Author Manuscript Author Manuscript Author Manuscript Author Manuscript

HHS Public Access
Author manuscript
Child Dev. Author manuscript; available in PMC 2021 September 29.

Published in final edited form as:
Child Dev. 2021 September ; 92(5): 2035–2052. doi:10.1111/cdev.13578.

Extracurricular Activities, Screen Media Activity, and Sleep May Be Modifiable Factors Related to Children's Cognitive Functioning: Evidence From the ABCD Study®

Namik Kirlic,
Laureate Institute for Brain Research

Janna M. Colaizzi,
Laureate Institute for Brain Research

Kelly T. Cosgrove,
Laureate Institute for Brain Research

Zsofia P. Cohen,
Laureate Institute for Brain Research

Hung-Wen Yeh,
Laureate Institute for Brain Research and Children's Mercy Hospital

Florence Breslin,
Laureate Institute for Brain Research

Amanda S. Morris,
Laureate Institute for Brain Research and Oklahoma State University

Robin L. Aupperle,
Laureate Institute for Brain Research and University of Tulsa

Manpreet K. Singh,
Stanford University School of Medicine

Martin P. Paulus
Laureate Institute for Brain Research

Abstract

This study used a machine learning framework in conjunction with a large battery of measures from 9,718 school-age children (ages 9–11) from the Adolescent Brain Cognitive Development℠ (ABCD) Study to identify factors associated with fluid cognitive functioning (FCF), or the

Correspondence concerning this article should be addressed to Namik Kirlic, Laureate Institute for Brain Research, 6655 South Yale Ave, Tulsa, OK 74136. nkirlic@laureateinstitute.org.

Conflict of interest: The authors have no conflicts of interest relevant to this paper to disclose.

Ethical approval: The University of California, San Diego, the institutional review board has indicated that analyses using the publicly released ABCD Study® data are not human subjects research and therefore do not require their own approval.

Supporting Information
Additional supporting information may be found in the online version of this article at the publisher's website:
Appendix S1. Supplementary Materials

Author Manuscript
Author Manuscript
Author Manuscript
Author Manuscript

capacity to learn, solve problems, and adapt to novel situations. The identified algorithm explained 14.74% of the variance in FCF, replicating previously reported socioeconomic and mental health contributors to FCF, and adding novel and potentially modifiable contributors, including extracurricular involvement, screen media activity, and sleep duration. Pragmatic interventions targeting these contributors may enhance cognitive performance and protect against their negative impact on FCF in children.

The capacity to learn, solve problems, and adapt to novel situations (fluid cognitive functioning [FCF]) is vital for children's success in achieving positive developmental outcomes. FCF positively relates to self-regulation, academic achievement, and psychological well-being during childhood, adolescence, and into young adulthood (Blair & Razza, 2007; McClelland, Acock, Piccinin, Rhea, & Stallings, 2013; McClelland & Cameron, 2012). Although adverse environments can have a sustained negative impact on FCF and its associated outcomes, the plasticity of the developing brain presents an opportunity to directly intervene by enhancing FCF to buffer against adversity. Thus, research identifying factors contributing to FCF in childhood is essential for developing meaningful interventions to promote positive long-term outcomes, particularly in the context of exposure to adversity or stress (Platt et al., 2018).

FCF consists of broad abilities in executive function, attention, inhibition, processing speed, and memory, and represents a global assessment of one's ability to think, act, and learn (Cattell, 1971; Goulet & Baltes, 2013; Horn, 1968). It is understood that FCF reaches its peak in early adulthood and declines across the remainder of the life span (Horn & Cattell, 1967). However, a large number of factors influences performance on FCF measures, some of which are difficult to modify (e.g., parental education), whereas others lend themselves well to personal or systemic interventions (e.g., exercise). To guide our process of selecting variables of interest in this study, we first and foremost relied on previous literature, which has identified demographic, socioeconomic, mental health, stress exposure, and health-related behaviors as important correlates of FCF. Next, we examined the broad Adolescent Brain Cognitive Development (ABCD) Study® data set for unique variables of interest (e.g., screen media activity) that theoretically may be relevant in the context of FCF. Our goal was to ultimately be able to identify correlates of FCF that may be modifiable either through lifestyle changes or existing interventions and therefore could be potential targets in future experimental efforts.

Among the most robust contributors of poor FCF in children are those associated with low socioeconomic status (SES; Farah et al., 2006; Noble, Norman, & Farah, 2005). These effects are lasting, as individuals who experience childhood poverty exhibit working memory deficits as adults (Evans & Schamberg, 2009). On the other hand, higher FCF may be a protective factor in socioeconomic disparity as it is often a moderator between SES and individual outcomes (Lawson, Hook, & Farah, 2018). Stress exposure often co-occurs with low SES, and in fact may mediate the relation between poverty and executive function in children (Piccolo, Sbicigo, Grassi-Oliveira, & Fumagalli de Salles, 2014). Research shows that negative parenting practices and household chaos are associated with increased levels of stress during childhood and result in FCF deficits, even when controlling for the effects

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

of poverty (Vernon-Feagans, Willoughby, & Garrett-Peters, 2016). Furthermore, early life stress, characterized by abuse, neglect, parental psychopathology and substance abuse, and family dysfunction in the form of conflict, domestic violence, and separation from one or multiple caregivers, in particular can have detrimental effects on cognitive and executive function across the life span (Irigaray et al., 2013).

