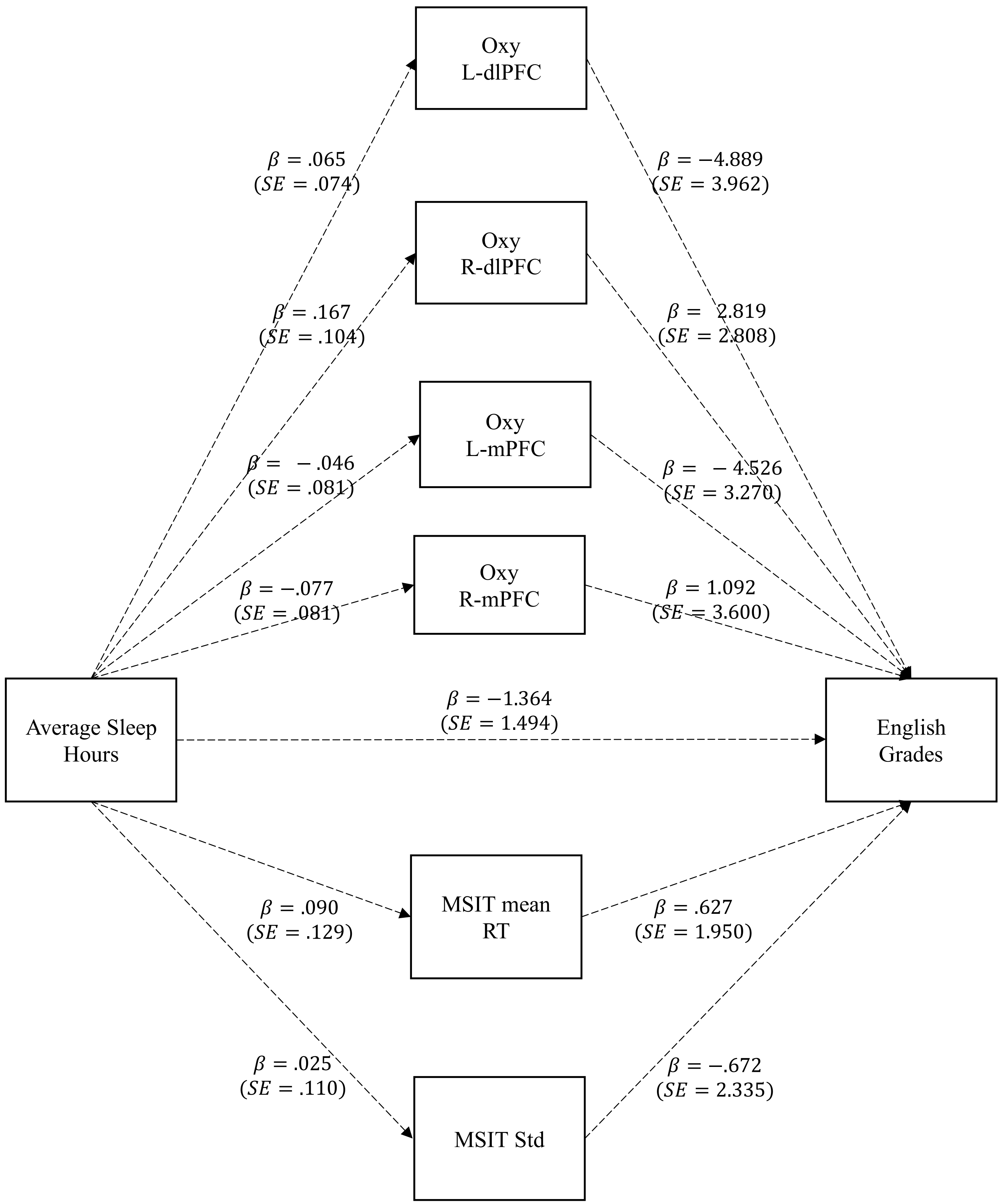


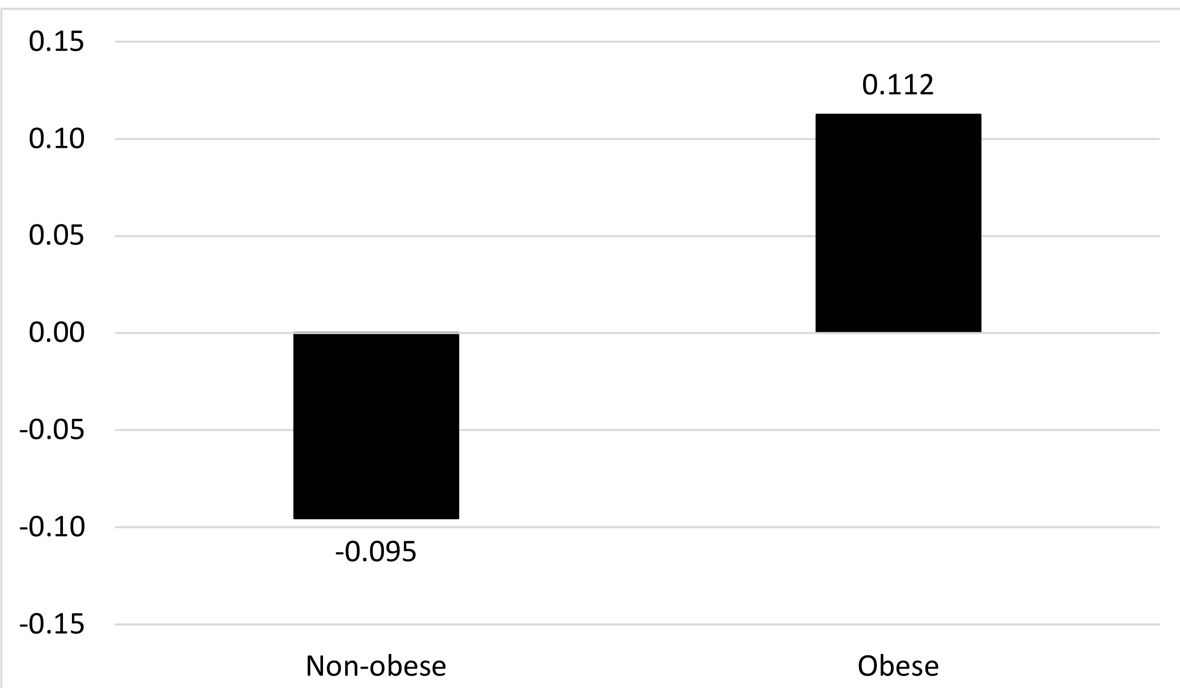
Figure 14. *Multiple mediation model predicting English grades from accelerometer-assessed sleep hours through brain health parameters, controlling for MSIT % correct responses*



