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THE INTERACTION OF EARLY LIFE EXPERIENCES, PHYSICAL HEALTH, AND SOCIO-ECONOMIC STATUS ON NEUROCOGNITIVE FUNCTION IN YOUTH

Janis Gaudreau
University of Rhode Island, janis_gaudreau@uri.edu

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JANIS GAUDREAU

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JANIS GAUDREAU

APPROVED:

Thesis Committee:

Major Professor Nicole Logan

Vanessa Harwood

Christine Clarkin

Mollie Ruben

Brenton DeBoef

DEAN OF THE GRADUATE SCHOOL

UNIVERSITY OF RHODE ISLAND

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Abstract

Previous research demonstrates that cognitive and brain function and development during childhood are associated with greater physical activity (PA) levels, fitness, income, less adverse early life experiences (ELE), healthier body mass index (BMI), body composition of lean and fat mass, and fewer experiences of mental health disorders.

We used the Child Mind Institute's Healthy Brain Network open-access dataset to evaluate neurocognitive outcomes in children. We predicted that children with combined greater SES and positive physical health outcomes, alongside fewer adverse ELE, will exhibit greater cognitive function and resting-state electroencephalography (EEG) outcomes, and fitness and PA will positively protect neurocognitive function despite the attenuated functioning associated with adverse ELE and poor health.

Regressions on cognitive function outcomes (working memory, executive function, attention control, processing speed) were used as dependent variables. Demographic variables (IQ, parent education, occupational prestige, neighborhood safety, and household income) (step 1), PA, fitness, body composition, and BMI (step 2), and adverse early life experiences (ADHD, anxiety, learning problems, aggressive and problematic behaviors) (step 3) were added hierarchically. Between-group resting-state EEG data was analyzed to determine differences due to greater levels of PA and SES.

Regressions indicated that three prominent aspects of SES (household income, parental education, parental occupation) were positively associated with

cognitive functioning, despite the presence of ELE (learning problems, ADHD, social anxiety), for processing speed ($R^2 = 0.060$, $p = 0.001$), working memory index ($R^2 = 0.150$, $p < 0.001$), list-sort working memory ($R^2 = 0.123$, $p = 0.000$), and flanker attentional control ($R^2 = 0.118$, $p < 0.001$). For executive function ability (card-sort task), fitness was also a positive predictor despite the negative influence of learning problems ($R^2 = 0.063$, $p = 0.002$). Greater EEG power spectral density (PSD) was observed in the beta frequency band for children with greater PA levels ($p = .010$, low: 154.67 ± 2094.62, high: 456.50 ± 3350.85) and greater SES ($p = 0.019$, low: 1.12 ± 3.77, high: 217.64 ± 2413.48) compared to their peers with lower PA and SES.

SES (specifically, household income, parent's education, and occupation), PA, and fitness were robust predictors of greater cognitive functioning skills. Notably, fitness was protective against executive function ability on the card-sort task despite evidence of learning problems in children. This trend was unique to executive function and was not found in tasks of working memory and processing speed abilities. Greater household income and parents' education were also positive predictors of cognitive function despite the presence of ADHD, learning problems, and social anxiety. Interestingly, PSD effects were only observed for the beta frequency band and not for the alpha or theta bands, which suggests that the effects of PA and SES are sensitive to alert cognitive states compared to relaxed states and functioning memory, supporting the notion that PA, fitness, and SES are sensitive predictors of executive function. Overall, greater fitness, PA levels, household income, and parental education during childhood provided protective effects on executive functions despite adverse early life experiences.

Acknowledgments

I thank my advisor, Dr. Nicole Logan, for her unwavering encouragement and patience over the past year, and my committee members for their brilliant suggestions during this project. I'd also like to thank my friend Emily for her invaluable support and my family for their endless motivation.

Dedication

This thesis is dedicated to my Uncle Wayne.

Table of Contents

List of Tables

List of Figures

CHAPTER 1

Introduction

Brain development during childhood involves complex interactions between biological, psychological, and neurological changes that occur between birth and adulthood (Houston et al., 2014). Neural maturation of the brain during this time is associated with variability among cognitive, social, emotional, speech, language, and motor skills (Ciccia et al., 2009). These skills are commonly established in early childhood through movement and sensory stimulation (Supta et al., 2021). Evidence shows that physical activity (PA), socio-economic status (SES), and early-life experiences (ELE) highly influence proper brain maturation by way of these motor and sensory skills (Dunn, 2012). Related factors that also influence the ability of children to participate in PA include (i.) demographic variables (i.e., age, sex, and weight); (ii.) social variables (i.e., parental modeling or monitoring of PA); (iii.) neighborhood variables (i.e. access to sidewalks, parks, and playgrounds, along with knowing and talking to neighbors); and (iv.) policy variables (i.e. mandatory inclusion of recess time, sidewalks, and bicycle paths) (Spitzer et al., 2022, Carver et al., 2023, Wright et al., 2016, van Loon et al., 2014). Taken together, many of the factors that influence PA participation also influence brain maturation.

Previous research has demonstrated greater cognitive and brain functions during childhood are associated with greater physical activity levels (Hillman et al., 2009; Hillman et al., 2014), fitness (Hillman et al., 2009; Hillman et al., 2014; Mora-Gonzalez et al., 2019), family income (Noble et al., 2015, Dalmaijer et al., 2023), less exposure to a disruptive family life (Noble et al., 2015; Wade et al., 2022; McLaughlin et al., 2011), a healthier body mass index (BMI) and body composition of lean and fat mass (Mora-Gonzalez et al., 2019), and fewer experiences of mental health disorders (Houston et al., 2015; McLaughlin et al., 2011). PA has been shown to improve behavioral and neural indices of attentional allocation, inhibitory control, working memory, as well as academic achievement (Elish et al., 2022; Hillman et al., 2014; Latino et al., 2023; Spitzer et al., 2022; Walker et al., 2023; Wright et al., 2016). In contrast, social conditions related to low SES disadvantages worldwide, such as poverty, crime, and unemployment rates, have been associated with mental, behavioral, and cognitive problems (Perez-Del-Pulgar et al., 2021; Zubrick et al., 2015) and motor, sensory, and social problems in later life (Lipina & Posner, 2012). In addition, behavioral and structural changes from low SES environments or other adverse early life events have resulted in health-risk behaviors associated with early morbidity and mortality (Wade et al., 2022). Said changes have been thought to be due to the interrupted pivotal periods of brain plasticity, allowing for proper development into adulthood (Gabard-Durnam & McLaughlin, 2020). However, prior research has not yet documented the combined influence of these effects on the developmental trajectory of optimal neurocognitive function in childhood. Therefore, accounting for the complex interactions between physical development, demographic and socio-economic considerations, ELE, and instances of disrupted mental health is an important next step in addressing developmental cognitive neuroscience research.

To address these questions, the following study will consider how SES (income, parents' education and occupational prestige, neighborhood safety), physical health (PA, fitness, BMI, body composition), and ELE (childhood behaviors, presence of attention-deficit hyperactivity disorder (ADHD), learning problems, stress, depression, anxiety) interact to account for the variability on childhood neurocognitive function. Behavioral performance of the NIH Toolbox Cognitive domain and the Wechsler Intelligence Scale for Children: 5th Ed (WISC-V) will be considered for cognitive functions, and resting state electroencephalography (EEG) will be used as an index of neurocognitive function in childhood. This study will utilize the large open-access human-subjects database from the Child Mind Institute's (CMI) Healthy Brain Network (HBN).

To confirm previous research with this open-access dataset, we first hypothesize that individuals with combined greater SES and physical health outcomes, alongside fewer ELE instances, will exhibit greater neurocognitive function on the NIH Toolbox, WISC-V, and EEG assessments. Second, we novelly hypothesize that PA will positively protect neurocognitive function, despite the attenuated functioning associated with lower SES, obesity as per BMI and body composition assessments, or adverse ELE. Third, we predict that the protective effects of PA on neurocognitive function (despite adverse SES, body composition, and/or ELE) will reach a threshold in the cross-sectional dataset, such that the over-accumulation of negative childhood experiences will likely outweigh the positive effects of PA. Lastly, we hypothesize that supervised machine-learning techniques will complement traditional linear regression analyses to yield a compatible pattern of results. For brevity, hypotheses 3 and 4 were not included in the current study. Further explanation can be found in the Limitations section.

CHAPTER 2

Review of Literature

Physical Activity and Neurocognitive Functions

PA highly impacts typical child and adolescent brain development. Greater levels of PA have been robustly associated with greater cognitive functioning (Bryan et al., 2022; Wright et al., 2016), mental well-being (Latino et al., 2023), and overall health (Hillman et al., 2014; Walker et al., 2023). PA is any voluntary bodily movement produced by skeletal muscles that requires energy expenditure (Casperson et al., 1985). PA includes all activities of daily living, including transport (walking or cycling to school and work) and leisure time (household chores, gardening, playtime, dog-walking); it also encompasses planned bouts of exercise such as fitness classes, sports, and outdoor recreational activities. Both moderate- and vigorous-intensity physical activities (MVPA) have been shown to improve health and cognitive function (Pindus, 2016). Although the long-term health benefits of PA are well known, 50-70% of young school-aged children in the United States do not reach the minimum 60 minutes of MVPA each day as recommended by the Center for Disease Control (CDC) (US Department of Health and Human Services, 2022). In contrast, sedentary time is characterized by waking behaviors that require little energy or occur in a sitting position such as reading, watching television, using a computer, or playing video games, and has been estimated to consume approximately 8 hours per day for children (LeBlanc et al., 2015).

An abundance of research has demonstrated the positive effect of PA on cognitive processes throughout the lifespan (Hillman et al., 2014; Spitzer et al., 2022; Walker et al., 2023; van Loon et al., 2014; Wright et al., 2016). Notably, PA has been shown to improve behavioral (i.e., task performance) and neural (i.e., EEG) indices of attentional allocation, inhibitory control, working memory, as well as academic achievement (Elish et al., 2022; Hillman et al., 2014; Latino et al., 2023; Spitzer et al., 2022; Walker et al., 2023; Wright et al., 2016). While mechanistic questions remain about the neural processes in response to exercise, robust research suggests PA promotes neurogenesis and plasticity, as evidenced by increased volume within cortical and subcortical structures and increased angiogenesis and blood flow to the brain in rodent models (Gabard-Durnam & McLaughlin, 2020). This is particularly important for areas involved with memory (Diamond, 2013; van der Fels et al., 2015) and executive functioning (Latino et al., 2023; Mora-Gonzalez et al., 2019; Spitzer et al., 2022) including inhibitory control, working memory, cognitive flexibility, logical reasoning, and fluid intelligence (Diamond, 2013). In human-subjects exercise neuroscience research, central nervous system biomarkers are used to assess the indirect effect of neurogenesis due to PA via neuroimaging techniques (Voss et al., 2013). For example, resting state electroencephalography (EEG) recordings represent spontaneous neural activity, reflecting the typical brain state (Bai et al., 2017).

Previous EEG studies demonstrate that the alpha frequency band, a neural oscillatory pattern in the frequency range of 7.5 to 12 hertz (Hz), is positively susceptible to exercise interventions (Basso & Suzuki, 2017). Oscillatory power in the Alpha frequency band reflects lower cortical activation associated with relaxation and diminished anxiety (Basso & Suzuki, 2017). The power spectral density (PSD) and band power retrieved from resting state EEG recordings allow further insight into the neuroelectric strength of frontoparietal connections associated with cognitive and executive functioning processes (Rogala et al., 2020). The EEG frequency bands are defined as (i.) gamma waves (γ; >35 hz) exhibiting concentration; (ii.) beta (β; 12–35 hz) showing active attention; (iii.) alpha waves (α; 8–12 hz) displaying very relaxed, passive attention; whereas (iv.) theta (θ; 4–8 hz) indicating deeply relaxed cognitive states and (v.) delta (δ; 0.5–4 hz) displaying sleep (Saby & Marshall, 2012). There is limited research on the PSD of the EEG signal in children. However, previous studies have shown that differential PSD patterns affect adults, possibly due to maturational factors such as brain size, skull thickening, and synaptic density (Rogala et al., 2020).

Prior results have shown resting state EEG to complement other metrics (i.e., self-report, behavioral observations), particularly in children with ADHD (Furlong et al., 2021). Previous studies investigating resting state EEG of older children with learning disorders have found differences in power bands, particularly alpha, and the synchronicity of oscillating brain activity that underlies functional brain networks (Ahmadlou & Adeli, 2010; Alba et al., 2016; Barry et al., 2002; Barry et al., 2011; Bowyer, 2016; Clarke et al., 2007; Furlong et al., 2021; Robbie et al., 2016). Although differences in neural network connectivity have been found in various populations, there is no clear understanding of the network organization properties that differ (Furlong et al., 2021). Therefore, further investigation into the PSD and band power output of the EEG signal in children, a population in which the brain is constantly undergoing maturation, is critical to help understand neurocognitive functions.

Childhood Obesity and Physical Activity

The World Health Organization (WHO) considers childhood obesity a serious, global public health issue. In the United States, nearly 20% of the US population is obese, including approximately 14.7 million children and adolescents (CDC, 2022; Inoue et al., 2023). In 2020 alone, the percentage of obesity globally has more than doubled among children and tripled among adolescents (World Health Organization, 2020). Numbers have continued to rise since the beginning of the COVID-19 pandemic (Elish et al., 2022). In turn, obesity can also lead to life-long, severe medical diagnoses, particularly cardiovascular disease and Type II diabetes (CDC, 2022; Goto et al., 2022; Inoue et al., 2023; Ogden et al., 2018; Sahoo et al., 2015; Timperio et al., 2015) as well as significantly impacting cardiorespiratory fitness, social and emotional well-being, self-esteem, academic performance, and quality of life for children and adolescents (Inoue et al., 2023; Timperio & Veitch, 2015; Sahoo et al., 2015). Childhood obesity is associated with impaired executive functioning processes and structures (Mora-Gonzalez et al., 2019; Logan et al., 2021; Logan et al., 2022; Seum et al., 2022). Although PA has been shown to play a critical role in childhood obesity prevention and in turn, cognitive protection (Carver et al., 2023; Spitzer et al., 2022; van Loon et al., 1982; Walker et al., 2023; Wang et al., 2023; Wright et al., 2016), many other factors, including diet, sociocultural elements, familial factors, environmental, and psychological aspects have the potential also to influence childhood obesity (Seum et al., 2022). Furthermore, rising inequalities are presented through childhood obesity trends (Seum et al., 2022; van Loon et al., 2014; Wright et al., 2016). Though we are aware of the effects of PA and obesity on the outcomes mentioned above, there is a lack of longitudinal effects regarding PA and BMI on physiological, behavioral, and academic outcomes for racially diverse children (Wright et al., 2016). Inner-city females, Hispanic, and elementary children with either overweight or obesity have shown lower MVPA compared to their peers (Wang et al., 2023) causing racial and sex disparities to be especially prevalent in research surrounding PA and cognitive functioning of children and adolescents of various SES (Noble et al., 2015; Wade et al., 2022; McLaughlin et al., 2011). National governing statistical bodies (i.e., NHANES - National Health and Nutrition Examination Survey) continue to create a more complex, intersectional relationship between PA, gender, weight, and race/ethnicity (Wright et al., 2016).