Although co-occurring with environmental stress exposure and SES, factors related to mental and physical health are also frequently implicated in studies of childhood FCF. FCF deficits are commonly seen in psychiatric disorders, including neurodevelopmental disorders (Biederman et al., 2004), as well as mood and anxiety disorders (Goodall et al., 2018; Kavanaugh & Holler, 2014). Furthermore, prenatal experiences, such as exposure to alcohol, tobacco, and illicit drugs are associated with later FCF difficulties (Gautam, Warner, Kan, & Sowell, 2015). Sleep disturbances can also have a negative impact on FCF, albeit only a few studies have empirically investigated the relation between sleep problems and FCF in children. One such study found that children who receive insufficient sleep (i.e., fewer than the recommended number of hours for their age) were more likely to receive poorer scores on mother- and teacher-report measures of FCF (Taveras, Rifas-Shiman, Bub, Gillman, & Oken, 2017). Bodyweight is yet another health-related predictor of FCF. Obese children and adolescents exhibit significantly poorer inhibitory control than youth with healthy weights (Reinert, Po’e, & Barkin, 2013), suggesting that there is a relation between physical health and FCF. Notably, however, physical activity is positively associated with FCF and may be particularly beneficial for youth who are overweight or obese (Bustamante, Williams, & Davis, 2016). Finally, recent years have seen a rapidly increasing attention on the potential effect of screen media activities (e.g., watching television or videos, playing video games, or using social media) on health and well-being in children and adolescents. This attention is not misplaced given that broad screen media activity is among the most commonly used recreational activities in this age group (Kenney & Gortmaker, 2017; Loprinzi & Davis, 2016), and the results are scarce with respect to its effect on brain structure and function or FCF. However, data examining the relation between television use and cognitive function point to lower executive function and language delays (Kostyrka-Allchorne, Cooper, & Simpson, 2017). Taken together, these data show the multitude of environmental and behavioral factors that demonstrate or have the potential for a relation with FCF during development. However, these factors are likely interrelated and occur in same environments. For example, a child living in poverty with a caregiver who works multiple jobs and is less able to monitor activities, may be spending less time engaging in physical activity and more time engaging in screen media to pass time. Therefore, overcoming these obstacles and delineating the relative importance of various previously examined and novel factors in their relation to FCF may guide future experimental studies and subsequent targeted interventions.

Despite significant research efforts, our knowledge of factors associated with FCF remains limited. This is in part due to studies with small sample sizes and over-reliance on traditional statistical approaches limited in their ability to examine large sets of unique variables simultaneously. This has impeded the development of interventions that may meaningfully impact FCF deficits in children. Given that pathophysiology of FCF deficits is complex and likely influenced by numerous factors of potentially shared variance,

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

sophisticated multivariate statistical models employing large data sets are necessary to identify generalizable associations between FCF and factors of adequate prospective clinical utility.

While traditional statistical methods are better suited to model a handful of variables at a time using linear methods, machine learning (ML) approaches allow for robust modeling of a large number of factors and are not constrained by nonlinearity (McArdle & Ritschard, 2013). This is thought to more closely reflect the true state of complex phenomena such as cognitive functioning. ML approaches with cross-sectional data cannot infer causation; however, by iteratively testing all possible relations and identifying a set of important associations, they can improve upon theory-driven definitions of associations between important factors and FCF.

Although ML approaches are most often used to generate highly accurate "black box" prediction algorithms, this is not the only application of ML. Certain fundamental elements of ML (i.e., the use of rigorous cross-validation to more effectively guard against over-fitting, the application of a data-driven approach to model construction, and the use of algorithms that appropriately account for complexity and nonlinearity) offer advantages over traditional modeling approaches, even when a black box prediction algorithm is not the end goal. The use of variable importance (VI) metrics allows for improved interpretability of ML models and enables investigators to clearly identify important correlates. While this application of VI is less widely used within the existing research on cognitive functioning, it has been applied successfully in other fields to aid biomarker discovery (Parvandeh, Yeh, Paulus, & McKinney, 2020) and can be particularly illuminating when multiple algorithms highlight the same features as most important.

With a large, diverse data set of school-age children and variables across a number of broad domains relevant to cognitive function, the ABCD℠ Study is uniquely positioned to comprehensively assess factors associated with FCF. Therefore, this study used a ML framework to examine the associations between a range of key variables associated with baseline FCF across demographic, environmental, mental and physical health, and behavioral domains. This study takes an exploratory approach to identify whether algorithms developed based on these measures rank important factors associated with FCF. Secondarily, we aimed to identify novel and modifiable factors that could potentially be targeted with scalable prevention and intervention efforts in youth who would benefit most from an enhancement of FCF.

Method

Participants

The ABCD Study® is a large multisite, longitudinal study following 9- to 11-year-old children in the United States over a 10-year period. It is designed to assess developmental changes across a comprehensive range of domains, including brain structure and function, cognition, behavior, and mental health (Jernigan, Brown, & Dowling, 2018). The current report examines the complete baseline sample (N = 11,877; Data release 2.0.1). Informed consent and assent were obtained from a parent or legal guardian and the child, respectively, and all procedures were approved by a central Institutional Review Board. The University of California, San Diego, the institutional review board has indicated that analyses using the publicly released ABCD Study® data are not human subjects research and therefore do not require their own approval. Table 1 presents the sociocultural characteristics of the sample.

We excluded from the analysis participants without data for the FCF composite score. Next, in order to limit dependence in the response variable, we randomly selected one child per family where multiple siblings were assessed, resulting in a total of 9,718 participants with a mean age of 9.89 years old ($SD = 0.62$).

Measures

FCF (Youth Battery)—FCF was measured using the NIH Toolbox® Neurocognitive Battery specified for ages 7–17 (Gershon et al., 2013; Luciana et al., 2018). This 35-min battery is comprehensive, psychometrically sound, and widely used which allows for synchronization and comparison of cognitive performance with other studies. A composite FCF score is generated by a combination of scores from the following tasks: *Dimensional Change Card Sort* measuring ability to plan, organize, and execute goal-directed behaviors; *Flanker Inhibitory Control and Attention* measuring the ability to handle multiple environmental stimuli; *Picture Sequence Memory* measuring episodic memory including the acquisition, storage, and retrieval of information; *List Sorting Working Memory* measuring the ability to store, manipulate, and hold new information; and *Pattern Comparison Processing Speed* measuring the ability to process new information within a certain amount of time. Scores from each of these tasks are adjusted based on age and standardized based on a normative sample of children and adolescents (Casaletto et al., 2015). These composite scores show good test–retest reliability, as well as validity in children (Akshoomoff et al., 2013). For additional details regarding task descriptions, validity, and reliability, as well as the justification and use, including preliminary data, within the ABCD Study® (see Luciana et al., 2018).

Demographic and Environmental Information Variables—Parents reported demographic information regarding household and immediate family members using the PhenX survey toolkit (Barch et al., 2018). SES was measured in part using relative income disparity, a neighborhood-level subscore of the Area Deprivation Index defined as the log of 100× ratio of number of households with < $10,000 income to number of households with ≥$50,000 annual income in a participant's neighborhood (Singh, 2003). Other neighborhood-level factors were used, including neighborhood crime rates based on U.S. Census data (Bagot et al., 2018), PhenX Toolkit subscales for the perceived safety and presence of crime in one's neighborhood (Safety from Crime subscale; Zucker et al., 2018), and child accessibility to substances (Community Risk and Protective Factors subscale; Lisdahl et al., 2018). Finally, a PhenX subscale for basic needs unaffordability (Diemer, Mistry, Wadsworth, Lopez, & Reimers, 2012) was also used indicating whether families had ever experienced a lack of various services (e.g., medical care, utilities, food) due to unaffordability.