3.3 Conditional process models

A set of conditional process models were tested to examine the extent to which lifestyle behaviour associations with academic performance mediated through brain health variables might be conditional upon age, gender and BMI. A significant moderation effect emerged regarding BMI on the indirect effect of average active minutes on English and Math grades through MSIT SD (ΔR^2= .086, F=6.318 (1, 45), ρ =.016). Specifically, average active minutes had a stronger effect on the MSIT SD for those in the highest BMI category (β = .431, SE= .192, ρ= .030). The corresponding effect sizes were .112 for those in the obesity range ($\geq 95^{th}$ percentile) and -.095 for all others ($<95^{th}$ percentile; Figure 15).

Figure 15. *Effect sizes for active minutes predicting MSIT SD*



All additional models produced null moderated mediational effects; the corresponding coefficients are presented in Appendices 7 to 12.

4 Discussion

The purpose of this study was to examine the extent to which the relationships between physical activity, lifestyle behaviours and academic performance were mediated by brain health parameters in a sample of adolescents. A prospective observational design was employed, using accelerometry-assessed physical activity and sleep as well as other variables measured by self-report. Brain health was estimated using by fNIRS indicators of PFC oxygenation as well as performance on a cognitive interference task. Findings revealed that higher levels of accelerometer-assessed physical activity, as well as less frequent fast-food consumption both independently predicted significantly better performance on the interference task when controlling for age. The association between physical activity and task performance on the interference task was found to be moderated by gender, such that the effect was significantly stronger for female adolescents versus males. Furthermore, higher levels of physical activity were associated with larger increases in task-related oxygenation in the R-dlPFC during interference blocks, and relative to baseline. Although significant relationships between activity and two indicators of brain health were present, there were no clear links between active minutes or fast-food consumption and academic achievement, either directly or mediated by brain health variables.

A multiple mediation approach was used to investigate the relationship between each lifestyle predictor and each academic outcome, as mediated through all brain health mediators (task parameters and functional imaging parameters). Fast-food consumption was associated with MSIT performance (% correct responses), but eating habits were not significantly associated with any other MSIT indicator (i.e., MSIT mean RT and SD) or oxygenation in any ROI. In addition, the relationship between fast-food consumption and MSIT mean RT or SD was not significant when the % of correct responses was adjusted for in the model. Higher levels of self-reported substance use were associated with poorer performance in Math; however, there was no evidence that any of the brain health parameters mediated this relationship. Finally, average sleep hours were not significantly associated with either of the academic outcomes, or indirectly associated with the brain health parameters.

Conditional process (i.e., moderated mediation) models were used to explore the extent to which the multiple mediation models were moderated by age, gender or BMI. A significant moderating effect emerged for BMI on the indirect effect of average active minutes on English and Math grades through reaction time variability on the interference task. Average active minutes was found to have a stronger effect on interference task variability for those in the highest BMI category. Initial models also suggested that BMI was a significant moderator in the relationship between substance use and task performance, where performance on the interference task was better for those whose BMI fell within the obese range. However, there was no moderating effect of BMI in the relationship between substance use and task mean reaction time, or reaction time variability when utilizing the conditional process models. Finally, BMI was shown to moderate the relationship between active minutes and reaction time variability, such that those with greater active minutes and in the greatest BMI category had a significantly greater MSIT SD.

Although there was no direct effect of physical activity on either English or Math achievement, greater levels of physical activity were associated with better performance on the cognitive interference task and higher levels of neuronal activation in the dlPFC during the interference task. Here we see two potential indicators of the benefit of exercise on the brain health of adolescents: the benefit on cognitive performance and through increased activation in an important executive control node within the PFC (i.e., the right lateral dlPFC) during task engagement. This is consistent with a wealth of experimental findings, which have found cognitive benefits of physical activity across age ranges (57,66,73) and when investigating the effects of activity on task related performance using various interference tasks (e.g., Stroop, Flanker; 58,110,111).