Household education and income levels have also become strong predictors of childhood obesity. This could be because lower education and income levels are more likely to have limited access to healthy diets and be less physically active (Goto et al., 2022; Sahoo et al., 2015). Previous literature has identified inequalities in mortality and cardiovascular disease, which is highly prevalent among populations with obesity, between low and high-income households (Seum et al., 2022; Sugiyama et al., 2016). Since poverty and obesity have been shown to affect a family for generations, it is crucial to evaluate the associations between parental education and childhood obesity to consider practical strategies to reduce disparity (Goto et al., 2022; Inoue et al., 2023).

Demographic Factors and Physical Activity

SES is a multifaceted measurement of income, educational attainment, occupational prestige, subjective social status, and social class perceptions. It reliably predicts psychological outcomes throughout the lifespan (VandenBos, 2015). SES reflects quality-of-life attributes and opportunities afforded to people within society and is a consistent predictor of a vast array of psychological outcomes (VandenBos, 2015). SES components that are directly related to income are deprivation of primary (i.e., food, clothing, bills), lifestyle (i.e., car, microwave, dishwasher), housing facilities (i.e., shower, flushing toilet, hot water), deterioration (i.e., leaks, rot), and environmental problems (i.e., noise, pollution, inadequate space) (Dalmaijer et al., 2023). Social conditions related to low SES disadvantages worldwide, such as poverty, crime, and unemployment rates, have been associated with mental, behavioral, and cognitive problems (Perez-Del-Pulgar et al., 2021; Zubrick et al., 2015) as well as motor, sensory, and social problems in later life (Lipina & Posner, 2012). SES has also demonstrated lifelong associations with life satisfaction, academic achievement, emotion regulation, cognitive function, and decision-making tendencies (Dalmaijer et al., 2023). Furthermore, individuals from low-SES backgrounds also exhibit hypoactivation of the executive network (Liu & Li, 2023), which is associated with decreased efficiency of executive functions. This pattern of results yields the significance of further investigation into the effect of SES and related predispositions to effectively understand the influence and interaction of various environmental variables on cognitive functioning, specifically in children.

Access to PA opportunities through the SES lens is important to consider. PA in socioeconomically disadvantaged areas is significantly low due to a lack of accessibility, safety, and cost (Carver et al., 2023; van Loon et al., 1982). Previous research has shown that children from lower SES households are more likely to receive their daily PA in school than their high SES peers (Wright et al., 2016). In-school PA (i.e., recess, physical education courses, sports practices) has shown promise for improving outcomes in the classroom through standardized testing (Elish et al., 2022; Walker et al., 2023) while allowing students to fulfill their recommended daily PA regardless of their home status. Parks and playgrounds are free of charge and are particularly important for promoting active play in all areas regardless of SES (Carver et al., 2023; van Loon et al., 1982). Unfortunately, the adverse effects of SES-influenced inequality are seen worldwide. Those residing in low-income areas have shown significant mental health differences compared to high-income areas despite public health effects to improve equity. Countries such as the United States, Wales, and Denmark have seen poorer mental health statuses (i.e., major depression) for those living with low income in comparison to those with a high-income status (Sugiyama et al., 2016). Due to the unfulfilled research regarding SES, their associated environmental factors, interaction, and influence on overall brain health, they are crucial to consider explicitly regarding function academically, cognitively, and within the mental health of children.

Early Life Experiences

Developing children experience several atypical trajectories within their early lives that have the potential to influence their overall cognitive health. These stressors can be broken into three major categories: (i) demographic circumstances, (ii) atypical development, and (iii) mental health disorders. Within demographic circumstances, children may experience household chaos and stress due to low-SES environments, which are associated with further less-desirable experiences, such as reduced parental attachment, harsh discipline, and poorer parental mental health (Dalmaijer et al., 2023). Children are also at critical periods developmentally, whereby learning problems, behavioral problems, attention-deficit and hyperactivity issues begin to arise. In addition, children with these combined atypical demographic and developmental trajectories might also be susceptible to experiencing mental health difficulties; therefore, assessing depression, anxiety, and social anxiety is important as they progress into adolescence, with the first onset of mental health problems typically occurring before the age of 18 (Juwariah et al., 2022).

Demographic Circumstances

Cognitive ability, which is robustly associated with SES, is one of the best predictors of later life success, as high SES families typically have greater access to quality and quantity of resources representative of a cognitively stimulating environment (Cermakova et al., 2023), and the combined influence which parental income and occupation have toward their child's educational and career opportunities. This effect weakens over the lifetime but is shown to have the strongest and most influential impact during early childhood (Cermakova et al., 2023). Therefore, research should be expanded to encapsulate additional effects on neurocognitive development for children from disadvantaged SES backgrounds.

Importantly, those who reside in lower SES areas are more likely to have high levels of psychological distress compared to those living in high SES areas. This could be due to the perceived or actual threat of safety in low-income areas which have also shown significant adverse effects on socioemotional and cognitive skills compared to their counterparts living in high-income areas (Gabard-Durnam & McLaughlin, 2020; Kolb & Gibb, 2014). Such safety concerns are thought to affect families living in these areas directly, negatively impacting mental health (Pérez-Del-Pulgar et al., 2021).

Atypical Development

There is no single cause of atypical development and developmental disorders such as ADHD, general learning problems, and behavioral or conduct disorders (Tharper et al., 2012). The risk factors that contribute to the origins of behavioral disorders might not necessarily be the same as those that influence their course and outcomes. Still, it is essential to note and evaluate the influence of these factors during early childhood (Tharper et al., 2012). Furthermore, adverse social and family environments such as low parental education, social class, poverty, bullying, negative parenting, and maltreatment have been associated with ADHD diagnosis (Tharper et al., 2012). Therefore, the family and demographic environment are important factors to consider in children's atypical development and cognitive performance.

Adverse events such as psychosocial neglect and violence, in addition to physical, sexual, and emotional abuse (Wade et al., 2022) account for around half of the mental health issues during childhood (Green et al., 2010; Wade et al., 2022; McLaughlin et al., 2012), but they are also strongly correlated with higher rates of an extensive number of mental health problems, including mood, anxiety, and substance use disorders (Green et al., 2010; Kessler et al., 2010; Kim, 2010; McLaughlin et al., 2010; Wade et al., 2022) regardless of age. Research has shown that over half of children will experience at least one early adverse event before adulthood (McLaughlin et al., 2011), with the widely used Adverse Childhood Experiences Questionnaire (ACES) categorizing those with greater than 4 adverse experiences as at greater risk for toxic stress in adulthood. It is not uncommon for mechanisms of environmental adaptation to foster survival under such conditions of stress and adversity. Such behavioral and structural changes have resulted in health-risk behaviors associated with early morbidity and mortality (Wade et al., 2022). Said changes have been thought to be due to the interrupted pivotal periods of brain plasticity or the progression and change of structure and function in the brain, allowing for proper development into adulthood (Gabard-Durnam & McLaughlin, 2020). Therefore, because of the common occurrence among youth and the explicit effect on cognition, emotion, and behavior, additional insight is necessary to evaluate the consequences of early life experiences in children.

Mental Health

The most common mental health problems in developing children and adolescents are depression and anxiety (Juwariah et al., 2022). Major depression is characterized by feelings of persistently sad or irritable mood that affect a child's thinking and behavior at home, in school, and with peers. The National Institute of Mental Health estimates that more than 10% of adolescents experience major depression each year. With early onset, childhood, and adolescence, depression can predict future episodes of depression into adulthood (Lewis & Boyd, 2014). The peak age of mental disorder onset is about 14.5 years, with approximately 35% of children and adolescents being evaluated and diagnosed before the age of 14. The probability of occurrence by age 14 is as follows: neurodevelopmental disorders (61.5%), anxiety-related disorders (38.1%), stress disorders (16.9%), and mood disorders (2.5%) (Solmi et al., 2022).

Social anxiety disorder in children can cause them to avoid things that worry them, hide their feelings, lash out, or be outwardly angry or aggressive

(Ehmke et al., 2024). There are various ways to assess generalized anxiety and related disorders, including robust measures such as the Screen for Child Anxiety Related Disorders (SCARED), the Extended Strengths and Weaknesses Assessment of Normal Behavior (E-SWAN), and the Conners Rating Scale questionnaire. The SCARED, E-SWAN, and Conners are used as the gold standard to screen children for anxiety disorders, including general anxiety disorder, separation anxiety disorder, panic disorder, social/school phobias, ADHD symptoms, and impulse regulation behaviors, respectively (Brites et al., 2015).

Little is known about how early-life adversity, mental health, and cognition affect one another or how the effects unfold over time. Still, previous longitudinal modeling has shown the enduring adverse effect early-life adversity has on mental health. It supports the notion that poorer mental health is associated with poorer cognitive performance later in development, particularly working memory and vocabulary outcome (Nweze et al., 2023). Previous research has shown that early-life adversity is associated with long-term consequences on mental health above and beyond self-maintenance, with mental health disorder symptoms beginning to occur as early as 3 years old (Nweze et al., 2023). Oppositely, decreases in mental health difficulties following early-life adversity were associated with improved cognitive performance (Nweze et al., 2023). Consequently, there are still many unknown interactions to understand, such as when the pivotal period of reversal occurs and how long adverse exposures and mental health disorders can influence cognitive and academic functioning.

In conclusion, evaluating cognitive, behavioral, and emotional functioning in children and adolescents is crucial to understanding the effect of PA, BMI, fitness, SES, and other malleable factors culminating in early and late adulthood. Specifically, further investigation into EEG output in maturing children, adverse exposures, and mental health disorders can affect cognitive and academic functioning. Therefore, because of their common occurrence among youth and the explicit effect on cognition, emotion, and behavior, additional insight is necessary to evaluate the hindering effects of early life experiences and SES and their interaction with the previously seen positive effects of PA and fitness to assess variations of neurocognitive function in children.

CHAPTER 3

Methods

Participants

The data used for this thesis is from an open-access dataset by the Child Mind Institute's Healthy Brain Network (Alexander et al., 2017), with a total sample size of 4296. A subset of these participants (N = 1164) completed all testing protocols of the dependent variables of interest (cognitive function on the NIH Toolbox and the WISC-V) and the independent variables of interest (i.e., demographics, physical health, ELE). From this sample, 7 participants were excluded due to having outliers (± 3SD) in their cognitive data; therefore, primary analyses of cognitive function outcomes were run on N = 1157 participants. A secondary analysis of EEG outcomes was considered. For the secondary analyses, participants with EEG data (N = 887) were taken from the original total sample (N = 4296) to examine the between-group differences due to individual variables of interest. As noted in the *Protocol* section below, not all participants received the same assessment protocol; therefore, not all participants have the same data. The overlap of participants with both cognitive and EEG data was minimal. Therefore, EEG analyses were considered secondary.

Participants were recruited through health and community fairs, print advertising, digital marketing, email efforts, website adverts, social media, and community lists, all within New York. The Chesapeake Institutional Review Board approved the study [https://www.chesapeake.edu/about/irpa-irb] (Alexander et al., 2017). Before conducting the research, written informed consent was obtained from participants ages 18 or older. For participants younger than 18, written consent was obtained from their legal guardians and written assent was obtained from the participant.

Inclusion criteria included male or female individuals ages 5 - 21. Children ages 5-17 must have the capacity to understand the study and informed consent, and parents must also have the capacity to sign informed consent. If over the age of 18, the participant must have the capacity to understand and sign informed consent on their own. Participants also had to be fluent in English.

Exclusion criteria included individuals with (i.) moderate to severe impairment in cognitive (i.e., IQ below 66) and/or general function; (ii.) acute encephalopathy caused by brain injury or disease; (iii.) known degeneration disorder; (iv.) hearing or visual impairment that prevents participation in study-related tasks; (v.) diagnosis within the past 6 months of Schizophrenia, Schizoaffective Disorder, or Bipolar Disorder without treatment; (vi.) acute manic or psychotic episode without current, ongoing treatment; (vii.) onset within the last 3 months of suicidality or homicidally for which there is no current, on-going treatment; (viii.) history of lifetime substance dependence requiring chemical replacement therapy; (ix.) acute intoxication at time of any study visit.

Potential participants completed an interview to obtain information on their psychiatric and medical history. With few exceptions, psychiatric, medical, or neurological illness did not exclude participation. Exclusion criteria involved the presence of acute safety concerns (i.e., danger to self or others), cognitive or behavioral impairments that could interfere with participation (i.e., being nonverbal, IQ less than 66), or medical concerns that were expected to confound EEG findings. Participants taking stimulant medication were asked to discontinue their medication during the days of participation, as stimulants are known to affect cognitive and behavioral testing, as well as functional brain mapping (Alexander et al., 2017). Medication taken on the day of participation was recorded.

A *post hoc sensitivity* power analysis using G*Power was calculated to estimate the appropriate power and effect size, given the current sample size N = 1,157. Given 12 predictors for each regression model and α set at .001, total estimated power = 0.99, with an effect size f = 0.97, thus we are sufficiently powered for traditional statistical analyses.

Procedure

During the cross-sectional data collection, participants attended 4 sessions and spent approximately 3 hours in each session. All participants completed a psychiatric screening using a web-based version of the Schedule for Affective Disorders and Schizophrenia; Children's version (KSADS) (Kaufman et al., 1997) and Autism Diagnostic Observation Schedule (ADOS) (Lord et al., 2012) for suspected autism, as well as the Clinical Evaluation of Language Fundamentals (CELF) (Semel et al., 1995) for evaluation of language disorders. An important feature to note is that all participants did not complete all, or the same, testing protocols within the study as noted above, further demonstrated in Appendix C.

Visit 1. The first visit was comprised of child/adolescent assent (parents provided informed consent), a series of questionnaires, a clinical pre-interview, and the Wechsler Intelligence Scale for Children-V (WISC-V) (Wechsler, 2005) or the Wechsler Adult Intelligence Scale-IV (WAIS) (Wechsler, 2008) to measure cognitive function in children and older adolescents, respectively.

Visit 2. The children underwent a magnetic resonance imaging (MRI) scan during the second visit. We will not be using this data in the current analysis.

Visit 3. Fitness and Body Composition. The third visit consisted of a battery of cognitive assessments from the NIH Toolbox and various fitness measurements. Height, weight, waist circumference, blood pressure, and heart rate were collected, along with cardiovascular fitness using the FITNESSGRAM (GreenLight Fitness, 2022; The Cooper Institute, 2010) test battery (measures of actual and predicted aerobic capacity, muscular strength, muscular endurance, flexibility, and body composition). Bioelectric impedance measures, used for calculating various indices of body composition (i.e., body mass index, percent body fat, percent water weight), were taken using the RJL Systems Quantum III BIA system.