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Family Mental Health and Environment Variables—The parent-reported Achenbach Adult Self-Report Questionnaire (Barch et al., 2018) provided parental psychopathology and adaptive functioning scores. With the Family History Assessment Module Screener (Barch et al., 2018), parents reported a history of psychopathology among first- and second-degree relatives. Additional family-level variables were markers of the family environment including the Family Conflict subscale of the Family Environment Scale (Moos & Moos, 1994; Zucker et al., 2018) completed by both the parent and the child. Children also reported on their perception of parental monitoring (e.g., parent–child contact, level of disclosure) using the Parental Monitoring Scale (Chilcoat & Anthony, 1996; Zucker et al., 2018) and of parental warmth, acceptance, and responsiveness via the Acceptance Subscale of the Child Report of Behavior Inventory (Schaefer, 1965; Zucker et al., 2018).

Child Mental Health Variables—Parents reported child dimensional psychopathology using the Achenbach Child Behavior Checklist (Barch et al., 2018) from which we used empirically based composite scores for internalizing and externalizing symptoms. Parents also reported on their child's level of mania symptoms with the Parent General Behavior Inventory for Children and Adolescents (Barch et al., 2018). Child trauma exposure was measured from a posttraumatic stress symptom subscale of the Kiddie Schedule for Affective Disorders and Schizophrenia for *Diagnostic and Statistical Manual of Mental Disorders,* 5th ed. that was modified for use in ABCD Study® (Barch et al., 2018). Finally, child self-reports of behavior included the four subscales of the Behavioral Inhibition and Behavioral Activation Scales (Barch et al., 2018) and the Urgency, Premeditation, Perseverance, Sensation Seeking, Positive Urgency subscales on the Impulsive Behavior Scale for Children (Barch et al., 2018).

Child Physical Health and Extracurricular Engagement Variables—Parents reported child sleep behaviors and habits with the Sleep Disturbances Scale for Children (Bruni et al., 1996). The present analyses focused on items regarding sleep initiation ("How long [in minutes] after going to bed does your child usually fall asleep?") and sleep maintenance ("How many hours of sleep does your child get on most nights?"). Extracurricular activities were assessed with the parent-reported Sports and Activities Involvement Questionnaire (Huppertz et al., 2016). Physical exercise was assessed using the child-reported Youth Risk Behavior Survey (CDC, 2016) and objective physical health measures of body mass index and waist circumference were collected using the National Health and Nutrition Examination Survey (CDC (Division of Nutrition), 2016). Finally, children estimated the amount of time (response options from "none", "< 30 min", "30 min", then 1-hr increments up to 4+ hr) typically spent engaging in various screen media activities on a typical weekday and weekend day. Categories included passive use such as watching TV, movies, or Internet videos, and active or social use such as playing video games, texting, video chatting, or visiting social media sites (Bagot et al., 2018). For additional information on measures and scoring, see Supporting Information.

Analysis

Statistical analyses were conducted in R 3.5.1 using RStudio (RStudio Team, 2015). Descriptive statistics were obtained using the R package "psych" (Revelle, 2017).

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Machine Learning—In order to build a model that would best characterize the age-corrected FCF composite scores, 52 unique variables (Table S1) derived from the above measures were submitted to ML analyses.

ML algorithms rely on unique assumptions and may result in variations in prediction accuracy, but no single algorithm is known to always outperform others on predictive accuracy. We, therefore, chose to use the "wisdom of crowds" approach (Marbach et al., 2012), which combines predictions from multiple base learners (prediction algorithms). We utilized multiple "out of box" ML methods, followed by combining the predictions across methods by stacking or meta ensemble (Breiman, 1996; Van der Laan, Polley, & Hubbard, 2007; Wolpert, 1992). A nested cross-validation (nCV), in which the inner loop is used to build base and stacked models and the outer loop to evaluate model performance, was conducted to assess the performance of stack ensembles in independent, unseen data sets. The nCV procedure was repeated five times to quantify the variability of prediction accuracy and VI.

We applied four base learners in the inner loop for each training set, including elastic net (Barsaglini, Sartori, Benetti, Pettersson-Yeo, & Mechelli, 2014), support vector regression (SVR; Suykens & Vandewalle, 1999), conditional inference forest (CIF; Hothorn, Hornik, & Zeileis, 2006), and k-Nearest Neighbors (knn; Keller, Gray, & Givens, 1985). For each base learner, the tuning parameter(s) were optimized by fivefold cross-validation. Specifically, each training set was partitioned into five distinct subsets, where four subsets were used for the training process to evaluate different hyperparameter values; as a preprocess procedure, predictors with lower than 10% variability were removed, and the remaining variables were standardized to 0 mean and unit variance. Optimal hyperparameter values were chosen through random search (Bergstra & Bengio, 2012) and the "best" rule (Hastie, Tibshirani, & Friedman, 2009) using R^2 as the model performance metric. Next, we obtained four sets of predicted values, one from each base learner and their corresponding optimal hyperparameter values.

Within the inner cross-validation loop, each method produced a single best model and R^2 of the training sample (training R^2). A stacked model was built by taking the arithmetic mean of predictions from each base learner, weighted by each model's training R^2. In the outer loop, we applied the stacked model to predict the response in the corresponding validation set. Predicted values of the validation sets were combined and compared with the observed values to compute R^2. With five replications of partitions, we summarized the performance by the mean and 95% confidence interval of R^2.

We assessed VI using stacking, where each base model provided importance for each feature. The different individual methods had varying VI measures: absolute values of regression coefficients for the elastic net, an "out-of-bag" mean square error obtained by permutation for CIF, and a "filter" approach for SVR and knn wherein the response variable was regressed on each feature one at a time by a loess (Locally Weighted Scatter-plot Smoother), and the R^2 was computed as the VI. VI measures were scaled between 0 and 100 for each individual model. The stacked importance was computed as the weighted average of the importance across models using the weights determined by the stacking

Author Manuscript

model described earlier. This produced a single set of VI values for each stacked model in the outer loop of nCV. VI was averaged across folds to obtain a single set of values. Five random partitions were used (five repeats of nCV), and 95% confidence intervals for VI taken as each variable's mean importance ± 1.96 times its standard deviation. We computed Spearman correlation coefficients and FDR-corrected p-values for comparison purposes (Table 2). Analyses for prediction models were implemented using the "caret" package (Kuhn, 2008) and marginal relations between FCF and each predictor was assessed by partial-dependence plots ("pdp" package; Greenwell, 2017). For additional information on ML algorithm selection, see Supporting Information, methods.