Furthermore, a meta-analysis summarizing the impact of physical activity interventions on executive functions in adolescents indicated that acute physical activity had a moderate and positive effect on executive functions overall (*d*=.52) in addition to a moderate positive effect on inhibition or interference control (*d*=.46; 78). In agreement with these findings, functional neuroimaging studies utilizing fNIRS, fMRI and EEG have found significant increases in task-related activation in the lateral PFC, as well as greater activation in the left middle frontal gyrus and right middle frontal gyrus following physical activity or when comparing fit to unfit youth (58,67,68,79). Although stronger activation in the L-dlPFC is commonly associated with interference tasks (as exemplified by initial contrasts of OxyHb per channel for control and interference blocks of the MSIT) some studies have found bilateral activation in the dlPFC during interference tasks following exercise interventions (3,6). Nonetheless, the association between active minutes and oxygenation in the R-dlPFC supports the notion that physical activity does promote greater activation in the PFC. These findings are in line with what was hypothesized and provide support for the brain benefits of physical activity.

Contrary to hypotheses, there was no direct association between physical activity and either indicator of academic achievement. This pattern of findings is consistent with the null findings of the population-based preliminary study (See section 1.4). It is important to note that the direction of the association in the highly powered population-based study and the relationship found between physical activity and English grades in the current thesis study (which had the benefit of using accelerometry rather than self-report) were both slightly negative rather than positive; that is, both studies suggest a slight academic disadvantage for those adolescents who engage in high levels of activity. It is of note, however, that both studies were observational in nature, rather than experimental. While observational studies are useful, experimental designs involving randomization to condition are preferable for causal interference (116). A handful of prior experimental studies have found some positive effects using such designs (59,68,117).

There are other potential explanations for a null mediational effect of physical activity on academic achievement. Although an indication of a brain benefit of activity was found, it is possible that such activity-induced brain benefits were simply not strong enough to induce changes in academic achievement. Meta-analyses on the topic have shown a small effect of physical activity on academic performance in children (82,118), and so high statistical power may be required to detect a translatable effect. The current study, as well as the highly powered preliminary study, found a slight negative effect on academic achievement, which argues against this possibility. Alternatively, academic performance is an outcome that is highly multi-determined, such that it relies on the cooperation of many cognitive processes (e.g., working memory, controlled attention; 33,115) and is a construct that can be influenced by many external factors, including socioeconomic status, race and gender (116,117). Consequently, activity may only marginally impact academic performance because the total universe of influences is so expansive. Likewise, the time-competition hypothesis, which implies a negative association between physical activity and academic performance, could also help explain the observed null relationship, or an interaction between the brain benefit and time-competition hypotheses, such that any brain health benefits of activity could be offset by the time detracted from academic pursuits. The pattern of data in the current study is most consistent with this latter interpretation.

Interestingly, performance on the cognitive interference task was moderated by gender, such that the effect of physical activity on task performance was stronger for females than for males. Sex has previously been shown to moderate the effects of physical activity effects on the brain, but primarily in older adults (122). It has been hypothesized that differences between females and males sex steroid hormones could impact cognition (e.g., estrogen, testosterone). It is possible that the hormonal environment during pubertal development may have enduring effects on both the structure and function of the brain from the adolescent developmental period and onwards (122,123). This may explain why the current findings suggest that such sex differences may extend to lower age ranges. Alternatively, BDNF concentrations have been shown to increase after acute bouts of physical activity, independent of age (57). The relationship between physical activity and increased BDNF may be especially prominent in females because estradiol can also upregulate BDNF in the brain (122,124). Notably, the observed moderating effect of sex carries important implications for the promotion of physical activity. Female adolescents may benefit most from physical activity interventions as this group experiences greater brain benefits, but also because the proportion of female adolescents who participate in physical activity decreases with age (125). It could be argued from this perspective that greater emphasis on physical education for females could be undertaken in schools, especially targeting those in upper years (i.e., grade 11 or 12), if any associated time competition effects could be offset.

In addition to the effects of physical activity on task performance, more frequent fast-food consumption was associated with poorer performance on the cognitive interference task. The capacity to control eating behaviours is strongly tied to executive functions, where resisting high calorie, low nutrient foods in favour of nutrient dense foods requires a level of self-regulation (50,126). However, the correlational nature of this study does not allow for interpretations of the temporal relationship between these two variables. It is possible that increased fast food consumption can negatively impact executive functioning, but equally as possible that reduced executive functioning can predict greater fast food consumption. Previous studies have identified a negative relationship between poor dietary habits and reduced executive functioning (127,128); for example, a prospective longitudinal study of 602 adolescents found that an high intake of fast-foods, red and processed meats, and fried and refined foods at age 14 was associated with a higher number of errors on an executive function task three years later (128). In contrast, experimental studies involving transient up- or down-regulation of the lateral PFC have produced causal changes in food consumption, which supports the alternative temporal relationship (129,130). Moreover, a longitudinal study conducted by Cappelli et al. found that low executive functioning at baseline predicted more frequent high calorie, low nutrient food consumption 2.5 years later (42). While either relationship may be valid (or a reciprocal relationship may be present), there is a current lack of longitudinal studies on the topic and very few intervention studies that manipulate diet in order to measure the relative impact on cognitive control in adolescents. Notwithstanding, the results of this study do emphasize importance of dietary quality on executive functioning in this age group.