Visit 4. EEG measurements. At the final visit, EEG data was collected. Participants completed the EEG tasks in a sound-attenuated and dark experiment room, 70 cm from a 17-inch CRT monitor (SONY Trinitron Multiscan G220, display dimensions 330×240 mm, resolution 800×600 pixels, vertical refresh rate of 100 Hz). The resting state EEG task used for the current analysis consisted of the participant sitting still for 4 minutes, 2 minutes with their eyes open, and 2 minutes with their eyes closed. EEG acquisition high-density EEG data were recorded at a sampling rate of 500 Hz with a bandpass of 0.1 to 100 Hz, using a 128-channel EEG Geodesic Hydrocel system. The recording reference was at Cz. Electrode impedance was tested every 30 minutes of recording, and saline was added if needed. Participants 12 years old or younger were joined during the testing session by an additional research assistant, and participants over age 12 completed the computer tasks in the room alone.

Materials

To access phenotypic data, a Data Usage Agreement was signed by Principal Investigator Dr. Nicole Logan and the associated institution, the University of Rhode Island. Phenotypic data was accessed through the Longitudinal Online Research and Imaging System (LORIS), a web-based data management software for neuroimaging studies. LORIS complies with HIPAA standards and implementation rules.

Questionnaires. Demographics such as sex, age, and handedness were collected. Children and parents completed a series of questionnaires and a clinical pre-interview. All the tests in this section were administered by, or directly under the supervision of, licensed clinicians. The clinical staff consisted of a combination of psychologists and social workers, with psychopharmacological consultation support provided by psychiatrists. All questionnaires underwent a validity check. The following questionnaires were asked as part of the protocol and will be used in the current proposed analysis.

Demographics. Demographic and administrative information about participants including age, sex, protocol completion status, and commercial use of the data.

Financial Support Questionnaire (FSQ). The financial support questionnaire assesses household income, public assistance received, and health insurance information.

Barratt Simplified Measure of Social Status (Barratt). This measure is built on the work of Hollingshead 1957 and 1975 who devised a simple measure of Social Status based on marital status, retired/employed status (retired individuals used their last occupation), educational attainment, and occupational prestige. This is a measure of social status, a proxy for SES. This is not a measure of social class, which is best seen as a cultural identity (Barratt, 2006).

Child Behavior Checklist (CBCL). The CBCL is a device by which parents or other individuals who know the child well rate a child's problem behaviors and competencies. The CBCL can also measure a child's change in behavior over time or following a treatment. It consists of 118 items related to behavior problems, scored on a 3-point scale ranging from not true to often true of the child (Achenbach, 1991).

Screen for Child Anxiety Related Disorders - Parent report (SCARED_P). The SCARED is a child and parent self-report instrument used to screen for childhood anxiety disorders including general anxiety disorder, separation anxiety disorder, panic disorder, and social phobia. In addition, it assesses symptoms related to school phobias (Birmaher et al., 1999).

Extended Strengths and Weaknesses Assessment of Normal Behavior-Parent Report (ESWAN). The E-SWAN is a parent report instrument used to help assess multiple DSM Disorders and evaluate problem behavior in children and adolescents. The disorders include depression, Disruptive Mood Dysregulation Disorder (DMDD), social anxiety, and panic disorder (Swanson et al., 2012).

Child Flourishing Scale (CFS). The child flourishing scale measures indicators of positive development of children and adolescents (National Survey of Children's Health, 2016).

Child Mind Institute Symptom Checker. Assesses general psychiatric symptoms of individuals.

PhenX Neighborhood Safety. This measure evaluates a respondent's feelings toward neighborhood-level crime and safety. Studies show that neighborhood safety is relevant to various health outcomes, such as birth weight (Mujahid et al., 2007).

NIH Toolbox. *A* multidimensional set of brief measures assessing cognitive, emotional, motor, and sensory function from ages 3 to 85, meeting the need for a standard set of measures that can be used as a "common currency" across diverse study designs and settings (Gershon et al., 2013). The particular measures we will use for the current analysis are the Flanker Inhibitory Control and Attention Test (subdomain: attention, executive function) to assess the ability to focus attention and inhibit automatic response tendencies that can interfere with goal attainment; the Dimensional Change Card Sort Test (subdomain: executive function) to measure the capacity for switching among multiple aspects of a strategy or task;

the List Sorting Working Memory Test (subdomain: memory, working) to assess the ability to process, store and manipulate information across a series of tasks; and the Pattern Comparison Processing Speed Test (subdomain: processing speed) the speed of visually detecting whether two stimuli are the same or different (Gershon et al., 2013).

Wechsler Intelligence Scale for Children (WISC). The WISC-V is a measure of cognitive function in children and adolescents. Participants will complete the 10 core subtests: similarities, vocabulary, blocks, matrix, figure weights, digit span, coding, symbol search, visual puzzles, and pictures span, completed by participants aged 6-17 (Wechsler, 2014). The particular measures we will use for the current analysis are the fluid reasoning index including subtests matrix reasoning (presented with an array of pictures with one missing square, and select the picture that fits the array from five options), and figure weights (view a stimulus book that pictures shapes on a scale with one empty side and select the choice that keeps the scale balanced); Working Memory with subtests digit span (listen to sequences of numbers orally and to repeat them as heard, in reverse order, and in ascending order), and picture Span (view pictures in a stimulus book and select from options to indicate the pictures they saw, in order if possible); and IQ which is calculated by the performance on the subtests Verbal Comprehension Index, Visual Spatial Index, Fluid Reasoning Index, Working Memory Index, and Processing Speed Index (Wechsler, 2014).

Wechsler Individual Achievement Test - III (WIAT). All subjects will be administered a test of academic achievement. The WIAT is a comprehensive yet flexible measurement tool useful for achievement skills assessment, learning disability diagnosis, special education placement, and clinical appraisal for preschool children through adults. Norms allow for assessment of those from ages 4 to 85 (Wechsler, 2005).

Physical Activity Questionnaire for Older Children (PAQ_C). The PAQ-C seeks information on children's participation in vigorous activities over the last 7 days. A checklist is used to determine if a child engages in physical activity during a given period, such as the weekend or a weekday. Data was coded as: 1 = very light vigorous PA, 2 = light vigorous PA, 3 = moderate vigorous PA, 4 = heavy vigorous PA, and 5 = exceptional vigorous PA. The PAQ-C is completed by participants aged 8-14 (Janz et al., 2008).

Physical Activity Questionnaire for Adolescents (PAQ_A). The PAQ-A (a slightly modified version of the PAQ-C with the "recess" item removed) is a self-administered, 7-day recall instrument. It was developed to assess general physical activity levels for high school students in grades 9 to 12 and approximately 14 to 19 years of age. Data was coded as: 1 = very light vigorous PA, 2 = light vigorous PA, 3 = moderate vigorous PA, 4 = heavy vigorous PA, and 5 = exceptional vigorous PA. The PAQ-A is completed by participants aged 14-21 (Janz et al., 2008).

Screen for Child Anxiety Related Disorders—Self-report (SCARED_SR). The SCARED is a child and parent self-report instrument used to screen for childhood anxiety disorders, including general anxiety disorder, separation anxiety disorder, panic disorder, and social phobia. In addition, it assesses symptoms related to school phobias, completed by participants above the age of 8 (Birmaher et al., 1999).

Conners ADHD Rating Scales - Self Report, Short Form. The Conners ADHD Rating Scale is an instrument that uses self-report ratings to help assess ADHD and evaluate problem behavior in children and adolescents, completed by participants ages 8-21 (Conners, 2001).

Adverse Childhood Experiences Scale (ACES). Assessments of verbal, physical, or sexual abuse, as well as family dysfunction (e.g., an incarcerated, mentally ill, or substance-abusing family member; domestic violence; or absence of a parent because of divorce or separation). ACES have been linked to a range of adverse health outcomes in adulthood, including substance abuse, depression, cardiovascular disease, diabetes, cancer, and premature mortality, completed by participants over the age of 18 (Felitti et al., 1998).

PhenX School Risk. This measure can be used to identify specific school-related risk and protective factors that can predict adolescent (and later life) substance use and abuse, completed by participants between ages 12 and 18 (Beyers et al., 2004; Hemphill et al., 2011).

Children's Global Assessment Scale (CGAS). The CGAS is a numeric scale used by mental health clinicians to rate the general functioning of youths under 18. Scores range from 1 to 90 or 1 to 100, with high scores indicating better functioning (Shaffer et al., 1983).

EEG Analysis

EEG Data Acquisition. High-density EEG data were recorded at a sampling rate of 500 Hz with a bandpass of 0.1 to 100 Hz, using a 128-channel EEG Geodesic Hydrocel system. The recording reference was at Cz (vertex of the head). Head circumference was measured for each participant, and an appropriately sized EEG net was selected. The impedance of each electrode was checked before recording to ensure good contact and was kept below 40 kOhm. The time to prepare the EEG net was >30 min. Impedance was tested every 30 min of recording, and saline was added if needed (Langer et al., 2017).

Resting-State EEG Paradigm. Endogenous brain activity without external stimulation was acquired with a resting-state EEG paradigm, which is beneficial for pediatric populations. Resting-state EEG data is reflective of the brain areas that are commonly engaged during cognitive stimulation; therefore, it is a highly reliable assessment and can potentially provide stable biological markers that can be related to cognitive performance across individuals. During resting-state data collection, participants were instructed to "fixate on the central cross" on a computer monitor and to "open or close your eyes when you hear the request." Eyes-open and eyes-closed EEG acquisition were collected. Following standardized EEG preprocessing (described below), the data were filtered between 1.5 and 30 Hz and segmented into eyes-closed and eyes-open segments. Only the eyes-closed segments were further analyzed for the current study.

EEG Data Preprocessing and Analysis. EEG data was processed using Matlab (R2021b) via the open-source software Harvard Automated Pre-processing

Pipeline (HAPPE) (Gabard-Durnam et al. 2018). HAPINNES, an extension of HAPPE, is a standardized, automated pipeline designed to process raw resting state EEG data. Additional Matlab toolboxes include Signal Processing Toolbox, Optimization Toolbox, Statistics Toolbox, and Wavelet Toolbox. A complete description of the data extraction, electrode quality check, artifact signal correction, and principal component analysis of the raw EEG data can be found in Langer et al. (2017). The artifact-free EEG data was calculated against the average reference and segmented into 2-second epochs. In a second step, a discrete Fourier transformation algorithm was applied to the 2-second epochs, and the power spectrum of 1.5–30 Hz (resolution: 0.5 Hz) was calculated. The spectra for each channel were averaged over all epochs for each subject. Next, the group mean spectral amplitude was computed and displayed as an average over all electrodes and for each electrode individually. Finally, the group mean relative power spectra data were integrated. Absolute band power was computed for each frequency band. Subsequently, relative band power (V^2) and PSD (V^2/Hz) were derived. For this analysis, we used the relative (V^2/Hz) values of each frequency band: beta (β; 12–35 hz), alpha (α; 8–12 hz), and theta (θ; 4–8 hz) at the midline electrodes: Pz, Fz, FCz, Fpz, CPz, and Cz (reference). A subset of participants (N = 887) was used to analyze secondary EEG outcomes in the current study.

Statistical Analyses

Pearson product-moment correlations were initially conducted between dependent variables (EEG Power, cognitive outcomes from the NIH Toolbox and WISC-V assessments) and all demographic variables (age, sex, IQ, household income, neighborhood safety, school environment, school risk, parent's education and occupation), physical health variables (self-reported PA, BMI percentiles, body composition for lean/fat mass, estimated cardiorespiratory fitness), and ELE outcomes (Conners Rating Scale, ESWAN, CBCL, SCARED). For all cognitive outcomes (NIH Toolbox and WISC-V), age-corrected values were used to standardize the outcome, with scores typically ranging from (30 to 175).

Next, independent samples t-tests were conducted to determine if there were any differences in the dependent variables (EEG Power, cognitive outcomes from the NIH Toolbox, and WISC) between groups based on key predictor variables. Physical activity was grouped by low (1; very light and 2; light) and high (3; moderate, 4; heavy, and 5; exceptional), according to self-reported averages of the Physical Activity Questionnaires for Children (PAQ-C) and Adolescents (PAQ-A). Estimated cardiorespiratory fitness was grouped by low (<33rd percentile) and high (>67th percentile). BMI was split into two groups according to CDC percentiles for boys and girls, whereby 'healthy' BMI included children in the normal weight category (5-85th percentile), and 'high' BMI included children in both the overweight category (85-95th percentile) and the obesity category (≥95th percentile). SES was grouped by 'low' (<$49,999) and 'high' (>$100,000) household incomes. Significant outcomes for EEG Power or cognitive outcomes were considered for interpretation.

Multiple hierarchical linear regressions were also conducted to assess the central hypotheses: the association of physical activity and related outcomes (self-reported PA, BMI percentiles, body composition for lean/fat mass, predicted cardiorespiratory fitness) on cognitive outcomes, controlling for the ELE and demographic variables. Regression analyses were conducted to investigate our hypotheses based on the sensitive and continuous nature of the independent variables (self-reported PA, BMI percentiles, body composition for lean/fat mass, and estimated cardiorespiratory fitness). Regressions with NIH Toolbox (performance on Dimensional Change Card Sort Test, Flanker Inhibitory Control and Attention Test, List Sorting Working Memory Test) and WISC (Processing Speed Index, Working Memory Index, Fluid Reasoning Index) cognitive outcomes were used as dependent variables. First, any demographic variables (age, sex, IQ, household income, neighborhood safety, school environment, school risk, parent's education, and occupation) significantly correlated with the dependent variable of interest were used in Step 1 of the model. Second, the significant correlated independent variables of interest (self-reported PA, BMI percentiles, body composition for lean/fat mass, and estimated cardiorespiratory fitness) were used in Step 2. Last, the significant early-life stress variables (Conners Rating Scale, ESWAN, CBCL, SCARED) were used in Step 3. This analysis was performed separately for each dependent variable (i.e., NIH ToolBox: Card-Sort, Flanker, List-Sorting; and WISC: Processing Speed Index, Working Memory Index, Fluid Reasoning Index). The α-level was set at 0.05. Significant regressions ($p < 0.05$) are reported in detail below. Multiple comparisons were corrected using Benjamini and Hochberg's false discovery rate (FDR), at a value of 0.05, after pooling the P values from the correlation analyses.

CHAPTER 4

Results

Participant Characteristics

Table 1 presents the participant characteristics and demographics (N, means, range, SD). Overall, 4296 participants assented (with parental consent for children under 18 years) and completed some unique variations of the four-day cross-sectional protocol. Due to the nature of this protocol, the participant's enrollment date into the study determines which tasks they completed; see Appendix C. Therefore, many participants had missing data in several domains of interest for the current study, including questionnaires of demographics and ELE, physical characteristic assessments, cognitive testing (NIH Toolbox and WISC), and EEG assessments. Consequently, 3139 participants were excluded due to data availability surrounding our specific research questions. Potential outliers ±3 SD of mean behavioral responses (i.e., cognitive task performance) were considered, and an additional 7 participants were excluded due to outliers in the data. Thus, the final analyses on cognitive outcomes were conducted on 1157 participants (441 females, 716 males) with a mean ± SD age of 11.99 ± 2.96 years (range 5-21 years). Ethnicity (238 Hispanic, 796 non-Hispanic, and 80 unknown) and race (603 Caucasian, 149 Black or African American, 104 Hispanic, 38 Asian, 8 Indian, 1 Native American Indian, 194 Mixed or Other Race, 19 Unknown) were reported. The average household income was 9.03 ± 3.26% (equivalent to $80,000-$89,999 yearly household income), parental education of 17.81 ± 3.22, equivalent to partial college attendance, and parental occupation of 32.69 ± 12.26, equivalent to occupations such as supervisor, librarian, aircraft mechanic, artist and artisan, electrician, administrator, military enlisted personnel, and buyer. A full breakdown of demographics can be found in Table 1a and 1b. A smaller and separate cohort of participants completed EEG assessments, and this dataset was considered for secondary analysis. Therefore, EEG outcome analyses were completed on a separate subset of the original 3139 participants that did not overlap with the NIH cognitive outcomes (N =887).