Follow-Up Analyses—Following identification by the ML model of variables with the highest importance, we conducted follow-up analyses using linear mixed effects (LME; R-package "lme4," Bates, Maechler, Bolker, & Walker, 2014) models on variables constituting potentially modifiable (i.e., changeable factor through lifestyle or existing intervention) behaviors, including weekday screen media activity and extracurricular involvement, to further delineate their effects on FCF. These variables were selected from the 15 variables with the highest importance. Regarding weekday screen media, type of activities was entered as fixed effects with ABCD site and Family ID entered as a random effect. Spearman correlations examined relations between different types of screen media. Regarding extracurricular involvement, the numerous activities were combined into three distinct categories: individual physical, group physical, and art-related activities and entered as fixed effects with ABCD site and Family ID entered as a random effect. LMEs were also used to examine the relations between screen media activity and sleep. Given the large sample size, the analysis focused on effect sizes rather than statistically significant relations.

Results

Table 1 presents the demographic and clinical characteristics of the final sample. Participants largely evidenced FCF in the average range (M = 95.57, SD = 17.48; Figure S3).

Machine Learning

ML analysis identified a model with 47 variables that explained 14.74% of variance (95% CI [14.53, 14.88]) in FCF (Figure S4; Table 2). Of the top 15 variables with the highest importance (Figure 1), those negatively related to FCF were (a) socioeconomic: family income less than $50,000, relative income disparity, racial minority status, and unaffordability of basic needs; and (b) child-specific: motivation to follow one's goals, symptoms of mania, weekday screen media activity, positive urgency, externalizing behaviors, and lack of perseverance. Variables positively related to FCF were (a) environmental: parents married, parents living together, and increased neighborhood safety; and (b) child-specific: extracurricular involvement and sleep duration. Figure 2 shows the partial dependence (PD) plots of marginal effect on each variable with the highest importance has on FCF, that is, the expected FCF as a function of each variable with the highest importance. PD plots indicated a nonlinear relation between FCF and extracurricular involvement, weekday screen time, neighborhood safety and crime, and basic needs unaffordability.

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Follow-Up Analyses

LME analysis revealed a small positive relation between FCF and art-related (F(1, 9,490) = 75.90, $p < .001$), and team (F(1, 9,494) = 42.32, $p < .001$) and individual sport (F(1, 9,492) = 30.24, $p < .001$) activities (Figure S5). Greater engagement with extracurricular activities related positively to family income [rs = .39, $p < .001$] and caregiver level of education [rs = .42, $p < .001$].

LME analysis revealed small negative relations between FCF and weekday time spent watching Internet videos (F(1, 9,673) = 59.95, $p < .001$), playing mature-rated video games (F(1, 9,673) = 33.51, $p < .001$), watching TV shows and movies (F(1, 9,672) = 29.28, $p < .001$), video chatting (F(1, 9,670) = 27.18, $p < .001$), watching mature-rated movies (F(1, 9,670) = 12.69, $p < .001$), and using social media (F(1, 9,664) = 6.79, $p < .01$), whereas time spent playing video games (F(1, 9,669) = 0.13, $p = .72$) and texting (F(1, 9,669) = 0.10, $p = .75$) did not show a relation with FCF (Figure S5). Time spent on various screen time media activities was significantly intercorrelated ($p < .001$; Figure S6).

LME analysis revealed small negative relations between sleep length and weekday time spent watching Internet videos (F(1, 9,669) = 116.15, $p < .001$), playing mature-rated video games (F(1, 9,670) = 71.86, $p < .001$), using social media (F(1, 9,662) = 27.36, $p < .001$), watching mature-rated movies (F(1, 9,667) = 21.45, $p < .001$), watching TV shows and movies (F(1, 9,668) = 21.07, $p < .001$), time spent texting (F(1, 9,666) = 7.99, $p < .005$), whereas video chatting (F(1, 9,666) = 6.81, $p < .01$) showed a small positive and time spent playing video games (F(1, 9,665) = 0.32, $p = .57$) showed no relation with sleep length.

Discussion

To our knowledge, this study is the first to use a ML framework to examine associations between a large number of unique demographic, environmental, and child factors with FCF in a large group of school-age children. This is an important task given that FCF relates to long-term psychological, academic, and occupational outcomes. We observed a normally distributed range of FCF scores in this large, socioculturally diverse sample of 9,718 children from across the United States. Notably, a significant percentage (6.3%) performed in the extremely low range, whereas an additional 11.8% performed in the borderline range.

Using a data-driven atheoretical approach, our model explained approximately 15% of variance in FCF scores. Although this effect may appear small, particularly given a large number of predictors, it is important to consider a number of factors relevant to the ABCD Study® sample (Dick et al., 2020). First, data show that broad population-based samples often evidence smaller effects than carefully defined and controlled clinical samples (Miller et al., 2016; Rothman, Greenland, & Lash, 2008). Furthermore, there are also findings that suggest that the strength of many previously identified neurodevelopmental associations stemming from smaller samples have been significantly inflated (Button et al., 2013; Ioannidis, 2008). Second, because we took a broad exploratory approach to the ML analysis, we included measures that may have inherently weak relations with cognitive functioning, but nevertheless, represent factors that may meaningfully contribute to this construct. Finally, recent evidence shows that self-report and behavioral measures often do

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

not correlate well with each other, in part due to psychometric challenges across various assessments (Dang, King, & Inzlicht, 2020). Nevertheless, although variance explained by the present model suggests that there are other factors that play a significant role in determining cognitive functioning in children, our findings are meaningful in that they identify factors that may guide future experimental studies, including targeted intervention trials.

Fifteen variables with the highest importance associated with FCF that were identified by the ML analysis fell into two broad categories: socioeconomic-environmental and child-specific. With respect to socioeconomic-environmental variables, greater FCF scores were related to (a) higher family income, (b) parents married and/or living together, (c) parents with graduate-level education, and (d) increased perceived neighborhood safety. Lower FCF scores, on the other hand, were related to (a) racial minority status and (b) SES including lower family income, increased relative income disparity, and increased unaffordability for basic needs.