Multiple mediation models revealed that greater substance use predicted poorer Math grades. This is consistent with hypotheses, and prior findings that substance use among adolescents negatively impacts academic achievement (56,131). Cross-sectional studies have demonstrated a negative relationship between history of substance and academics (131,132). In addition, a large-scale longitudinal study investigating the effects of alcohol and cannabis use found that those who had history of substance use also had poorer academic performance and academic disengagement (133). Likewise, a systematic review conducted by Townsend and colleagues found a consistent relationship between substance use and dropping out of high school, even when accounting for heterogeneity in measures of substance use and definitions of dropout (56). Because substance use experimentation and substance use disorders often emerge in adolescents (134) and this variable was the only significant predictor of academic achievement, high schools should be especially aware of the impact of substance use when tailoring preventative initiatives.

Conditional process models revealed that BMI was a moderator in the relationship between substance use and cognitive interference task performance. The findings suggested that those who used substances and who were obese performed significantly better on the MSIT when compared to those in lower BMI categories. It has been shown that adolescents with problematic tobacco and cannabis smoking were at an increased risk of developing obesity (135) which suggests a relationship between the two variables. However, it remains unclear as to why a higher BMI category would be associated with greater MSIT performance for those who use substances. Future research will be required to examine the reliability and meaning of this unanticipated finding.

4.1 Strengths and Limitations

A key limitation of this study was the observational research design, which limits the extent to which causal effects can be identified. Likewise, some variables were studied with temporal lags (e.g., prospective) but not others, making directionality inferences challenging in the latter. Furthermore, the number of recording days using the Fitbit Inspire watch is a limitation in that the novelty of the wearable technology may have increased reactivity; participants may have increased their physical activity in response to receiving the Fitbit. With longer wear times there would be an opportunity to reliably assess habitual activity without interference from reactivity. In addition, excluding measurement over the weekend could have led to the exclusion of some forms of physical activity entirely (e.g., cycling, organized team sports, other leisure activities that may disproportionally occur on the weekends). It is not possible to predict to what effect this may have had on the findings, as these limitations could have biased the results in any direction, or not at all. Another limitation is the small sample size, which may have resulted in reduced statistical power to detect effects, which could have impacted the ability to detect significant associations. Although the sample size was above the minimum required number of participants for a moderate effect size (r=.4), and relatively large in comparison to other fNIRS studies (i.e., N= 20-40; 43,67,110), a larger sample size could have increased the power and allowed for more nuanced associations to be discovered. Furthermore, the field setting introduced noise into the fNIRS measurements, which in turn may have contributed to missing data and lower quality data overall. This study relied on the availability of space at each school and it was difficult to standardize the environmental parameters, which included different levels of light, noise and ambient temperature; all of these could contribute to unwanted random variability in the measurement of fNIRS parameters. Finally, the use of self-reported academic achievement variables may have been subject to reporting biases, such as social desirability bias and recall bias. When assessing the negative relationship between active minutes and both academic indicators, it is possible that students could have inaccurately recounted their grades and/or intentionally inflated the grades they did receive potentially leading to an under-estimation of associations.

The key strengths of this study included the use of objective measures of brain activation, physical activity and sleep; the latter two in particular are thought to be more reliable and valid than self-report measures (95,112). In addition, the use of both fNIRS imaging and a standardized cognitive task allowed for the derivation of several indicators of brain health, both in terms of behavioural markers of executive function and task related activation in the PFC. Furthermore, the field setting allowed for direct recruitment of students in a naturalistic environment. Finally, there are relatively few studies that employ a brain imaging protocol in order to investigate how lifestyle behaviours impact academic performance through brain health parameters, and even fewer who examine these relationships in adolescents. Therefore, this study fills a gap in the current literature on the subject and highlights important directions for future research.

One secondary purpose of this study was to establish a highly efficient data collection session performed on-site at schools combining fNIRS measurements, cognitive testing, and self-report assessments in as minimal time possible. This was a fully intentional effort to explore the limits of “light touch” data collection in applied neuroscience research, in the interest of very large-scale studies that might be planned in the future. This study showed that such approaches for on-site data collection in school settings are feasible. However, the highly minimalistic approach to measurement of self-reported lifestyle variables may have attenuated some of the predictive relationships due to unreliability in measurement. For example, the measures of eating and substance use were more similar to those typically used in experience-sampling paradigms, where rapid response is valued over more reliable multi-itemed scales.

When assessing the brain health of adolescents in a school setting, there are several advantages to the use of a portable fNIRS system. Firstly, the portability of the device allowed for deployment to several school locations, as well as the recruitment and measurement of a relatively large sample of adolescents (in comparison to other fNIRS and fMRI studies). In addition, the quick set up time and calibration of the device allowed for a quick turn-around time in between participants, allowing around 15 participants to be run within a single school day. Disadvantages in relation to this protocol included the inability to standardize school environments and sensitivity of the equipment. While the school setting was advantageous in that it allowed for enhanced recruitment of adolescents due to the high concentration of students within the building, the on-site data collection approach relied on space availability of each school. It is not possible to ensure available space is free from distractions, and it is possible that a school with limited space may not be able to participate. Moreover, outside of the lab environment, the fNIRS device was subject to more technical challenges and sensitive to noise due to difference in the room set up between schools (i.e., power outlet location, table height, etc.).