Table 1a.

Participant characteristics and demographics

		N	%	Mean	SD	Range
Sample Size (total)		4296				
Sample Size (analyzed)		1164				
Sample Size (outliers excluded)		**1157**				
Sex	Female	441	61.9			
	Male	716	38.1			
Ethnicity	Hispanic	238	20.6			
	Non-Hisanic	796	68.8			
	Unknown	80	6.9			
Race	Caucasian	603	54			
	Black or African American	149	13.4			
	Hispanic	104	9.3			
	Asian	38	3.4			
	Indian	8	0.7			
	Native American Indian	1	0.1			
	Mixed or Other Race	194	17.4			
	Unknown	19	1.7			
Age				11.99	2.96	5-21
Height (cm)				152.97	15.69	117-193
Weight (kg)				49.63	19.58	20-143
BMI	Percentile			63.54	30.61	1-100%
	Underweight (0-5th Percentile)	56	4.8			
	Normal Weight (5-85th Percentile)	903	78			
	Overweight (85-95th Percentile)	108	9.3			
	Obesity (>95th Percentile)	90	7.8			
Body Composition	Lean Mass			74.82	71.24	kg/m^2
	Fat Mass			4.49	15.81	kg/m^2

Table 1b.
Participant characteristics and demographics

Physical Activity	All (PAQ-C & PAC-A Activity Summary Score)			1.02	2.83	1-5
	Low PA	570	55.9	1.77	0.41	1-2
	High PA	513	44.1	3.26	0.48	3-5
Estimated Fitness				46.97	9.52	9-77
SES	Parental Education (BSMSS)			College Education		Less than 7th grade - Graduate Degree
	Parental Occupational Prestige* (BSMSS)			32.69		5 - 45
	Household Income			$90,000 to $99,999		<$10,000 to >$150,000
	PhenX Neighborhood Safety			2.04	0.94	1-5
	PhenX School Enviornment			2.98	0.49	1-5
	PhenX School Risk			2.63	0.32	1-5
IQ				98.46	16.81	1-146
Early Life Stressors	Adverse Early Life Experiences (ACES)			0.97	1.55	0-9
	Child Anxiety Related Disorders (SCARED)			15.35	12.8	0-81
	Child Behavior Checklist (CBCL)			57.57	10.86	24-85
	Conners Defiance/Aggression			56.03	14.33	40-90
	Conners Hyperactivity/Impulsivity			60.02	12.78	40-90
	Conners Inattention			64.53	14.56	40-90
	Conners Learning Problems			59.39	13.15	40-90
	ESWAN: Depression			0.03	0.78	-3-3
	ESWAN: Disruptive Mood Dysregulation Disorder			-0.19	1.09	-3-3
	ESWAN: Panic Disorder			-0.11	0.92	-3-3
	ESWAN: Social Anxiety			0.2	1.09	-3-3

**Note:
5=Day laborer, janitor, house cleaner, farm worker, food counter sales, food preparation worker, busboy;
10=Garbage collector, short-order cook, cab driver, shoe sales, assembly line workers, masons, baggage porter;
15=Automobile mechanic, typist, locksmith, farmer, carpenter, receptionist, construction laborer, hairdresser;
20=Automobile mechanic, typist, locksmith, farmer, carpenter, receptionist, construction laborer, hairdresser;
25=Machinist, musician, bookkeeper, secretary, insurance sales, cabinet maker, personnel specialist, welder;
30=Supervisor, librarian, aircraft mechanic, artist and artisan, electrician, administrator, military enlisted personnel, buyer;
35=Nurse, skilled technician, medical technician, counselor, manager, police and fire personnel, financial manager, physical, occupational, speech therapist;
40=Mechanical, nuclear, and electrical engineer, educational administrator, veterinarian, military officer, elementary, high school and special education teacher;
45=Physician, attorney, professor, chemical and aerospace engineer, judge, CEO, senior manager, public official, psychologist, pharmacist, accountant.*

Associations between Demographics and Neurocognitive Function. Age was positively correlated with processing speed performance ($r = 0.181$, $p = .001$) and negatively correlated with flanker ($r = -0.213$, $p = .001$). Parental education was positively correlated with all the cognitive outcomes: Processing speed ($r = 0.071$, $p = .017$), Flanker ($r = 0.145$, $p = .001$), working memory ($r = 0.287$, $p = .001$), Card sort ($r = 0.129$, $p = 0.001$), and list sort ($r = 0.241$, $p = .001$). Parent occupation was positively correlated with working memory ($r = 0.213$, $p = .001$), flanker ($r = 0.112$, $p = .001$), Card sort, ($r = 0.115$, $p = 0.001$), and list sort ($r = 0.187$, $p = .001$). Household income was positively correlated with working memory ($r = 0.215$, $p = 0.001$), flanker ($r = 0.144$, $p = 0.001$), card sort ($r = 0.149$, $p = 0.001$), and list sort ($r = 0.200$, $p =0.001$) as seen in Figure 1. Neighborhood safety was negatively correlated with processing speed ($r = -0.064$, $p = .033$), working memory ($r = -0.094$, $p = .003$), and list sort ($r = -0.066$, $p = .028$). School risk was negatively correlated with list sort ($r = -0.091$, $p = 0.037$). IQ was positively correlated with fluid reasoning ($r = 0.850$, $p = 0.001$). Relative theta PSD was significantly correlated with the school environment ($r = -0.200$, $p = 0.027$). A full breakdown of all correlations between demographics and neurocognitive function can be found in Tables 2 and 3.

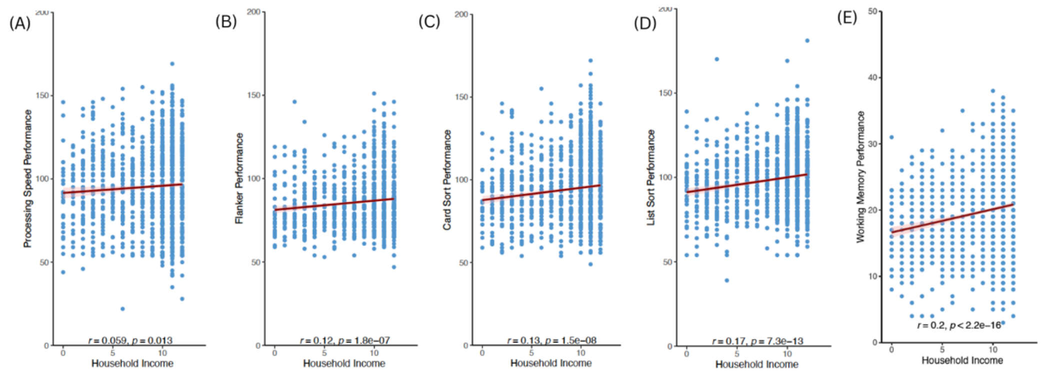


Fig 1. Scatter plots depicting Pearson Correlations between Cognitive Performance and Household Income. The y-axis represents the age-corrected cognitive task outcomes, including (A) Processing Speed, (B) Flanker, (C) Card-Sort, (D) List-Sort, and (E) Working Memory. The x-axis represents the distribution of household income, a component of SES. Significant correlations were used in regression models.

Associations between Physical Characteristics and Neurocognitive Function. Predicted cardiorespiratory fitness was positively correlated with working memory (r = 0.124, p = 0.018), flanker (r = 0.133, p = 0.004), card sort (r = 0.110, p = 0.019), and list-sort (r = 0.099, p = 0.035) as seen in Figure 2. BMI was negatively correlated with working memory (r = -0.100, p = 0.002), flanker (r = -0.095, p = 0.001) and list sort (r = -0.068, p = 0.007). Physical activity was positively correlated with flanker (r = 0.074, p = 0.015) and card sort (r = 0.073, p = 0.016). PA levels significantly correlated with relatively high-alpha (r = 0.101, p = 0.021) and low-alpha (r = 0.086, p = 0.048) PSD frequency bands. Lean body mass was positively correlated with all relative PSD frequency bands: beta (r = 0.367, p = 0.001), high-alpha (r = 0.337, p = 0.001), low-alpha (r = 0.331, p = 0.001), theta (r = 0.239, p = 0.001). Lean body mass was also positively correlated with relative beta PSD (r = 0.313, p = 0.001). Fat mass was negatively correlated with relative PSD in almost all frequency bands; beta (r = -0.128, p = 0.037), high-alpha (r = -0.134, p = 0.029), and low-alpha (r = -0.124, p = 0.044).

A full breakdown of all correlations between physical characteristics and neurocognitive function can be found in Tables 2 and 3.

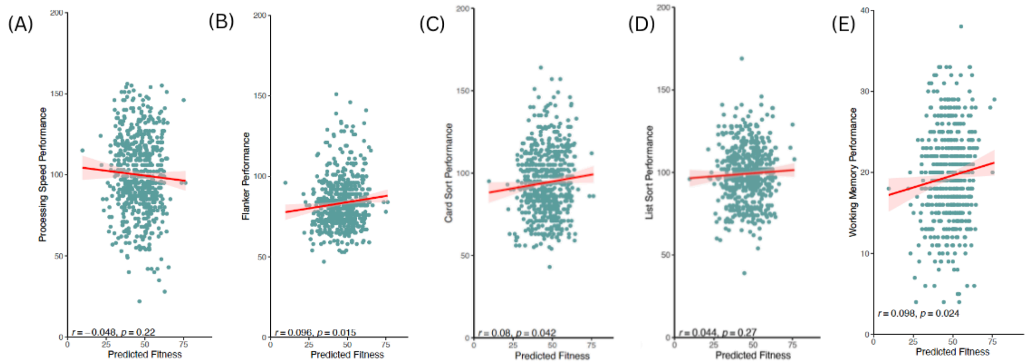


Fig 2. Scatter plots depicting Pearson Correlations between Cognitive Performance and Predicted Cardiorespiratory Fitness. The y-axis represents the age-corrected cognitive task outcomes, including (A) Processing Speed, (B) Flanker, (C) Card-Sort, (D) List-Sort, and (E) Working Memory. The x-axis represents the distribution of fitness, a component of physical health. Significant correlations were used in regression models.

Associations between Early Life Experiences (ELE Characteristics and Neurocognitive Function. Conners Learning problems were negatively correlated with processing speed (r = -0.126, p = .001), working memory (r = -0.315, p = .001), flanker (r = -0.199, p = .001), Card sort (r = -0.195, p = .001), and list sort (r = -0.237, p = .001) as seen in Figure 3. CBCL was negatively correlated with Card sort (r = -0.063, p = 0.034). SCARED was negatively correlated with List sort (r = -0.064, p = .018). Social anxiety was negatively correlated with flanker (r = -.100, p = .001) and card sort (r = -0.081, p = .006). Defiance and aggression were negatively correlated with Processing speed (r = -0.125, p = 0.001) and List sort (r = -0.080, p = 0.002). Hyperactivity/impulsivity was positively correlated with flanker (r = 0.059, p = 0.048). ACES was positively correlated with high (r = 0.194, p = 0.001) and low (r = 0.179, p = 0.001) alpha PSD, as well as beta PSD (r = 0.122, p = 0.022). ESWAN Disruptive Mood Dysregulation Disorder (DMDD) symptomatology was positively correlated with theta PSD EEG (r = 0.111, p = 0.038). Panic disorder symptomatology was negatively correlated with high alpha PSD (r = -0.112, p = 0.036). A full breakdown of all correlations between physical characteristics and neurocognitive function can be found in Tables 2 and 3.

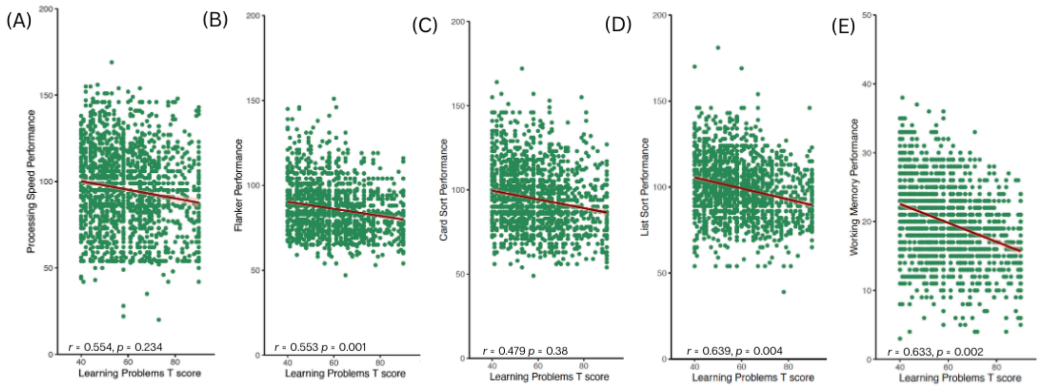


Fig 3. Scatter plots depicting Pearson Correlations between Cognitive Performance and Learning Problems. The y-axis represents the age-corrected cognitive task outcomes, including (A) Processing Speed, (B) Flanker, (C) Card-Sort, (D) List-Sort, and (E) Working Memory. The x-axis represents the distribution of learning problems, a component of ELE. Significant correlations were used in regression models.

Table 2.