Regarding child-specific predictors, lower FCF scores were related to (a) youth general psychopathology, including increased symptoms of mania and externalizing behaviors, as well as (b) increased youth self-reported drive, or motivation to complete one’s goals. In contrast, greater FCF scores were related to (a) more hours of sleep, (b) more hours spent engaged in any type of extracurricular activity (e.g., individual physical, group physical, and art-related activities), and (c) fewer hours spent on screen media activity during the week. In particular, less time spent watching TV shows, movies, and Internet videos, using social media platforms, and video chatting were all related to greater FCF. In addition, less time spent both watching R-rated films and playing mature-rated video games were associated with greater FCF.

Our findings confirm previous reports (Lawson et al., 2018) and further underscore the significant adverse effect of socioeconomic deprivation on FCF. Our findings extend previous literature beyond measures of income and education, further highlighting the adverse impact of relative income disparity and unaffordability of basic needs, such as food, residence, and medical care. The associated chronic stress may mediate the relation between poverty and FCF (Blair et al., 2011; Piccolo et al., 2014). For example, research shows that negative parenting and household chaos lead to heightened stress exposure during childhood and result in FCF deficits, even when controlling for the direct effects of poverty (Vernon-Feagans et al., 2016). Childhood maltreatment, parental psychopathology, and family dysfunction, in particular, can have detrimental effects on cognitive and executive function across the life span (Irigaray et al., 2013). Therefore, impoverished circumstances may create an environment characterized by chronic stress, which, in turn, has a lasting impact on the neurobiological foundations of cognitive development (Evans & Schamberg, 2009; Lawson et al., 2018).

Psychopathology closely follows exposure to chronic stress (Kessler et al., 2010). Our findings pointing to negative relations between FCF and symptoms of mania and externalizing problems support previous work that impairment in processes underlying irritability, changes in mood, and aggressive and rule-breaking behavior, such as effortful

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

control, self-regulation, and impulse control relate to impairments in FCF (Gartstein & Fagot, 2003; Horn, Roessner, & Holtmann, 2011; Mezzacappa, Kindlon, & Earls, 1999). The negative relation between FCF and exaggerated motivation to inflexibly pursue one's goals is also in line with this research. Specifically, the selection of goal-directed actions based on their predicted values may impact performance on FCF measures in a negative way by allocating attention and resources toward the processing of present or future salient stimuli that maximize rewards (Pessoa, 2009). Similarly, impulsivity, including tendencies to act rashly under extreme positive emotions and inability to remain focused on task, may negatively impact performance on measures of FCF and intelligence, as well as academic performance (Fino et al., 2014; Lozano, Gordillo, & Pérez, 2014; Stautz, Pechey, Couturier, Deary, & Marteau, 2016). Poor sleep habits in children, often a consequence of poverty and environmental stress (Williamson & Mindell, 2019), may also add to a set of existing risk factors for poor FCF. For example, children with insufficient sleep evidence deficits in inhibitory responses, working memory, executive function, and emotional control (Taveras et al., 2017). In fact, deficits across behavioral, emotional, and cognitive domains may reflect a central disruption in ability to self-regulate (Nigg, 2017). Future experimental studies may be able to test this potential underlying mechanism and its relation to a range of outcomes, as well as its malleability to interventions. Nevertheless, co-occurring socioeconomic disadvantages, adverse environments, and mental health problems and behavioral traits may have a significant adverse effect on the neurobiological development and functional performance of developing children.

Conversely, there is converging evidence that involvement in constructive, nonacademic activity accompanies persistent positive and potentially dose–response outcomes in cognitive performance and academic achievement (Eccles, Barber, Stone, & Hunt, 2003; Fredricks, 2012). Our data, however, point to a nonlinear relation between these variables and suggest that there may be a point of diminishing returns. Previous studies have reported similar findings with respect to various aspects of academic life, including academic performance, educational and occupational aspirations, self-esteem, and agency (Marsh, 1992; Marsh & Kleitman, 2002). While speculative, excessive involvement with extracurricular activities (three or more activities in the present sample) may contribute to these and additional factors, such as fatigue and burnout, which, in turn may adversely impact performance on FCF measures. Nevertheless, participation in arts is associated with improvement in a range of cognitive domains (Rauscher, Shaw, & Ky, 1993; Schellenberg, 2004; Winsler, Gara, Alegrado, Castro, & Tavassolie, 2019), whereas participation in physical activities and organized, supervised sports has been associated with increased self-regulation, inhibition, and problem solving (Jacobson & Matthaeus, 2014; Piché, Fitzpatrick, & Pagani, 2015). In this sample, involvement with extracurricular activities was positively associated with measures of SES, including family income and caregiver education. While child's extracurricular engagement may in part reflect family's SES, which in turn has been known to be related to cognitive functioning, data from previous research show that extracurricular involvement exerts unique effects on cognitive functioning. Specifically, extracurricular enrichment promotes new learning and skill acquisition, creativity, self-efficacy, formation of strong social bonds with nonfamilial adults and peers, identity development, and physical health (Eccles et al., 2003; Etnier & Chang, 2009), which may translate into improved

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

cognitive performances and educational attainment (Jacobson & Matthaeus, 2014), even in at-risk children (Peck, Roeser, Zarrett, & Eccles, 2008).

The research on the impact of screen media activity on development is complex. A recent report showed that increased screen media activity was associated with poorer sleep quality and shorter sleep duration, which in turn related to increased problem behaviors (Guerrero, Barnes, Chaput, & Tremblay, 2019), both of which are known to be negatively associated with FCF (Taveras et al., 2017; Short & Chee, 2019). A recent finding with the first half of the ABCD Study® sample examining the direct relation between FCF and screen media activity found that gaming activities had a positive relation with FCF, whereas social media activities related negatively to FCF (Paulus et al., 2019). Our data on the full sample also suggest that different types of screen media activity may have divergent effects on cognitive function, specifically that time spent watching TV, movies, and Internet videos and playing mature-rated video games had the strongest dose–response negative relation with FCF. Nevertheless, all types of media use positively correlated with each other, suggesting that there may also be an additive effect of time spent with screen time media (Figure S6). It is also noteworthy that while weekend screen media activity is negatively associated with FCF, it was not modeled as among the most important variables in the ML analysis (Table 2). Relative to weekdays, weekend screen media activity may serve as a relaxation activity that interferes less with other processes, such as sleep, which have a more direct impact on cognitive functioning. It is also noteworthy that a nonlinear relation between weekday screen time and FCF was observed. This suggests that limited time spent on devices during the week may not have detrimental effects. Similarly, for youth engaging excessively, reducing the time spent with screen media activity may result in improvements in cognitive functioning, while maintaining the potential beneficial aspects of these activities.