4.2 Future directions

There are several important avenues for future research. In terms of design improvements, a longitudinal design could help to identify changes in the brain health over time and provide a clearer indicator of the temporal relationship and direction of association between lifestyle habits and academic outcomes. Furthermore, including an objective measure of academic performance could help to reduce social desirability and recall bias; this would increase the statistical power to detect effects. Future studies could scale up this protocol in order to reach a larger number of schools; this would help to increase the size and diversity of the sample. Targeting schools in rural versus urban versus locations would enable comparisons between location. Furthermore, the portability of this technology also allows for greater access marginalized communities who are often overlooked in brain imaging research. Targeting other age groups could also identify how brain health changes throughout the lifespan.

The Fitbit watches relied on acceleration in order to track activity and so other forms of activity that are not reliant on acceleration may not be captured within active minutes (107). Although aerobic exercise tends to have the strongest effect on cognitive performance, weight training and meditative activities have also been shown to positively impact cognition (136,137). Future studies could investigate the impact of other forms of physical activity, and whether or not weight training or yoga could also confer cognitive benefits.

This study found a negative effect of frequent substance use on Math grades. Each substance has the potential to impact the structure and function of the brain in different ways. For example, Aloi and colleagues found that adolescents with an alcohol use disorder versus cannabis use disorder differed in patterns of brain activation in relation to the Stroop interference task (138). Alcohol use disorder severity was associated with decreased recruitment in regions including the dlPFC and inferior parietal lobule, whereas severity of a cannabis use disorder was associated with increased activation for in regions including the posterior cingulate cortex, precuneus and inferior parietal lobule for interference versus control trials (138). Elucidating the forms of substance use that impact academic performance to the greatest extent could help inform harm reduction approaches in order to bolster achievement in adolescents who use substances.

4.3 Conclusion

Utilizing a sample of adolescents, this study aimed to identify to what extent the relationship between lifestyle behaviours and academic performance was mediated by brain health. Although there was no direct association present between accelerometer-assessed physical activity and either English or Math grades, greater active minutes did have a positive effect on interference task performance and on lateral PFC recruitment during the task. This provides support for the cognitive enhancement potential of physical activity, but not for the hypothesized mediating role of brain health on academic achievement. The effect of active minutes on cognitive task performance was also moderated by gender, such that females experienced a greater benefit of physical activity compared to males.

Investigation into the other lifestyle behaviours found that fast-food consumption was negatively associated with performance on the cognitive interference task, and that more frequent substance use predicted poorer math grades. Interestingly, BMI also moderated the relationship between substance use and the % correct responses on interference task performance, such that those who used substance and who had a greater BMI also had greater MSIT performance. BMI was also a moderator in the relationship between active minutes and reaction time variability.

Altogether, the results of this study demonstrate the importance of lifestyle factors in the cognition and academic performance of the adolescent population. This study lends support to prevention efforts targeted towards the cognitive enhancements of physical activity, especially if these programs target females and those with a greater BMI. Future studies could attempt to investigate the temporality of this relationship in more detail. The adolescence life phase also comes with greater autonomy surrounding diet, and a time when substance use disorders can appear. Prevention efforts targeting both lifestyle variables are especially important in this age group.

This is the first study to my knowledge that utilized objective fNIRS measurements of PFC oxygenation and accelerometer indicators of activity and sleep in a field setting to study a sample of adolescents. Not only are the findings applicable to school administration looking to bolster academic achievement and cognitive performance in youth, the findings can provide information pertaining to the logistics of employing fNIRS technology in on-site locations in future school-based studies of brain health in adolescent populations.

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Appendices

Appendix 1: Measure of demographics, health behaviours and academic performance

Health Behaviours:

What is your age? _______________

What is your gender?

Male Female Other

How many times eaten have you eaten “fast-food” (eg. McDonalds, Burger King, etc.) in past week?

____

How many times have you experimented in the past month with a substances (eg. alcohol, cannabis, other)?

0 times. 1-2 times 3-5 times 6+ times

What was the final grade that you received last year (2018-2019) in Math class? _______________

What was the final grade that you received last year (2018-2019) in English class? ________________

Appendix 2: Weekly Calendar

Weekly Calendar							
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
6:00 AM							
7:00 AM							
8:00 AM							
9:00 AM							
10:00 AM							
11:00 AM							
Noon							
1:00 PM							

2:00 PM							
3:00 PM							
4:00 PM							
5:00 PM							
6:00 PM							
7:00 PM							
8:00 PM							
9:00 PM							
10:00 PM							
Overnight							

Reasons for removing the Fitbit Inspire (Please indicate the day):

Appendix 3: CES-D scale

Below is a list of the ways you might have felt or behaved. Please tell me how often you have felt this way during the last week.	**Rarely to Not at all (Less than 1 day)**	**Some or a little of the time (1-2 days)**	**Occasionally or a moderate amount of time (3-4 days)**	**Most or all of the time (5-7 days**
1. I was bothered by things that don’t usually bother me	0	1	2	3
2. I did not feel like eating; my appetite was poor	0	1	2	3
3. I felt like I could not shake off the blues, even with help from family or friends	0	1	2	3
4. I felt that I was just as good as other people	0	1	2	3
5. I had trouble keeping my mind on what I was doing	0	1	2	3
6. I felt depressed	0	1	2	3
7. I felt that everything I did was an effort	0	1	2	3