Correlations between demographics and neurocognitive outcomes

significant at $p > 0.05$; **significant at $p > 0.001$

	Cognitive Outcomes					
Demographics	**Processing Speed**	**Working Memory**	**Fluid Reasoning**	**Flanker**	**Card-Sort**	**List-Sort**
Age	0.181**	-0.050	0.005	-0.213**	-0.057	0.016
IQ	-0.011	-0.027	0.850**	-0.021	0.064	0.040
Household income	0.057	0.215**	0.019	0.144**	0.149**	0.200**
Parents Education	0.071*	0.287**	-0.008	0.145**	0.129**	0.241**
Parents Occupation	0.037	0.213**	0.015	0.112**	0.115**	0.187**
PhenX Neighborhood Safety	-0.064*	-0.094**	0.002	-0.035	-0.033	-0.066*
PhenX School Enviornment	-0.037	-0.054	0.019	-0.021	0.019	0.008
PhenX School Risk	0.052	-0.078	-0.071	-0.053	-0.026	-0.091*
Physical Characteristics						
Physical Activity	-0.011	0.020	-0.058	0.074*	0.073*	0.006
Estimated Cardiorespiratory Fitness	-0.002	0.124*	0.042	0.133**	0.110*	0.099*
BMI Percentile	0.001	-0.100**	-0.032	-0.095**	-0.045	-0.068*
Lean Body Mass	-0.040	0.009	-0.059	0.052	0.002	0.003
Fat Mass	0.034	0.000	0.059	-0.025	0.008	-0.002
Early Life Stress (ELS) Characteristics						
Adverse Early Life Experiences (ACES)	-0.013	-0.030	-0.008	-0.042	-0.011	0.070
Child Anxiety Related Disorders (SCARED)	-0.026	-0.056	-0.025	-0.055	-0.058	-0.064*
Child Behavior Checklist (CBCL)	-0.028	0.017	-0.028	-0.026	-0.063*	0.009
Conners Defiance/Aggression	-0.125**	-0.039	0.000	0.011	-0.047	-0.080**
Conners Hyperactivity/Impulsivity	0.004	0.046	-0.005	0.059*	0.027	0.011
Conners Inattention	-0.009	-0.046	0.046	-0.040	-0.053	-0.022
Conners Learning Problems	-0.126**	-0.315**	-0.012	-0.199**	-0.195**	-0.237**
ESWAN: Depression	0.023	0.000	-0.007	-0.022	-0.026	0.003
ESWAN: Disrupted Mood Dysregulation Disorder	-0.021	0.039	-0.009	0.022	-0.016	-0.003
ESWAN: Panic Disorder	0.026	0.047	0.032	0.023	0.013	0.039
ESWAN: Social Anxiety	-0.006	-0.061	-0.014	-.100**	-0.081**	-0.058

Table 3.

Correlations between demographics and neurocognitive function

**significant at p > 0.05; **significant at p > 0.001*

	Relative PSD EEG				Relative EEG Power			
	Beta	**High Alpha**	**Low Alpha**	**Theta**	**Beta**	**High Alpha**	**Low Alpha**	**Theta**
Demographics								
Age	-0.062	-0.062	-0.065	-0.028	0.010	.160**	0.029	-.146**
IQ	-0.054	-0.052	-0.012	0.031	-.078*	-0.042	-0.030	0.018
Household income	0.011	0.022	0.019	0.005	0.002	-0.048	-0.042	-0.007
Parents Education	0.048	0.064	0.054	0.001	0.035	-0.013	0.040	0.031
Parents Occupation	.105*	0.089	0.088	0.047	0.066	-0.071	0.018	0.059
PhenX Neighborhood Safety	0.031	0.005	0.015	0.025	0.040	0.044	0.035	0.013
PhenX School Enviornment	0.013	-0.036	-0.134	-.200*	0.080	0.111	0.055	0.116
PhenX School Risk	-0.053	-0.050	-0.071	-0.089	0.030	0.115	0.101	0.040
Physical Characteristics								
Physical Activity	0.070	.101*	.086*	0.019	0.084	-0.004	0.053	.090*
Estimated Cardiorespiratory Fitness	0.025	0.044	0.013	-0.018	0.085	.173*	.201*	.242**
BMI Percentile	0.069	0.005	0.024	0.084	0.048	-0.039	-0.047	-0.033
Lean Body Mass	.367**	.337**	.331**	.239**	.313**	-0.086	-0.013	0.053
Fat Mass	-.128*	-.134*	-.124*	-0.052	-0.117	0.010	-0.073	-.144*
Early Life Stress (ELS) Characteristics								
Adverse Early Life Experiences (ACES)	0.098	.194**	.179**	0.101	.122*	0.061	-0.006	-0.041
Child Anxiety Related Disorders (SCARED)	0.033	0.034	0.049	0.100	0.038	-0.044	-0.037	-0.009
Child Behavior Checklist (CBCL)	0.000	0.019	0.025	0.023	0.012	-0.033	-0.023	0.021
Conners Defiance/Aggression	0.023	0.009	0.031	0.101	0.004	-0.074	-0.020	0.067
Conners Hyperactivity/Impulsivity	0.007	-0.001	-0.002	-0.002	0.030	0.001	0.030	.106*
Conners Inattention	0.026	0.048	0.051	0.050	0.049	0.017	0.012	0.034
Conners Learning Problems	-0.013	-0.026	-0.011	0.042	0.002	0.039	0.062	0.063
ESWAN: Depression	-0.006	-0.028	-0.010	0.065	-0.030	-0.013	0.005	0.003
ESWAN: Disruptive Mood Dysregulation Disorder	0.043	0.071	0.082	.111*	0.011	-0.094	-0.038	0.058
ESWAN: Panic Disorder	-0.074	-.112*	-0.102	-0.025	-0.082	0.006	0.013	0.028
ESWAN: Social Anxiety	-0.054	-0.082	-0.061	0.046	-0.046	-0.007	0.006	0.005

Associations between Demographics and Physical Characteristics. Household income was negatively correlated with BMI percentile (r = -0.128, p = 0.001) and positively correlated with estimated cardiorespiratory fitness (r = 0.139, p = 0.004) and PA (r = 0.061, p = 0.045). Age was negatively correlated with estimated cardiorespiratory fitness (r = 0.061, p = 0.001), PA (r = -0.155, p = 0.001), lean body mass (r = -0.188, p = 0.001), and positively correlated with fat mass index (r = 0.121, p = 0.001). Parental education was negatively correlated with BMI (r = -.133, p = 0.001), fat mass index (r = -.066, p = 0.025), and positively correlated with lean body mass (r = .076, p = 0.010). Parental occupation was negatively correlated with BMI (r = -.090, p = 0.002), fat mass index (r = -.061, p = 0.039), and positively correlated with lean body mass (r = 0.070, p = 0.018). Neighborhood safety was negatively correlated with estimated cardiorespiratory fitness (r = -0.140, p = 0.004) and PA (r = -0.100, p = 0.001). School risk was negatively correlated with estimated cardiorespiratory fitness (-.171, p = 0.001), fat mass index (r = 0.149, p = 0.001), and lean body mass (r = -0.163, p = 0.001). IQ was negatively correlated with PA (r = -0.066, p = 0.036).

Associations between Demographics and Early Life Experiences (ELE) Characteristics. Household income was negatively correlated with ACES (r = -0.280, p = 0.001), SCARED (r = -0.108, p = 0.001), CBCL (r = -0.076, p = 0.011), Conners inattention (r = -0.096, p = 0.001), and Conners learning problems (r = -0.188, p = 0.001). Age was significantly correlated with ACES (r = 0.091, p = 0.011), CBCL (r = -0.069, p = 0.020), Conners defiance/aggression (r =

-0.265, p = 0.001), Conners hyperactivity/impulsivity (r = -0.153, p = 0.001), Conners learning problems (r = -0.082, p = 0.006), ESWAN DMDD (r = -0.164, p = 0.001), ESWAN depression (r = 0.085, p = 0.004), and ESWAN social anxiety (r = 0.122, p = 0.001). Parental education was significantly correlated with ACES (r = -0.100, p = 0.005), Conners inattention (r = -0.083, p = 0.006), Conners learning problems (r = -0.204, p = 0.001), ESWAN DMDD (r = -0.064, p = 0.033), ESWAN depression (r = -0.067, p = 0.025), and ESWAN social anxiety (r = -0.096, p = 0.001). Neighborhood safety was positively correlated with ACES (r = 0.108), p = 0.003), SCARED (r = 0.090, p = 0.003), CBCL (r = 0.068, p = 0.025), Conners defiance/aggression (r = 0.068, p = 0.026), Conners inattention (r = 0.107 , p = 0.001), Conners learning problems (r = 0.097, p = 0.001), ESWAN depression (r = 0.060, p = 0.048), ESWAN panic disorder (r = 0.080, p = 0.008), and social anxiety (r = 0.081, p = 0.007). School environment was negatively correlated with CBCL (r = -0.143, p = 0.002), Conners defiance/aggression (r = -0.196, p = 0.001), Conners inattention (r = -0.136, p = 0.004), ESWAN DMDD (r = -0.200, p = 0.001), ESWAN depression (r = -0.208, p = 0.001), ESWAN panic disorder (r = -0.108, p = 0.022), and ESWAN social anxiety (r = -0.113, p = 0.016). School risk was correlated with SCARED (r = 0.125, p = 0.005), ESWAN DMDD (r = -0.106, p = 0.016), ESWAN depression (r = -0.088, p = 0.045), and ESWAN social anxiety (r = -0.143, p = 0.001).

Associations between Physical Characteristics and Early Life Experiences (ELE) Characteristics. BMI was positively correlated with ACES (r = 0.123, p = 0.001), SCARED (r = 0.101, p = 0.001), CBCL (r = 0.074, p = 0.012), Conners hyperactivity (r = 0.79, p = 0.008), Conners learning problems (r = -0.143, p = 0.001), and Conners depression assessment (r = 0.093, p = 0.002). Estimated cardiorespiratory fitness was significantly correlated with SCARED (r = -0.285, p = 0.002), Conners defiance/aggression (r = 0.127, p = 0.008), ESWAN depression (r = -0.112, p = 0.018), ESWAN panic disorder (r = -0.112, p = 0.018), and ESWAN social anxiety (r = -0.135, p = 0.004). PA was negatively correlated with SCARED (r = -0.187, p = 0.001), CBCL (r = -0.090, p = 0.003), Conners inattention (r = -0.096, p = 0.002), Conners learning problems (r = -0.082, p = 0.007), ESWAN depression (r = -0.143, p = 0.001), ESWAN panic disorder (r = -0.096, p = 0.002), and ESWAN social anxiety (r = -0.196, p = 0.001). Lastly, lean body mass was negatively correlated with ACES (r = -0.79, p = 0.028) and ESWAN depression assessments (r = -0.066, p = 0.025).

Between-Groups Analysis

Physical Activity. The independent samples t-test showed a significant main effect of card sort performance t(1153)=2.33, p = .020, which displayed that higher PA levels were associated with higher cognitive performance (low PA: 95.03 ± 17.35, high PA: 92.58 ± 17.37). There was also a significant main effect of processing speed performance t(1146)=-2.03, p = .042, which revealed that higher PA levels were associated with greater cognitive processing performance (low PA: 94.08 ± 22.58, high PA: 96.94 ± 23.99). A significant main effect of flanker performance was also found, t(1154)=2.66, p = .008, which conveyed that higher PA levels were associated with greater response inhibition performance (low PA: 86.47 ± 13.85, high PA: 84.20 ± 14.29). A significant main effect of working memory performance was seen, $t(1001)=2.55$, $p = .011$, which shows that higher PA levels were associated with higher memory performance (low PA: 50.20 ± 30.69, high PA: 45.10 ± 29.72). Between groups analysis revealed a main effect of PA on beta PSD bands $t(526)=1.28$, $p = .010$, (low PA: 154.67 ± 2094.62, high PA: 456.50 ± 3350.85). A full breakdown of the between-group analysis between PA and neurocognitive function can be found in Table 4. Plots depicting between-group PA differences in EEG PSD in the beta frequency band can be seen in Figure 3 and 4. A bar graph depicting between-group PA differences can be seen in Figure 5.

Table 4.
Between-groups analysis between PA and neurocognitive function
*significant at p > 0.05; **significant at p > 0.001*

	Physical Activity (PA) Levels				
	Low		High		
NIH Toolbox	**Mean**	**SD**	**Mean**	**SD**	***p-value***
Flanker	86.47	13.85	84.2	14.29	0.008*
Card-Sort	95.03	17.35	92.58	17.37	0.020*
List-Sort	99.3	15.79	98.28	16.64	0.298
Processing Speed	94.08	22.58	96.94	23.99	0.042*
Working Memory	50.3	30.69	45.1	29.73	0.011*
Fluid Reasoning	98.71	16.5	100.54	16.57	0.079
Relative PSD					
Beta PSD	154.68	2094.63	465.50	3350.85	0.010*
High Alpha PSD	4.66	27.00	9.28	60.60	0.026*
Low Alpha PSD	6.04	28.79	9.46	46.61	0.088
Theta PSD	10.26	63.08	11.07	40.34	0.935
Early Life Stressors					
Child Anxiety Related Disorders (SCARED)	22.94	16.12	18.75	15.33	0.001**
Child Behavior Checklist (CBCL)	58.43	10.43	56.60	11.95	0.001**
Conners Learning Problems	60.12	13.26	58.02	13.25	0.002*
ESWAN: Social Anxiety	0.24	1.07	-0.04	1.06	0.001**

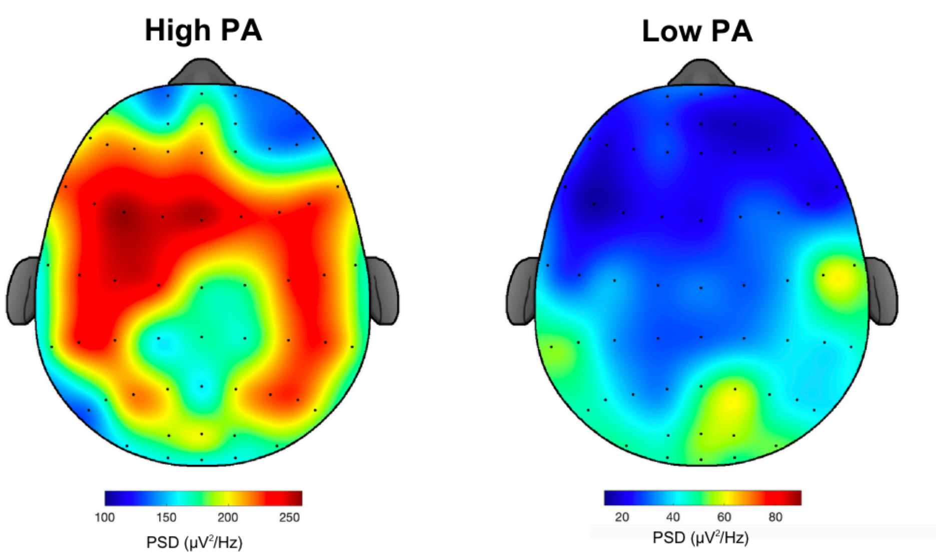


Fig 4. Topographical Map of PSD Values in High and Low PA Groups. Topographical plot of resting state EEG averaged for the high physical activity (PA) level group (left) and low physical activity (PA) level group (right) in the beta frequency band (i.e., 13 - 20 Hz). Power spectral densities are scaled in different ranges for better visualization of the between-group differences.