The variables identified as important correlates of FCF in this study, although unique, may be interrelated and reflect greater systemic issues facing families. It can be posited that families who live in impoverished environments have fewer resources (e.g., financial, time commitment due to more irregular work schedules) to provide opportunities for enriching extracurricular activities and supervision over healthy behavioral habits (i.e., sleep and screen media activity) in their children. Nevertheless, even though factors influencing FCF are complex, extracurricular enrichment, screen media activity, and sleep may be targeted by pragmatic, scalable, and systemic interventions. Psychoeducation with parents and children on these and related topics may result in significant behavioral changes. Indeed, one study found that psychoeducation targeting sleep habits had not only significant sustained effects on sleep behaviors, but was also associated with subsequent improvements in cognitive performance (Rey, Guignard-Perret, Imler-Weber, Garcia-Larrea, & Mazza, 2020). Furthermore, schools could increase participation in extracurricular activities among children by making them widely available and accessible. Addressing motivation and impulsivity with respect to performance on measures of functioning and achievement as well as engagement with extracurricular activities healthy habits may also be warranted. Such interventions resulting even in marginal improvements in FCF may translate into increased long-term scholastic performance and psychosocial outcomes. Importantly, it may be the case that targeting these factors increases resilience and cognitive performance among children particularly at risk for deficits in FCF secondary to exposure to adverse environments.

Limitations

The results presented here are cross-sectional. Therefore, causality cannot be inferred, and bidirectional relations between FCF and associated factors are possible. Although we employed repeated nCV to reduce the risk of overestimation of prediction accuracy, an external validation of the model with an independent sample would be useful in demonstrating its replicability. We only included data from the baseline assessment of these children. Additional research will be able to assess the predictive value of these factors in later years and at later developmental stages. Furthermore, we relied on self-report for a number of variables of interest, a measure approach known to be biased by both state and trait factors. The use of objective measures, such as, for example, wearable devices to measure sleep or built-in “screen time features” on media devices, will greatly improve our understanding of the effect that these variables have on cognitive functioning. Finally, although large and socioculturally diverse, our sample was limited to children from the United States. The result may differ in other contexts and warrant appropriate cross-cultural examinations.

Conclusion

We used a ML framework to identify variables associated with FCF in a large sample of school-age children. In addition to socioeconomic disparity factors previously associated with poor cognitive functioning, we identified a number of novel and potentially modifiable behavioral factors, including participation in extracurricular activities, screen media time activity, and sleep duration. Modifying these behaviors may not only serve to enhance cognitive performance but may also constitute protective factors against the negative impact of socioeconomic, environmental, and mental health factors on cognitive performance in at-risk children. The longitudinal data from the ABCD Study® will be able to begin to assess causality by examining how potential changes in these factors affect subsequent cognitive performance.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

The National Institute on Drug Abuse was involved in the design and conduct of the study and data management. The funders otherwise had no role in the analysis and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication. The Adolescent Brain Cognitive Development (ABCD) Consortium investigators designed and implemented the study and/or provided data but did not necessarily participate in the analysis or writing of this report. This paper reflects the views of the authors and may not reflect the opinions or views of the NIH or ABCD Consortium investigators. Data used in the preparation of this paper were obtained from the ABCD Study (https://abcdstudy.org), held in the NIMH Data Archive. This is a multisite, longitudinal study designed to recruit more than 10,000 children aged 9–10 years and follow-up with them over 10 years into early adulthood. The ABCD data repository grows and changes over time. A listing of participating sites and a complete listing of the study investigators can be found at https://abcdstudy.org/wp-content/uploads/2019/04/Consortium_Members.pdf. The ABCD data used in this report came from the NIMH Data Archive (https://doi.org/10.15154/1412097). Additionally, Namik Kirlic, Robin Aupperle, and Martin P. Paulus received research support from the National Institute of General Medical Sciences. RA received research support from the National Institute of Mental Health. Manpreet K. Singh has received research support from the Stanford's Maternal Child Health Research Institute and the Department of Psychiatry, the National Institute of Mental Health, the National Institute of Aging, the Patient-Centered Outcomes Research Institute, the Johnson and Johnson, the Allergan, and the Brain and Behavior Research Foundation. Partial data from this manuscript have been presented at the American College of Neuropsychopharmacology 2019 Annual Meeting.

The ABCD Study is supported by the National Institutes of Health (NIH) and additional federal partners under awards U01DA041022, U01DA041028, U01DA041048, U01DA041089, U01DA041106, U01DA041117, U01DA041120, U01DA041134, U01DA041148, U01DA041156, U01DA041174, U24DA041123, and U24DA041147. The study is also supported by the National Heart, Lung, and Blood Institute, the National Institute of Neurological Disorders and Stroke, the National Institute on Minority Health and Health Disparities, the NIH Office of Behavioral and Social Sciences Research, the NIH Office of Research on Women's Health, the Centers for Disease Control and Prevention–Division of Violence Prevention, the National Institute of Justice, the Centers for Disease Control and Prevention–Division of Adolescent and School Health, the National Science Foundation, and the National Endowment for the Arts. Dr. Namik Kirlic, Dr. Robin Aupperle, and Dr. Martin P. Paulus further report support from the National Institute of General Medical Sciences (P20GM121312) and the William K. Warren Foundation.

References

Akshoomoff N, Beaumont JL, Bauer PJ, Dikmen SS, Gershon RC, Mungas D, … Zelazo PD (2013). VIII. NIH Toolbox Cognition Battery (CB): Composite scores of crystallized, fluid, and overall cognition. Monographs of the Society for Research in Child Development, 78, 119–132. 10.1111/mono.12038 [PubMed: 23952206]

Bagot KS, Matthews SA, Mason M, Squeglia LM, Fowler J, Gray K, … Patrick K (2018). Current, future and potential use of mobile and wearable technologies and social media data in the ABCD study to increase understanding of contributors to child health. Developmental Cognitive Neuroscience, 32, 121–129. 10.1016/j.dcn.2018.03.008 [PubMed: 29636283]

Barch DM, Albaugh MD, Avenevoli S, Chang L, Clark DB, Glantz MD, … Sher KJ (2018). Demographic, physical and mental health assessments in the adolescent brain and cognitive development study: Rationale and description. Developmental Cognitive Neuroscience, 32, 55–66. 10.1016/j.dcn.2017.10.010 [PubMed: 29113758]

Barsaglini A, Sartori G, Benetti S, Pettersson-Yeo W, & Mechelli A (2014). The effects of psychotherapy on brain function: A systematic and critical review. Progress in Neurobiology, 114, 1–14. 10.1016/j.pneurobio.2013.10.006 [PubMed: 24189360]

Bates D, Maechler M, Bolker B, & Walker S (2014). lme4: Linear mixed-effects models using S4 classes. R version 1.1-7. Retrieved from http://CRAN.R-project.org/package=lme4

Bergstra J, & Bengio Y (2012). Random search for hyper-parameter optimization. Journal of Machine Learning Research, 13, 281–305.