8. I felt hopeful about the future	0	1	2	3
9. I thought my life had been a failure	0	1	2	3
10. I felt fearful	0	1	2	3
11. My sleep was restless	0	1	2	3
12. I was happy	0	1	2	3
13. I talked less than usual	0	1	2	3
14. I felt lonely	0	1	2	3
15. People were unfriendly	0	1	2	3
16. I enjoyed my life	0	1	2	3
17. I had crying spells	0	1	2	3
18. I felt sad	0	1	2	3

19. I felt that people disliked me	0	1	2	3
20. I could not get “going”	0	1	2	3

Total: **Add Columns:**

Appended from: Radloff, L. (1977). The CES-D Scale : A Self-Report Depression Scale for Research in the General Population. *Appl Psychol Meas*, 1(3):385-401.

Appendix 4: GAD-7 scale

Over the last two weeks, how often have you been bothered by the following problems?	**Not at all**	**Several days**	**More than half of the days**	**Nearly everyday**
1. Feeling nervous, anxious or no edge	0	1	2	3
2. Not being able to stop or control worrying	0	1	2	3
3. Worrying too much about different things	0	1	2	3
4. Trouble relaxing	0	1	2	3
5. Being so restless that it is hard to sit still	0	1	2	3
6. Becoming easily annoyed or irritable	0	1	2	3
7. Feeling afraid as if something awful might happen	0	1	2	3
Total:	**Add Columns:**			

If you checked off any problems, how difficult have these problems made it for you to do your work, take care of things at home, or get along with other people?

Not difficult at all	Somewhat difficult	Very difficult	Extremely difficult

Appended from: Spitzer, R.L., Kroenke, K., Williams, J.B.W., et al., (2006). A Brief Measure for Assessing Generalized Anxiety Disorder: The GAD-7. *Arch Intern Med, 166,* 1092- 1097

Appendix 5: Indirect effects of lifestyle behaviors on Math grades through brain health mediators

Variable name		Effect	*SE*	95% CI_{LL}	95%CI_{UL}
Average Active Minutes					
	Total	-.018	.038	-.099	.049
	L-dlPFC OxyHb	-.018	.024	-.073	.018
	R-dlPFC OxyHb	.011	.025	-.039	.064
	L-mdlPFC OxyHb	-.005	.012	-.029	.023
	R-mdlPFC OxyHb	-.011	.020	-.059	.018
	MSIT mean RT	.005	.017	-.031	.040
	MSIT SD	.001	.013	-.034	.022
Substance Use					
	Total	.549	1.186	-1.387	3.445
	L-dlPFC OxyHb	.046	.362	-.827	.726
	R-dlPFC OxyHb	.057	.377	-.878	.616
	L-mdlPFC OxyHb	.088	.482	-1.031	1.080
	R-mdlPFC OxyHb	-.074	.359	-.797	.765
	MSIT mean RT	-.049	.384	-.976	.685
	MSIT SD	.482	.718	-.298	2.383
Fast-food Consumption					
	Total	.367	.754	-1.344	1.657
	L-dlPFC OxyHb	-.027	.371	-1.023	.522
	R-dlPFC OxyHb	-.022	.333	-.709	.654

L-mdlPFC OxyHb	.012	.399	-.986	.652
R-mdlPFC OxyHb	.015	.366	-.702	.855
MSIT mean RT	.106	.301	-.485	.797
MSIT SD	.283	.384	-.457	1.120
Average Sleep Hours				
Total	-.353	.935	-2.376	1.361
L-dlPFC OxyHb	-.420	.687	-2.123	.664
R-dlPFC OxyHb	.306	.665	-.992	1.716
L-mdlPFC OxyHb	.033	.427	-.951	.813
R-mdlPFC OxyHb	-.144	.459	-.983	.962
MSIT mean RT	-.150	.494	-1.348	.728
MSIT SD	.023	.229	-.421	.572

Appendix 6: Indirect effects of lifestyle behaviors on English grades through brain health mediators

Variable name		Effect	*SE*	95% CI_{LL}	95% CI_{UL}
Average Active Minutes					
	Total	-.011	.027	-.072	.034
	L-dlPFC OxyHb	-.014	.021	-.067	.015
	R-dlPFC OxyHb	.020	.027	-.023	.081
	L-mdlPFC OxyHb	-.012	.011	-.037	.007
	R-mdlPFC OxyHb	-.003	.018	-.044	.028
	MSIT mean RT	-.001	.012	-.031	.018
	MSIT SD	-.001	.011	-.026	.022
Substance Use					
	Total	.360	.927	-1.098	2.590
	L-dlPFC OxyHb	.062	.403	-.893	.848
	R-dlPFC OxyHb	-.188	.328	-.917	.434
	L-mdlPFC OxyHb	.474	.557	-.245	1.861
	R-mdlPFC OxyHb	-.050	.344	-.701	.704
	MSIT mean RT	-.004	.164	-.371	.329
	MSIT SD	.066	.424	-.642	1.122
Fast-food Consumption					
	Total	-.104	.591	-1.200	1.228
	L-dlPFC OxyHb	-.026	.287	-.778	.439
	R-dlPFC OxyHb	-.075	.240	-.569	.435