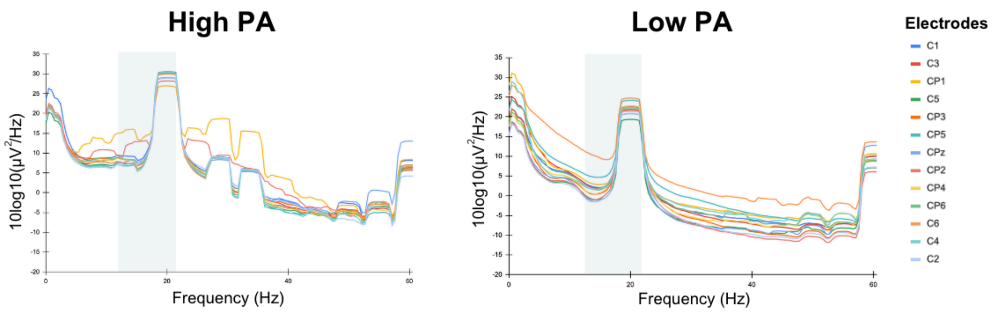


Fig 5. EEG PSD of High and Low PA Groups in the midline electrodes. The PSD corresponding to different midline electrodes (C1, C3, Cp1, C5, CP3, CP5, CPz, CP2, CP4, CP6, C6, C4, and C2) are shown in different colors, as shown in the box in the top right corner of the figure. The x-axis represents the frequency in Hz. The y-axis represents the relative amplitude of the power spectral densities on a logarithmic scale. The light blue area indicates the beta frequency band - the region of interest in the current study.

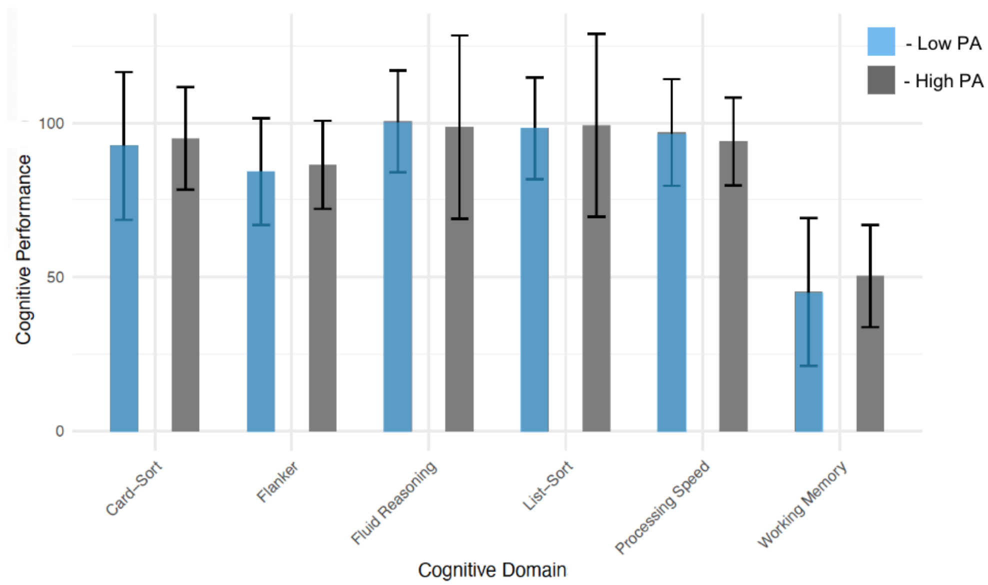


Fig 6. Between-Groups Analysis of Low and High PA on Cognitive Performance. The x-axis represents the cognitive domain, including NIH Toolbox (card-sort, flanker, list-sort) and WISC-V outcomes (processing speed, working memory). The y-axis represents cognitive performance. The blue bars indicate low physical activity levels, whereas the grey bars indicate high physical activity levels, with error bars depicting standard deviations.

Body Mass Index. The independent samples t-test provided a significant main effect of card sort performance, t(1153)=-2.309, p = .041, which indicated that higher BMI was associated with lower cognitive performance (healthy BMI: 94.64 ± 17.66, high BMI: 91.52 ± 15.80). As the secondary analysis was already limited in sample size, the classification of BMI further reduced the sample size, and we were not powered enough to run between-groups analysis by BMI. Therefore, the investigation into BMI and EEG was not pursued further.

Socioeconomic Status. The independent samples t-test produced a significant main effect of card sort performance t(808)=-5.82, p = .001, which suggested that higher SES levels were associated with higher cognitive performance (low SES: 88.77 ± 17.18, high SES: 96.96 ± 17.18). There was also a significant main effect of flanker performance t(809)=-6.30, p = .001, which shows that higher SES was associated with greater response inhibition performance (low SES: 80.64 ± 13.25, high SES: 96.33 ± 23.79). A significant main effect of working memory performance was also found, t(809)=-6.94, p = .001, which revealed that higher SES levels were associated with higher memory performance (low SES: 38.13 ± 28.89, high PA: 55.45 ± 30.12). A significant main effect of list sort performance t(808)=-5.82, p = .001, which conveyed that higher SES levels were associated with higher cognitive performance (low SES: 93.76 ± 15.42, high SES: 101.84 ± 16.15). The independent samples t-test generated a significant main effect of beta PSD, t(540)=-1.16, p = 0.019 (low SES: 1.12 ± 3.77, high SES: 217.64 ± 2413.48). A full breakdown of the between-group analysis between SES and neurocognitive function can be found in Table 5. Plots depicting between-group SES differences in EEG PSD in the beta frequency band can be seen in Figure 6 and 7. A bar graph depicting between-group SES differences can be seen in .

Table 5.

	Socioeconomic Status (SES) Groups				
	Low		High		
NIH Toolbox	**Mean**	**SD**	**Mean**	**SD**	***p-value***
Flanker	80.64	13.25	87.83	14.16	0.001**
Card-Sort	88.77	17.18	96.96	17.18	0.001**
List-Sort	92.76	15.42	101.84	16.15	0.001**
Processing Speed	93.17	22.08	96.33	23.79	0.099
Working Memory	38.13	28.89	55.45	30.12	0.001**
Fluid Reasoning	99.75	16.14	99.81	16.61	0.964
Relative PSD					
Beta PSD	1.12	3.77	217.65	2413.49	0.019*
High Alpha PSD	3.79	9.97	5.80	37.57	0.147
Low Alpha PSD	6.71	24.72	7.80	50.99	0.543
Theta PSD	15.44	86.40	11.66	85.61	0.381
Early Life Stressors					
Child Anxiety Related Disorders (SCARED)	25.76	17.34	21.36	15.38	0.001**
Child Behavior Checklist (CBCL)	59.43	11.45	57.22	10.38	0.001**
Conners Learning Problems	63.33	14.47	58.09	12.40	0.001**
ESWAN: Social Anxiety	0.32	1.09	0.15	1.09	0.019*

Between-groups analysis between SES and neurocognitive function
**significant at p > 0.05; **significant at p > 0.001*

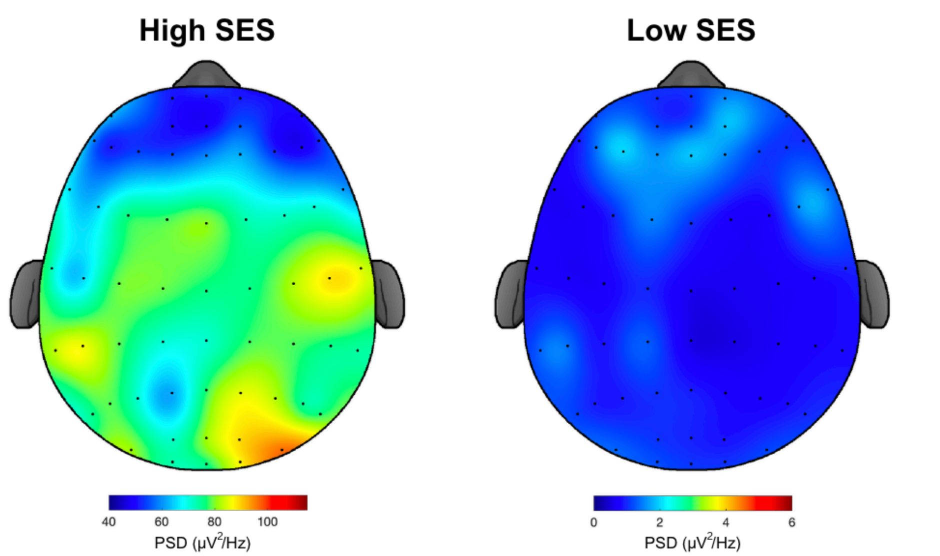


Fig 7. Topographical Map of PSD Values in High and Low SES Groups. Topographical plot of resting state EEG averaged for the high socio-economic status (SES) group (left) and low socio-economic status (SES) group (right) in the beta frequency band (i.e., 13 - 20 Hz). Power spectral densities are scaled in different ranges for better visualization of the between-group differences.

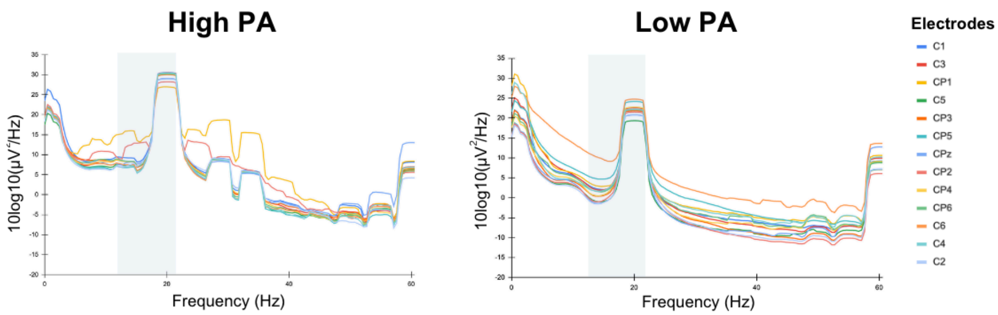


Fig 8. EEG PSD of High and Low PA Groups in the midline electrodes. The PSD corresponding to different midline electrodes (C1, C3, Cp1, C5, CP3, CP5, CPz, CP2, CP4, CP6, C6, C4, and C2) are shown in different colors, as shown in the box in the top right corner of the figure. The x-axis represents the frequency in Hz. The y-axis represents the relative amplitude of the power spectral densities on a logarithmic scale. The light blue area indicates the beta frequency band - the region of interest in the current study.

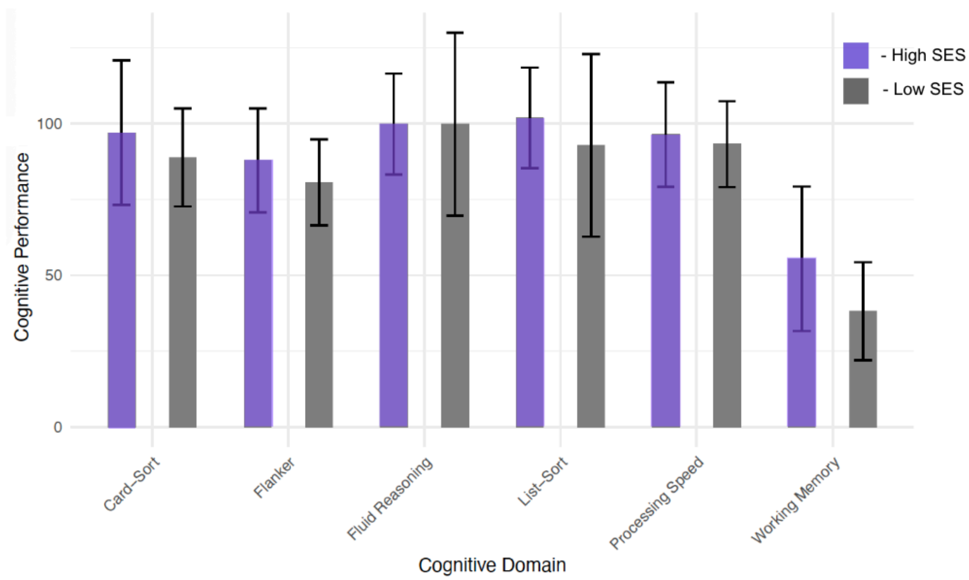


Fig 9. Between-Groups Analysis of Low and High SES on Cognitive Performance. The x-axis represents the cognitive domain, including NIH Toolbox (card-sort, flanker, list-sort) and WISC-V outcomes (processing speed, working memory). The y-axis represents cognitive performance. The blue bars indicate high socio-economic income, whereas the grey bars indicate low socio-economic status, with error bars depicting standard deviations.

Sex. The independent samples t-test resulted in a significant main effect of card sort performance t(1153)=-2.384, p = 0.017 (Male: 93.15 ± 17.77, Female: 95.66 ± 16.66), flanker performance, t(1154)=3.048, p = 0.002 (Male: 86.60 ± 14.60, Female: 84.02 ± 12.96), and processing speed performance, t(1146)=-2.867, p = 0.004 (Male: 93.63 ± 22.85, Female: 97.66 ± 23.45). The independent samples t-test yielded significant main effects of sex for almost all relative PSD; high-alpha PSD, t(301)=1.176, p = 0.042 (Male: 8.30 ± 56.81, Female: 1.95 ± 1.64), theta PSD, t(301)=1.454, p = 0.014 (Male: 9.68 ± 44.55, Female: 3.52 ± 3.64), beta PSD t(301)=1.31, p = 0.008 (Male: 390.40 ± 3121.26, Female: 0.48 ± 0.34), and low-alpha PSD, t(301)=1.28, p = 0.027 (Male: 8.29 ± 45.91, Female: 2.69 ± 2.50). A full breakdown of the between-group analysis between sex and neurocognitive function can be found in Table 6.

Table 6.
Between-group analysis between sex and neurocognitive function
**significant at p > 0.05; **significant at p > 0.001*

	Sex				
	Male		Female		
NIH Toolbox	**Mean**	**SD**	**Mean**	**SD**	***p-value***
Flanker	86.60	14.61	84.02	12.96	0.015*
Card-Sort	93.15	17.78	95.66	16.67	0.001**
List-Sort	99.39	15.77	98.15	16.67	0.328
Processing Speed	93.63	22.86	97.66	23.45	0.001**
Working Memory	47.73	30.75	49.41	29.91	0.229
Fluid Reasoning	99.79	16.94	98.77	15.90	0.46
Relative PSD					
Beta PSD	390.40	3121.26	0.49	0.35	0.008*
High Alpha PSD	8.30	56.81	1.96	1.64	0.042*
Low Alpha PSD	8.30	45.91	2.70	2.50	0.027*
Theta PSD	9.69	44.55	3.52	3.64	0.014*
Early Life Stressors					
Child Anxiety Related Disorders (SCARED)	19.36	14.76	26.42	17.44	0.001**
Child Behavior Checklist (CBCL)	57.92	10.26	56.89	11.39	0.065
Conners Learning Problems	59.35	13.55	60.21	13.01	0.216
ESWAN: Social Anxiety	0.22	1.06	0.14	1.14	0.214

Regression Analysis

Regression analyses show significant changes in R^2 for processing speed performance ($F(3, 1055)=13.37$, adjusted $R^2 = 0.060$, $p = 0.001$, $\eta^2 = 0.244$). Age ($t(1058)=6.377$, $\beta=0.192$, $p=0.001$), sex ($t(1058)=3.207$, $\beta=0.069$, $p=0.021$), and parent education ($t(1058)=2.353$, $\beta=0.071$, $p=0.019$) were all significant in predicting processing speed performance. There were no significant physical characteristic outcome correlations to include in step two of the model. Conners learning problems ($t(1058)=-2.847$, $\beta=-0.091$, $p=0.004$) entered at Step 3 were significant in predicting processing speed performance. A full breakdown of this regression can be found in Table 7.