Biederman J, Monuteaux MC, Doyle AE, Seidman LJ, Wilens TE, Ferrero F, … Faraone SV (2004). Impact of executive function deficits and attention-deficit/hyperactivity disorder (ADHD) on academic outcomes in children. Journal of Consulting and Clinical Psychology, 72, 757. 10.1037/0022-006X.72.5.757 [PubMed: 15482034]

Blair C, Granger DA, Willoughby M, Mills-Koonce R, Cox M, Greenberg MT, … Fortunato CK (2011). Salivary cortisol mediates effects of poverty and parenting on executive functions in early childhood. Child Development, 82, 1970–1984. 10.1111/j.1467-8624.2011.01643.x [PubMed: 22026915]

Blair C, & Razza RP (2007). Relating effortful control, executive function, and false belief understanding to emerging math and literacy ability in kindergarten. Child Development, 78, 647–663. 10.1111/j.1467-8624.2007.01019.x [PubMed: 17381795]

Breiman L (1996). Stacked regressions. Machine Learning, 24, 49–64. 10.1007/BF00117832

Bruni O, Ottaviano S, Guidetti V, Romoli M, Innocenzi M, Cortesi F, & Giannotti F (1996). The Sleep Disturbance Scale for Children. Construction and validation of an instrument to evaluate sleep disturbances in childhood and adolescence. Journal of Sleep Research, 5, 251–261. 10.1111/j.1365-2869.1996.00251.x [PubMed: 9065877]

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Bustamante EE, Williams CF, & Davis CL (2016). Physical activity interventions for neurocognitive and academic performance in overweight and obese youth: A systematic review. Pediatric Clinics, 63, 459–480. 10.1016/j.pcl.2016.02.004 [PubMed: 27261545]

Button KS, Ioannidis JP, Mokrysz C, Nosek BA, Flint J, Robinson ES, & Munafò MR (2013). Power failure: Why small sample size undermines the reliability of neuroscience. Nature Reviews Neuroscience, 14, 365–376. 10.1038/nrn3475 [PubMed: 23571845]

Casaletto KB, Umlauf A, Beaumont J, Gershon R, Slotkin J, Akshoomoff N, & Heaton RK (2015). Demographically corrected normative standards for the English version of the NIH Toolbox Cognition Battery. Journal of the International Neuropsychological Society, 21, 378–391. 10.1017/S1355617715000351 [PubMed: 26030001]

Cattell RB (1971). Abilities: Their structure, growth, and action. Boston, MA: Houghton Mifflin.

CDC (Division of Nutrition). (2016). Anthropometry procedures manual. Retrieved from https://wwwn.cdc.gov/nchs/data/nhanes/2015-2016/manuals/2016

CDC. (2016). Youth risk behavior survey. Retrieved from https://www.cdc.gov/healthyyouth/data/yrbs/

Chilcoat HD, & Anthony JC (1996). Impact of parent monitoring on initiation of drug use through late childhood. Journal of the American Academy of Child and Adolescent Psychiatry, 35, 91–100. 10.1097/00004583-199601000-00017 [PubMed: 8567618]

Dang J, King KM, & Inzlicht M (2020). Why are self-report and behavioral measures weakly correlated? Trends in Cognitive Sciences, 24, 267–269. 10.1016/j.tics.2020.01.007 [PubMed: 32160564]

Dick AS, Watts AL, Heeringa SG, Lopez DA, Bartsch H, Fan CC, … Haist F (2020). Meaningful effects in the adolescent brain cognitive development study. bioRxiv, 1–75. 10.1101/2020.09.01.276451

Diemer MA, Mistry RS, Wadsworth ME, Lopez I, & Reimers F (2012). Best practices in conceptualizing and measure social class in psycholgocial research. Analyses of Social Issues and Public Policy, 13, 77–113. 10.1111/asap.12001

Eccles JS, Barber BL, Stone M, & Hunt J (2003). Extracurricular activities and adolescent development. Journal of Social Issues, 59, 865–889. 10.1046/j.0022-4537.2003.00095.x

Etnier JL, & Chang Y-K (2009). The effect of physical activity on executive function: A brief commentary on definitions, measurement issues, and the current state of the literature. Journal of Sport and Exercise Psychology, 31, 469–483. 10.1123/jsep.31.4.469 [PubMed: 19842543]

Evans GW, & Schamberg MA (2009). Childhood poverty, chronic stress, and adult working memory. Proceedings of the National Academy of Sciences of the United States of America, 106, 6545–6549. 10.1073/pnas.0811910106 [PubMed: 19332779]

Farah MJ, Shera DM, Savage JH, Betancourt L, Giannetta JM, Brodsky NL, … Hurt H (2006). Childhood poverty: Specific associations with neurocognitive development. Brain Research, 1110, 166–174. 10.1016/j.brainres.2006.06.072 [PubMed: 16879809]

Fino E, Melogno S, Iliceto P, D’Aliesio S, Pinto MA, Candilera G, & Sabatello U (2014). Executive functions, impulsivity, and inhibitory control in adolescents: A structural equation model. Advances in Cognitive Psychology, 10, 32. 10.5709/acp-0154-5 [PubMed: 25157298]

Fredricks JA (2012). Extracurricular participation and academic outcomes: Testing the over-scheduling hypothesis. Journal of Youth and Adolescence, 41, 295–306. 10.1007/s10964-011-9704-0 [PubMed: 21814871]

Gartstein MA, & Fagot BI (2003). Parental depression, parenting and family adjustment, and child effortful control: Explaining externalizing behaviors for preschool children. Journal of Applied Developmental Psychology, 24, 143–177. 10.1016/S0193-3973(03)00043-1