	L-mdlPFC OxyHb	-.054	.426	-.742	1.042
	R-mdlPFC OxyHb	.002	.326	-.623	.766
	MSIT mean RT	.034	.144	-.238	.368
	MSIT SD	.016	.293	-.686	.537
Average Sleep Hours					
	Total	.319	.756	-1.232	1.907
	L-dlPFC OxyHb	-.316	.578	-1.907	.340
	R-dlPFC OxyHb	.472	.663	-.521	2.066
	L-mdlPFC OxyHb	.207	.432	-.374	1.324
	R-mdlPFC OxyHb	-.084	.414	-1.231	.489
	MSIT mean RT	.057	.375	-.421	1.114
	MSIT SD	-.017	.207	-.532	.382

Appendix 7: Moderating effects of age on the indirect effects of active minutes and fast-food consumption on Math grades through brain health parameters

Interaction term	Mediator	*ΔR²*	*F*	*df* (1,2)	*p*
Average Active Minutes X Age					
	L-dlPFC OxyHb	0.011	0.511	(1, 45)	0.478
	R-dlPFC OxyHb	0.001	0.065	(1, 45)	0.799
	L-mdlPFC OxyHb	0.004	0.207	(1, 45)	0.651
	R-mdlPFC OxyHb	0.000	0.012	(1, 45)	0.913
	MSIT mean RT	0.001	0.030	(1, 45)	0.863
	MSIT SD	0.000	0.005	(1, 45)	0.946
Fast-food Consumption X Age					
	L-dlPFC OxyHb	0.002	0.084	(1, 47)	0.774
	R-dlPFC OxyHb	0.016	0.916	(1, 47)	0.343
	L-mdlPFC OxyHb	0.054	2.702	(1, 47)	0.107
	R-mdlPFC OxyHb	0.006	0.303	(1, 47)	0.585
	MSIT mean RT	0.001	0.025	(1, 47)	0.876
	MSIT SD	0.018	1.185	(1, 47)	0.282

Appendix 8: Moderating effects of age on the indirect effects of active minutes and fast-food consumption on English grades through brain health parameters

Interaction term	Mediator	ΔR^2	*F*	*df* (1,2)	*p*
Average Active Minutes X Age					
	L-dlPFC OxyHb	0.011	0.511	(1, 45)	0.478
	R-dlPFC OxyHb	0.001	0.065	(1, 45)	0.799
	L-mdlPFC OxyHb	0.004	0.207	(1, 45)	0.651
	R-mdlPFC OxyHb	0.000	0.012	(1, 45)	0.913
	MSIT mean RT	0.001	0.030	(1, 45)	0.863
	MSIT SD	0.000	0.005	(1, 45)	0.946
Fast-food Consumption X Age					
	L-dlPFC OxyHb	0.002	0.084	(1, 48)	0.774
	R-dlPFC OxyHb	0.017	0.982	(1, 48)	0.327
	L-mdlPFC OxyHb	0.057	2.901	(1, 48)	0.095
	R-mdlPFC OxyHb	0.005	0.258	(1, 48)	0.614
	MSIT mean RT	0.000	0.007	(1, 48)	0.932
	MSIT SD	0.017	1.176	(1, 48)	0.284

Appendix 9: Moderating effects of gender on the indirect effects of active minutes and fast-food consumption on Math grades through brain health parameters

Interaction term	Mediator	ΔR^2	F	df (1,2)	p
Average Active Minutes X Gender					
	L-dlPFC OxyHb	0.002	0.068	(1, 44)	0.796
	R-dlPFC OxyHb	0.006	0.325	(1, 44)	0.572
	L-mdlPFC OxyHb	0.001	0.030	(1, 44)	0.864
	R-mdlPFC OxyHb	0.000	0.003	(1, 44)	0.956
	MSIT mean RT	0.004	0.219	(1, 44)	0.642
	MSIT SD	0.003	0.199	(1, 44)	0.658
Fast-food Consumption X Gender					
	L-dlPFC OxyHb	0.007	0.328	(1, 47)	0.570
	R-dlPFC OxyHb	0.000	0.005	(1, 47)	0.944
	L-mdlPFC OxyHb	0.010	0.453	(1, 47)	0.504
	R-mdlPFC OxyHb	0.033	1.652	(1, 47)	0.205
	MSIT mean RT	0.012	0.660	(1, 47)	0.421
	MSIT SD	0.013	0.856	(1, 47)	0.360

Appendix 10: Moderating effects of gender on the indirect effects of active minutes and fast-food consumption on English grades through brain health parameters

Interaction term	Mediator	ΔR^2	*F*	*df* (1,2)	*p*
Average Active Minutes X Gender					
	L-dlPFC OxyHb	0.002	0.068	(1, 44)	0.796
	R-dlPFC OxyHb	0.006	0.325	(1, 44)	0.572
	L-mdlPFC OxyHb	0.001	0.030	(1, 44)	0.864
	R-mdlPFC OxyHb	0.000	0.003	(1, 44)	0.956
	MSIT mean RT	0.004	0.219	(1, 44)	0.642
	MSIT SD	0.003	0.199	(1, 44)	0.658
Fast-food Consumption X Gender					
	L-dlPFC OxyHb	0.007	0.353	(1, 48)	0.555
	R-dlPFC OxyHb	0.000	0.016	(1, 48)	0.901
	L-mdlPFC OxyHb	0.007	0.346	(1, 48)	0.559
	R-mdlPFC OxyHb	0.030	1.508	(1, 48)	0.226
	MSIT mean RT	0.014	0.797	(1, 48)	0.376
	MSIT SD	0.013	0.881	(1, 48)	0.353