Table 7.
Regression analyses of processing speed performance
**significant at p > 0.05; **significant at p > 0.001*

	Processing Speed	β	*t*	*P-value*	*Lower 95 CI*	*Upper 95 CI*
Step 1	Age	0.192	6.377	<.001**	1.089	2.056
	Sex	0.069	2.307	0.021*	0.498	6.17
	Parents Education	0.071	2.353	0.019*	0.087	0.957
	PhenX Neighborhood Safety	-0.058	-1.912	0.056	-2.882	0.038
Step 2	Conners Defiance/Aggression	-0.051	-1.567	0.117	-0.188	0.021
	Conners Learning Problems	-0.091	-2.847	0.004*	-0.27	-0.05

Significant changes in R^2 were observed for working memory performance ($F(7, 311)=7.844$, adjusted $R^2 = 0.150$, $p = 0.000$, $\eta^2 = 0.387$). Parent's education ($t(318)=3.499$, $\beta=0.226$, $p=0.001$) entered at Step 1 significantly predicted working memory performance. Predicted cardiorespiratory fitness and BMI percentile were entered at Step 2 but were not significant predictors. Conners learning problem values (t(318)=-4.661, β=-0.251, p=0.001) were entered at Step 3. A full breakdown of this regression can be found in Table 8.

Table 8.
Regression analyses of working memory performance
**significant at p > 0.05; **significant at p > 0.001*

	Working Memory	β	*t*	*P-value*	*Lower 95 CI*	*Upper 95 CI*
Step 1	Sex	0.072	1.316	0.189	-2.352	11.855
	Parents Occupation	0.005	0.074	0.941	-0.339	0.366
	Parents Education	0.226	3.499	<.001**	0.98	3.498
	PhenX Neighborhood Safety	-0.052	-0.916	0.361	-5.167	1.885
	Household income	0.089	1.367	0.173	-0.404	2.245
Step 2	Predicted Cardiorespiratory Fitness	0.131	1.66	0.098	-0.08	0.938
	BMI Percentile	-0.06	-1.004	0.316	-0.193	0.063
Step 3	Conners Learning Problems	-0.251	-4.661	<.001**	-0.886	-0.36

Significant changes in R^2 were observed for flanker performance (F(10, 392)=7.844, adjusted R^2 = 0.118, p = 0.000, η^2 = 0.343). Age (t(402)=-1.965, β=-0.097, p=0.050), and household income (t(402)=3.050, β=0.178, p=0.002) were entered at Step 1 and were significant in predicting flanker performance. Predicted cardiorespiratory fitness, PA, and BMI percentile were entered in Step 2, but none were significant predictors. Conners learning problems (t(402)=-5.393, β=-0.277, p=0.001), Conners hyperactivity/impulsivity (t(402)=3.198, β=0.162, p=0.001), and ESWAN Social Anxiety (t(402)=-2.099, β=-0.103, p=0.036) were entered at Step 3 and were significant in predicting flanker performance. A full breakdown of this regression can be found in Table 9.

Table 9.
Regression analyses of flanker performance
**significant at p > 0.05; **significant at p > 0.001*

	Flanker	β	*t*	*P-value*	*Lower 95 CI*	*Upper 95 CI*
Step 1	Age	-0.097	-1.965	0.05*	-1.703	0
	Sex	-0.044	-0.891	0.373	-4.121	1.55
	Parents Occupation	-0.022	-0.37	0.712	-0.167	0.114
	Parents Education	0.068	1.139	0.255	-0.218	0.819
	Household income	0.178	3.05	0.002*	0.296	1.368
Step 2	Predicted Cardiorespiratory Fitness	0.08	0.982	0.327	-0.119	0.358
	Physical Activity	-0.012	-0.205	0.837	-1.994	1.617
	BMI Percentile	-0.055	-0.996	0.32	-0.079	0.026
Step 3	Conners Learning Problems	-0.277	-5.393	<.001**	-0.431	-0.201
	ESWANN Social Anxiety	-0.103	-2.099	0.036*	-2.716	-0.089
	Conners Hyperactivity/Impulsivity	0.162	3.198	0.001**	0.069	0.291

Significant changes in R^2 were observed for card sort performance ($F(8, 394)=4.400$, adjusted $R^2 = 0.063$, $p = 0.002$, $\eta^2 = 0.250$). Household income ($t(402)=2.933$, $\beta=0.172$, $p=0.004$) was entered at Step 1 and significantly predicted card sort performance. Predicted cardiorespiratory fitness was entered at Step 2 ($t(402)=2.428$, $\beta=0.173$, $p=0.016$) and was significant in predicting card sort performance. Conners learning problems ($t(402)=-3.860$, $\beta=-0.192$, $p=0.001$ entered at Step 3 and significantly predicted Card sort performance. A full breakdown of this regression can be found in Table 10.

Table 10.
Regression analyses of card sort performance
**significant at p > 0.05; **significant at p > 0.001*

	Card Sort	β	*t*	*P-value*	*Lower 95 CI*	*Upper 95 CI*
Step 1	Sex	0.053	1.063	0.288	-1.758	5.896
	Parents Occupation	-0.053	-0.877	0.381	-0.277	0.106
	Parents Education	0.074	1.245	0.214	-0.259	1.154
	Household income	0.172	2.933	0.004*	0.359	1.819
Step 2	Predicted Cardiorespiratory Fitness	0.173	2.428	0.016*	0.067	0.633
	Physical Activity	0.064	1.137	0.256	-1.015	3.802
Step 3	Conners Learning Problems	-0.192	-3.86	<.001**	-0.448	-0.146
	Child Behavior Checklist (CBCL)	0.015	0.29	0.772	-0.158	0.213
	ESWANN Social Anxiety	-0.049	-0.917	0.36	-2.859	1.04

Regression analyses yielded significant changes in R^2 for List sort performance ($F(10, 354)=6.085$, adjusted $R^2 = 0.123$, $p = 0.000$, $\eta^2 = 0.350$). Parents' education ($t(364)=2.286$, $\beta=0.137$, $p=0.023$) and household income ($t(364)=3.126$, $\beta=0.195$, $p=0.002$) were entered at Step 1 and were significant in predicting List sort performance. Predicted cardiorespiratory fitness and BMI percentile were entered at Step 2 but were not significant predictors of List sort performance. Conners learning problems ($t(364)=-4.643$, $\beta=-0.246$, $p=0.001$) entered at Step 3 were significant in predicting card sort performance. A full breakdown of this regression can be found in Table 11.

Table 11.
Regression analyses of list sort performance
**significant at p > 0.05; **significant at p > 0.001*

	List Sort	β	*t*	*P-value*	*Lower 95 CI*	*Upper 95 CI*
Step 1	Parents Occupation	-0.011	-0.165	0.869	-0.182	0.154
	Parents Education	0.137	2.286	0.023*	0.098	1.304
	Household income	0.195	3.126	0.002*	0.382	1.68
	PhenX Neighborhood Safety	0.015	0.273	0.785	-1.442	1.906
	PhenX School Risk	-0.085	-1.671	0.096	-9.097	0.739
Step 2	Predicted Cardiorespiratory Fitness	0.011	0.196	0.845	-0.165	0.202
	BMI Percentile	-0.105	-1.9	0.058	-0.116	0.002
Step 3	Conners Learning Problems	-0.246	-4.643	<.001**	-0.456	-0.185
	Child Behavior Checklist (CBCL)	0.007	0.129	0.897	-0.138	0.157
	Child Anxiety Related Disorders (SCARED)	0.013	0.233	0.816	-0.093	0.118

Overall, these regression analyses indicate that greater cardiorespiratory fitness was positively associated with greater neurocognitive function after controlling for demographics (age, sex, IQ, household income, neighborhood safety, school environment, school risk, parent’s education, and occupation); however, the ELE predictors also contributed significant variance to performance (Conners Rating Scale, ESWAN Social Anxiety, CBCL, SCARED).

CHAPTER 5

Discussion

Positive associations were found between parental occupation, parental education, household income, neighborhood safety, and school risk on almost all NIH toolbox cognitive outcome tasks, robustly suggesting that greater facets of SES are associated with greater cognitive functioning skills in domains of executive function, attention, inhibition, working memory, cognitive flexibility, and processing speed. In addition, three prominent aspects of SES (household income, parental education, and occupation) were also negatively correlated with BMI percentile, fat mass index, adverse childhood experiences (ACES), anxiety (SCARED), ADHD (CBCL), inattention, and learning problem outcomes. Still, these aspects of SES were positively correlated with PA, estimated cardiorespiratory fitness, and lean body mass. Our results are in line with prior research that children of parents with higher education and occupation statuses likely have lower BMI and fat mass and fewer learning problems and mental health diagnoses in comparison to their peers (Seum et al., 2022). Furthermore, neighborhood safety was negatively correlated with estimated cardiorespiratory fitness and PA, indicating that those who live in safer neighborhoods, most likely due to higher income and overall SES, tend to exhibit higher levels of PA and fitness, also in line with previous research (Cermakova et al., 2023; Dalmaijer et al., 2023; Sugiyama et al., 2016). Additionally, similar trends were seen with resting state EEG power outcomes, where SES and PA were sensitive to neuroelectric representation of cognitive processes. Children with greater household incomes and greater PA levels demonstrated greater PSD in the beta frequency. Although resting-state EEG was measured without simultaneous cognitive stimulation, the beta rhythm obtained is representative of increased alertness and cognitive processes (Sammler et al., 2007). Interestingly, neuroelectric PSD effects were only observed for the beta frequency band and not for the alpha and theta frequency bands, which suggests that the effects of PA and SES are sensitive to alert cognitive states (i.e., beta) compared to relaxed states (i.e., alpha) (Olaniyan et al., 2023), and memory (i.e., theta) (Anderson et al., 2010).

Overall, our behavioral and neuroelectric results support our first hypothesis, suggesting that children from higher SES families and inherently safer neighborhoods and schools demonstrate associations with greater neurocognitive functioning. Similarly, our results also provide support for robust positive associations that PA levels, fitness, and body composition have on cognitive functioning, supporting previous literature (Hillman et al., 2020). Our results also provide novel evidence regarding the classification of SES, such that household income in particular, as well as parental education and occupational prestige, routinely accounted for the variance in health factors and cognitive function compared to other SES variables, such as neighborhood safety and school safety. Therefore, given the effects observed in this large dataset, future research could reliably use these three facets of SES to account for childhood developmental outcomes.

To appropriately assess our second hypothesis, we employed a complex regression model on the cognitive outcomes of the NIH Toolbox and WISC-V. Our novel results demonstrated that fitness can have a positive protective effect on executive functions in particular (card sort task), despite the influence of ELE (Conners Learning Problems). These results extend support for previous literature, such that childhood executive function (i.e., attentional allocation and inhibitory control) is the primary domain of cognition, which is most sensitive to fitness, compared to other aspects of cognition such as language, perception, and memory). These results also contribute support to hypothesis 2, such that fitness was the key predictor of cognitive function despite additional ELE. Notably, PA, BMI, and body composition were not significant predictors of cognitive function, further supporting previous work. While fitness was sensitive to performance on the card sort task, two facets of SES (household income and parental education) were constant positive predictors of cognitive function in all other tasks (working memory, processing speed, flanker, and list sort) despite learning problems, ADHD, and social anxiety. However, several types of ELE were not protected against, including behavioral and emotional problems (CBCL questionnaire), defiance, and aggression (Conners subscale). Our results suggest that greater levels of fitness, household income, and parental education during childhood provide greater protective effects towards cognition despite adverse ELE specific to learning problems, ADHD, and social anxiety, providing unique support for hypothesis 2.

Limitations and Future Directions

While these findings support and extend previous work, they should be interpreted in light of several key limitations. First, general or cognitive fatigue and noncompliance during or between data collection could affect the reliability and validity of both child and parent questionnaires, which is not reported in the current dataset. For example, taking feelings and/or fatigue scales during data collection sessions would be a helpful reliability checker of participant fatigue. This data was not recorded in the current study and should be employed in future pediatric studies requiring extensive testing. In addition, PA was self-reported through the PAQ-C and PAQ-A. The validity and accuracy of self-reported data, particularly in children, should be considered when interpreting the current results.

Next, our original research questions also centered on the availability of important additional developmental and mental health data, as assessed via the Kiddie Schedule for Affective Disorders and Schizophrenia (KSADS), Columbia Suicide Severity Rating Scale (CSSRS), and the Yale Food Addiction Scale (YFAS) questionnaires. However, due to the limitation of the different data collection designs for different cohorts, not all participants completed these assessments as well as the primary outcome of interest in cognitive function assessments. Therefore, our regression models which do account for a lot of variance in SES, physical health, mental health, and ELE, do not capture the severity of KSADS, CSSRS, YFAS data and other severe mental health diagnosis on these outcomes. Due to the sensitive and important nature of these questionnaires (i.e., affective disorders, schizophrenia, suicide risk, and disordered eating) during development, future work should look to include this data.

Although there has been significant insight into the effects of the surrounding environment on developing children's health, there is currently no consensus on the optimal way to define neighborhood status in studies of neighborhood environment associations with child PA (Carver et al., 2023). Recently, researchers have used mixed measurements of SES, such as the MacArthur Scale (Liu & Li, 2023), which could be seen as outdated, developed in 2000. Considering our key SES results centered on household income, parental education, and occupational prestige, future research should consider this nuanced approach to define SES and consider the effects that mixed and outdated measurements have on data consistency and validity.

Executive functioning is a broadly defined measure of cognitive processes that make up goal-directed behavior through the prefrontal cortex. There is a large body of literature on executive function in children, however, there is limited research on adolescents, specifically the changes that occur during adolescent development (Daley et al., 2015). Although the card sort task is described as assessing cognitive flexibility and executive function, this gap in the literature should be considered when interpreting these results. In children, randomized controlled trials of PA have been shown to contribute to improvements in cognitive functioning (Hillman et al., 2014; Logan et al., 2020), however, it is still unclear whether high levels of executive function cause children to be more physically active and able to engage in play, or if more PA improves levels of executive functioning; thus creating a bidirectional link between the two (Daley et al., 2015). This notion reflects the undefined nature of executive function and the considerations that arise when evaluating these processes, particularly in children.

Additionally, our between-group analyses of cognitive function showed support for significant sex differences. This result was unexpected among such a large sample. However, the groups were not evenly matched in sample size and varied in age, which likely contributed to this variance. Previous research suggests that younger girls may demonstrate greater cognitive development, intelligence, and processing speed prior to puberty (Liao et al., 2023); however, these differences likely dissipate as children age. Future research on the influence of sex differences on cognition and mental health as children develop into adolescence is necessary.

Relatedly, covariates such as age and sex were not used in the independent samples t-tests. Previous research shows that covariates such as these could improve the accuracy and statistical power of analyses (Hedberg & Ayers, 2015); therefore, results may be less precise for the particular variables of interest, such as self-reported physical activity levels and learning problem scores.

Furthermore, as the secondary analysis of EEG outcomes was already limited in sample size, the classification of BMI further reduced the sample size, and we were not powered enough to run between-groups analysis by BMI. Therefore, the between-groups and regression effects between BMI and EEG were not pursued further. Future research should investigate the effect of BMI and body composition on resting-state EEG outcomes.

Also, due to the limitation associated with EEG data in the current sample, we did not have enough statistical power to test hypothesis 4. Specifically, we hypothesized that supervised machine learning techniques could be employed to predict the variability of the EEG signal in a data-driven manner. However, there was a lack of data available in the current analysis to formally equate supervised machine learning algorithms to the matched data labels of cognition, PA, fitness, SES, and ELE. In the future, we aim to explore the EEG dataset further without limiting the sample size to behavioral cognitive outcomes. We will examine how machine learning can be applied to complex data structures, such as this one, to aid the conceptualization of mental disorders, detect and predict the risk and trajectory of ELE symptoms, and study treatment outcomes and differential treatment responses (Jiang et al., 2020). This will also aid further investigation into hypothesis 3, whereby supervised machine learning analyses on our predictor set can help to determine the threshold of protective or attenuating effect neuroelectric function.

Lastly, one of the downfalls of using an open data set is the amount of missing data and protocol specifications that cannot be defined. The Full Protocol Summary in Appendix C reflects the protocol changes including tasks that were altered or periodically not included throughout the duration of the study. Due to this protocol, participants did not have matching data sets. Therefore, missing data analysis could be a future direction of the current study to evaluate all related effects of all the participants for more consistent and reliable results.

Conclusions

Overall, the interactions of early life experiences, physical health, and socio-economic status on neurocognitive function in youth are complex. However, several notable and robust results are identified herein. In particular, when employing the socio-economic status construct in developmental research, it is important to examine the most sensitive aspects. Our results suggest that household income and parental education are the strongest predictors of cognitive function, while parental occupational prestige should also be considered. Furthermore, fitness is a uniquely strong and reliable predictor of executive function in children. Greater physical activity and socioeconomic status levels are also associated with greater neuroelectric Beta power, indicative of efficient and alert cognitive states. As spectral power in the Beta frequency band is suggested to reflect executive function processes, these combined behavioral and neuroelectric results suggest that fitness, physical activity, and socioeconomic status greatly contribute to childhood cognitive functions despite adverse early life experiences such as learning problems, ADHD, and social anxiety. Subsequently, our results provide novel evidence for classifying key SES variables in developmental research, further support for fitness-promoting executive functions, and additional support for the notion that early life experiences such as learning problems, ADHD, and social anxiety can be overcome.

Appendix A: Full Protocol Summary (Alexander et al., 2017; Langer et al., 2017)

General Information

Demographics

CMI Symptom Checker

Edinburgh Handedness Inventory

Intake Interview

Physical Activity Questionnaire for Older Children (PAQ-C) (8–14)

Physical Activity Questionnaire for Adolescents (PAQ-A) (14–19)

Barratt Simplified Measure of Social Status

Financial Support Questionnaire

Medical History Questionnaire—Family

Pregnancy and Birth Questionnaire

Physical Measures

FITNESSGRAM (push-ups, curl-ups, trunk-lift, sit and reach, grip strength)

Cardiovascular/Endurance Fitness Test

Vitals (heart rate, blood pressure)

Measurements (height, weight, waist circumference, bio-impedance)

Blood draw

Saliva and hair samples

Baby tooth collection

Urine sample (Toxicology screen, pregnancy test: ages 11+)

Ishihara color vision test

Electroencephalography (EEG)/Eye tracking

Magnetic Resonance Imaging (MRI)

Peterson puberty scale (ages 6-17)

Sleep Disturbance Scale for Children (SDSC) (ages 6-15)

McMaster Pediatric Migraine Questionnaire

Traumatic Brain Injury (TBI)

Grooved pegboard

Cognition and Language Tasks

NIH Toolbox Tasks: Flanker, card sort, and processing speed

Temporal discounting task

Adaptive Cognitive Evaluation (ACE) (ages 5-12)

Wechsler Intelligence Scale for Children-V (WISC-V) (ages 6-17)

Wechsler Adult Intelligence Scale-IV (WAIS-IV)

Wechsler Abbreviated Scale of Intelligence-II (WASI) (ages 17+)

Wechsler Individual Achievement Test (WIAT)

Differential Ability Scales-II (DAS) (ages 5 or below or; IQ below 70)

Clinical Evaluation of Language Fundamentals-5th edition (CELF-5)

Goldman Fristoe Test of Articulation-II (GFTA)

Comprehensive Test of Phonological Processing-II (CTOPP)

Test of Word Reading Efficiency (TOWRE) (ages 6+)

Expressive Vocabulary Test (EVT) (when indicated)

Peabody Picture Vocabulary Test (PPVT) (when indicated)

Diagnostic Assessments

Kiddie Schedule for Affective Disorders and Schizophrenia (K-SADS)

Child and Adolescent Psychiatric Assessment Schedule (Cha-PAS) (when indicated)

Vineland Adaptive Behavior Scale-Parent/Caregiver rating form (when indicated)

Yale Global Tic Severity Scale (YGTSS) (when indicated for ages 6+)

Yale-Brown Obsessive Compulsive Scale (Y-BOCS) (when indicated for ages 18+)

Children's Yale-Brown Obsessive Compulsive Scale (when indicated for ages 6-18)

Behavioral Measures

Child Behavior Checklist (CBCL)

Youth Self Report (YSR) (ages 11-18)

Adult Self Report (ASR) (ages 18+)

Screen for Child Anxiety Related Disorders (SCARED) Parent Report & Self Report (ages 8-18)

Mood & Feelings Questionnaire (MFQ) Parent Report & Self Report (ages 8-18)

Affective Reactivity Index Self Report (ARI-S)

Columbia Suicide Severity Rating Scale (C-SSRS) Self Report (ages 7+)

Extended Strengths and Weaknesses Assessment of Normal Behavior (E-SWAN) (ages 5-17)

Strengths and Weaknesses of ADHD Symptoms and Normal Behavior Scale (SWAN) (ages 6+)

Conners ADHD Rating Scales Self Report Short Form (ages 8+)

Repetitive Behavior Scale (RBS)

Dishion Teacher

Autism Spectrum Screening Questionnaire (ASSQ)

Social Communication Questionnaire (SCQ)

Social Responsiveness Scale-2 (SRS-2)

Strengths and Difficulties Questionnaire

The Columbia Impairment Scale (CIS) Parent and Self Report

Social Aptitude Scale (SAS)

WHO Disability Assessment Schedule (WHODAS) Parent and Self Report

Food Frequency Questionnaire (FFQ) (ages 5-17)

Positive and Negative Affect Scale (PANAS)

Inventory of Callous-Unemotional Traits - Parent and Self Report

General Self Efficacy (GSE)

GRIT Scale

Positive Behavior Scale (PBS)

Child Flourishing Scale (CFS)

Gilliam Autism Rating Scale - 3 (GARS-3)

Family Structure, Stress and Trauma

Family History - Research Diagnostic Criteria (FH-RDC)

Parental Stress Index IV (PSI-IV)

Alabama Parenting Questionnaire - Parent & Self Report (APQ) (ages 6-18)

Children's Perception of Interparental Conflict (CPIC) (ages 8-18)

Distress Tolerance Index - Parental Self Report

Children's Coping Strategies Checklist - Revised (CCSC) (ages 8-18)

Negative Life Events Scale (NLES) - Parent & Self Report (ages 8-18)

Adverse Childhood Experiences Scale (ACES) (ages 18+)

Substance Use and Addiction Measures

Fagerstrom Test for Nicotine Dependence (FTND) (ages 18+)

Alcohol Use Disorders Identification Test (AUDIT) (ages 11+)

Modified Fagerstrom Tolerance Questionnaire - Adolescents (FTQA) (ages 13-17)

European School Survey Project on Alcohol & Other Drugs (ESPAD) (ages 10+)

Internet Addiction Test (IAT)

Internet Usage Questionnaire (IUQ) - Parent & Self Report

Parent - Child Internet Addiction Test (PCIAT)

Yale Food Addiction Scale (YFAS) and YFAS - Child

Longitudinal Follow Up Measures

Youth Services Survey (YSS) & Services Assessment for Children and Adolescents (SACA)

Follow-up: CBCL

Follow-up: Columbia Impairment Scale Parent and Self Report

Follow-up: WHODAS Parent and Self Report

Appendix B: Abbreviations and Acronyms (*in alphabetical order*)

Adverse Childhood Experiences (ACE)

Adverse Childhood Experiences Scale (ACES)

Affective Reactivity Index - Parent (ARI_P)

Affective Reactivity Index - Self Report (ARI_S)

Alabama Parenting Questionnaire – Parent Report (APQ_P)

Attention Deficit/Hyperactivity Disorder (ADHD)

Autism Spectrum Screening Questionnaire (ASSQ)

Center for Disease Control (CDC)

Child Behavior Checklist (CBCL)

Child Flourishing Scale (CFS)

Children's Global Assessment Scale (CGAS)

Children's Coping Strategies Checklist-Revised (CCSC)

Columbia Impairment Scale-Parent Report Version (CIS_P)

Columbia Impairment Scale-Self Report Version (CIS_SR)

Columbia Suicide Severity Rating Scale (CSSRS)

Disruptive Mood Dysregulation Disorder (DMDD)

Electroencephalogram (EEG)

Event-related potentials (ERPs)

Extended Strengths and Weaknesses Assessment of Normal Behavior-Parent Report (ESWAN)

False Discovery Rate (FDR)

Financial Support Questionnaire (FSQ)

General Self Efficacy (GSE)

Gilliam Autism Rating Scale-3 (GARS)

Harvard Automated Pre-processing Pipeline (HAPPE)

Internet Use Questionnaire (IUQ)

Inventory of Callous-Unemotional Traits – Parent Report (ICU_P)

Longitudinal Online Research and Imaging System (LORIS)

Magnetic Resonance Imaging (MRI)

Moderate-to-Vigorous Physical Activity (MVPA)

Mood and Feelings Questionnaire (MFQ)

National Health and Nutrition Examination Survey (NHANES)

National Institute of Health (NIH)

Parenting Stress Index Fourth Edition (PSI)

Physical Activity (PA)

Physical Activity Questionnaire for Adolescents (PAQ_A)

Physical Activity Questionnaire for Older Children (PAQ_C)

Positive Behavior Scale (PBS)

Repetitive Behavior Scale (RBS)

Screen for Child Anxiety Related Disorders - Parent report (SCARED_P)

Screen for Child Anxiety Related Disorders - Self-report (SCARED_SR)

Socioeconomic Status (SES)

Strengths and Difficulties Questionnaire (SDQ)

Strengths and Weaknesses Assessment of ADHD and Normal Behavior (SWAN)

Wechsler Adult Intelligence Scale-IV (WAIS)

Wechsler Individual Achievement Test - III (WIAT)

Wechsler Intelligence Scale for Children (WISC)

Wechsler Intelligence Scale for Children-V (WISC-V)

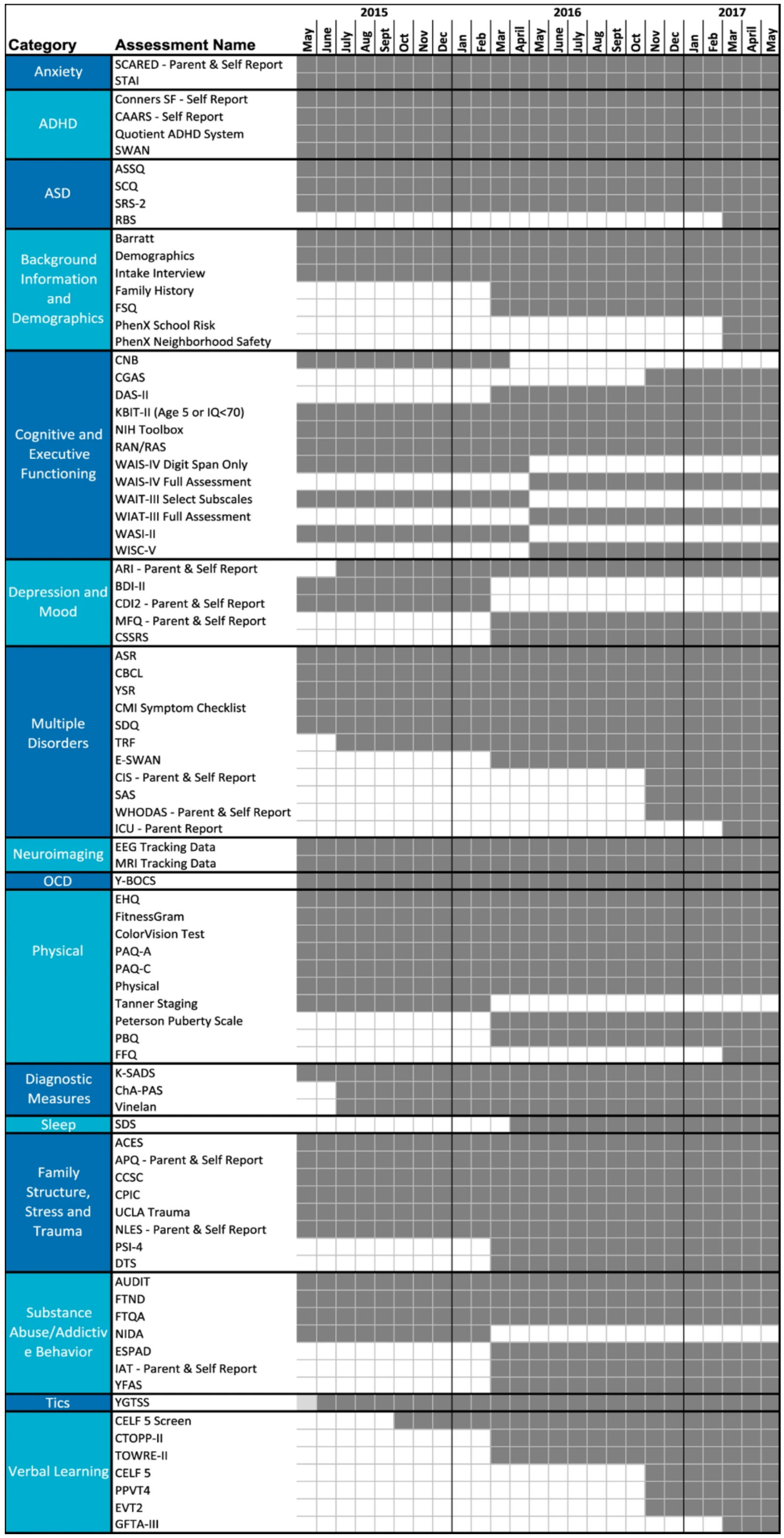
WHO Disability Assessment Schedule - Parent Report (WHODAS_P)

WHO Disability Assessment Schedule - Self Report (WHODAS_SR)

World Health Organization (WHO)

Yale Food Addiction Scale (YFAS)

Appendix C: Protocol Summary (Retrieved from Alexander et al., 2017 and Langer et al., 2017.



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