Appendix 11: Moderating effects of BMI on the indirect effects of active minutes and fast-food consumption on Math grades through brain health parameters

Interaction term	Mediator	ΔR^2	F	df (1,2)	p
Average Active Minutes X BMI					
	L-dlPFC OxyHb	0.015	0.794	(1,45)	0.378
	R-dlPFC OxyHb	0.033	1.779	(1,45)	0.189
	L-mdlPFC OxyHb	0.032	1.538	(1,45)	0.221
	R-mdlPFC OxyHb	0.036	1.778	(1,45)	0.189
	MSIT mean RT	0.000	0.014	(1,45)	0.908
	MSIT SD	0.086	6.318	(1,45)	0.016
Fast-food Consumption X BMI					
	L-dlPFC OxyHb	0.004	0.197	(1,47)	0.659
	R-dlPFC OxyHb	0.000	0.010	(1,47)	0.920
	L-mdlPFC OxyHb	0.000	.0210	(1,47)	0.885
	R-mdlPFC OxyHb	0.011	.5149	(1,47)	0.477
	MSIT mean RT	0.006	0.319	(1,47)	0.575
	MSIT SD	0.000	0.014	(1,47)	0.906

Appendix 12: Moderating effects of BMI on the indirect effects of active minutes and fast-food consumption on English grades through brain health parameters

Interaction term	Mediator	ΔR^2	F	df (1,2)	p
Average Active Minutes X BMI					
	L-dlPFC OxyHb	0.015	0.794	(1,45)	0.378
	R-dlPFC OxyHb	0.033	1.779	(1,45)	0.189
	L-mdlPFC OxyHb	0.032	1.538	(1,45)	0.221
	R-mdlPFC OxyHb	0.036	1.778	(1,45)	0.189
	MSIT mean RT	0.000	0.014	(1,45)	0.908
	MSIT SD	0.086	6.318	(1,45)	0.016
Fast-food Consumption X BMI					
	L-dlPFC OxyHb	0.002	0.084	(1,46)	0.774
	R-dlPFC OxyHb	0.000	0.021	(1,46)	0.886
	L-mdlPFC OxyHb	0.000	0.0132	(1,46)	0.909
	R-mdlPFC OxyHb	0.004	0.206	(1,46)	0.653
	MSIT mean RT	0.013	0.659	(1,46)	0.421
	MSIT SD	0.000	0.001	(1,46)	0.975

Figure captions

Figure 1: *Note.* Study processes and timelines are indicated for both baseline and follow-up data collection sessions.

Figure 2: *Note.* fNIRS measurement channel numbers overlayed on a grayscale anatomical brain.

Figure 3: *Note.* OxyHb response during the MSIT task in the left (CH1-8) and right (CH9-16) hemispheres of the prefrontal cortex.

Figure 4: *Note.* Health behaviours predicting MSIT accuracy, expressed as % correct responses. Coefficients are standardized beta weights; significant paths are in bold, dotted lines are non-significant; N=67.

Figure 5: *Note.* Solid bars represent magnitude of effect size for males and females separately. Absolute effect size value appears above each corresponding bar.

Figure 6: *Note*. Solid bars represent magnitude of effect size for non-obese and obese separately. Absolute effect size value appears above each corresponding bar. Age and gender-specific cut-offs were employed to define obesity categories as recommended by CDC (112).

Figure 7: *Note*. Multiple mediation model for average active minutes predicting Math grades through brain health parameters. Coefficients are standardized beta weights; significant paths are in bold, dotted lines are non-significant; *N*=67.

Figure 8: *Note*. Multiple mediation model for substance use predicting Math grades through brain health parameters. Coefficients are standardized beta weights; significant paths are in bold, dotted lines are non-significant; N=67.

Figure 9: *Note*. Multiple mediation model for fast-food consumption predicting Math grades through brain health parameters. Coefficients are standardized beta weights; significant paths are in bold, dotted lines are non-significant; N=67.

Figure 10: *Note*. Multiple mediation model for average sleep hours predicting Math grades through brain health parameters. Coefficients are standardized beta weights; significant paths are in bold, dotted lines are non-significant; *N*=67.

Figure 11: *Note*. Multiple mediation model for average active minutes predicting English grades through brain health parameters. Coefficients are standardized beta weights; significant paths are in bold, dotted lines are non-significant; *N*=67.

Figure 12: *Note*. Multiple mediation model for substance use predicting English grades through brain health parameters. Coefficients are standardized beta weights; significant paths are in bold, dotted lines are non-significant; *N*=67.

Figure 13: *Note*. Multiple mediation model for fast-food consumption predicting English grades through brain health parameters. Coefficients are standardized beta weights; significant paths are in bold, dotted lines are non-significant; *N*=67.

Figure 14: *Note*. Multiple mediation model for average sleep hours predicting English grades through brain health parameters. Coefficients are standardized beta weights; significant paths are in bold, dotted lines are non-significant; *N*=67

Figure 15: *Note.* Solid bars represent magnitude of effect size for non-obese and obese separately. Absolute effect size value appears above each corresponding bar. Age and gender-specific cut-offs were employed to define obesity categories as recommended by CDC (112).