Gautam P, Warner TD, Kan EC, & Sowell ER (2015). Executive function and cortical thickness in youths prenatally exposed to cocaine, alcohol and tobacco. Developmental Cognitive Neuroscience, 16, 155–165. 10.1016/j.dcn.2015.01.010 [PubMed: 25743199]

Gershon RC, Wagster MV, Hendrie HC, Fox NA, Cook KF, & Nowinski CJ (2013). NIH toolbox for assessment of neurological and behavioral function. Neurology, 80, 2–6. 10.1212/WNL.0b013e3182872e5f

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Goodall J, Fisher C, Hetrick S, Phillips L, Parrish EM, & Allott K (2018). Neurocognitive functioning in depressed young people: A systematic review and meta-analysis. Neuropsychology Review, 28, 216–231. 10.1007/s11065-018-9373-9 [PubMed: 29680959]

Goulet LR, & Baltes PB (2013). Life-span developmental psychology: Research and theory. New York, NY: Academic Press.

Greenwell BM (2017). pdp: An R package for constructing partial dependence plots. The R Journal, 9, 421.

Guerrero MD, Barnes JD, Chaput J-P, & Tremblay MS (2019). Screen time and problem behaviors in children: Exploring the mediating role of sleep duration. International Journal of Behavioral Nutrition and Physical Activity, 16, 105. 10.1186/s12966-019-0862-x

Hastie T, Tibshirani R, & Friedman J (2009). The elements of statistical learning (2nd ed.). New York, NY: Springer.

Horn JL (1968). Organization of abilities and the development of intelligence. Psychological Review, 75, 242. 10.1037/h0025662 [PubMed: 4875815]

Horn JL, & Cattell RB (1967). Age differences in fluid and crystallized intelligence. Acta Psychologica, 26, 107–129. 10.1016/0001-6918(67)90011-X [PubMed: 6037305]

Horn K, Roessner V, & Holtmann M (2011). Neurocognitive performance in children and adolescents with bipolar disorder: A review. European Child & Adolescent Psychiatry, 20, 433. 10.1007/s00787-011-0209-x [PubMed: 21904806]

Hothorn T, Hornik K, & Zeileis A (2006). Unbiased recursive partitioning: A conditional inference framework. Journal of Computational and Graphical Statistics, 15, 651–674. 10.1198/106186006X133933

Huppertz C, Bartels M, de Zeeuw EL, van Beijsterveldt CEM, Hudziak JJ, Willemsen G, … de Geus EJC (2016). Individual differences in exercise behavior: Stability and change in genetic and environmental determinants from age 7–18. Behavior Genetics, 46, 665–679. [PubMed: 27406597]

Ioannidis JP (2008). Why most discovered true associations are inflated. Epidemiology, 19, 640–648. 10.1097/EDE.0b013e31818131e7 [PubMed: 18633328]

Irigaray TQ, Pacheco JB, Grassi-Oliveira R, Fonseca RP, Leite JCC, & Kristensen CH (2013). Child maltreatment and later cognitive functioning: A systematic review. Psicologia: Reflexão e Crítica, 26, 376–387.

Jacobson J, & Matthaeus L (2014). Athletics and executive functioning: How athletic participation and sport type correlate with cognitive performance. Psychology of Sport and Exercise, 15, 521–527. 10.1016/j.psychsport.2014.05.005

Jernigan TL, Brown SA, & Dowling GJ (2018). The Adolescent Brain Cognitive Development Study. Journal of Research on Adolescence, 28, 154–156. [PubMed: 29460352]

Kavanaugh B, & Holler K (2014). Executive, emotional, and language functioning following childhood maltreatment and the influence of pediatric PTSD. Journal of Child & Adolescent Trauma, 7, 121–130. 10.1007/s40653-014-0014-z

Keller JM, Gray MR, & Givens JA (1985). A fuzzy k-nearest neighbor algorithm. IEEE Transactions on Systems, Man, and Cybernetics, 15, 580–585. 10.1109/TSMC.1985.6313426

Kenney EL, & Gortmaker SL (2017). United States adolescents' television, computer, videogame, smartphone, and tablet use: Associations with sugary drinks, sleep, physical activity, and obesity. The Journal of Pediatrics, 182, 144–149. 10.1016/j.jpeds.2016.11.015 [PubMed: 27988020]

Kessler RC, McLaughlin KA, Green JG, Gruber MJ, Sampson NA, Zaslavsky AM, … Williams DR (2010). Childhood adversities and adult psychopathology in the WHO World Mental Health Surveys. The British Journal of Psychiatry, 197, 378–385. 10.1192/bjp.bp.110.080499 [PubMed: 21037215]

Kostyrka-Allchorne K, Cooper NR, & Simpson A (2017). The relationship between television exposure and children's cognition and behaviour: A systematic review. Developmental Review, 44, 19–58. 10.1016/j.dr.2016.12.002

Kuhn M (2008). Caret package. Journal of Statistical Software, 28, 1–26. [PubMed: 27774042]

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Lawson GM, Hook CJ, & Farah MJ (2018). A meta-analysis of the relationship between socioeconomic status and executive function performance among children. Developmental Science, 21. 10.1111/desc.12529

Lisdahl KM, Sher KJ, Conway KP, Gonzalez R, Feldstein Ewing SW, Nixon SJ, … Heitzeg M (2018). Adolescent brain cognitive development (ABCD) study: Overview of substance use assessment methods. Developmental Cognitive Neuroscience, 32, 80–96. 10.1016/j.dcn.2018.02.007 [PubMed: 29559216]

Loprinzi PD, & Davis RE (2016). Secular trends in parent-reported television viewing among children in the United States, 2001–2012. Child: Care, Health and Development, 42, 288–291. 10.1111/cch.12304

Lozano J, Gordillo F, & Pérez M (2014). Impulsivity, intelligence, and academic performance: Testing the interaction hypothesis. Personality and Individual Differences, 61, 63–68. 10.1016/j.paid.2014.01.013

Luciana M, Bjork JM, Nagel BJ, Barch DM, Gonzalez R, Nixon SJ, & Banich MT (2018). Adolescent neurocognitive development and impacts of substance use: Overview of the adolescent brain cognitive development (ABCD) baseline neurocognition battery. Developmental Cognitive Neuroscience, 32, 67–79. 10.1016/j.dcn.2018.02.006 [PubMed: 29525452]

Marbach D, Costello JC, Küffner R, Vega NM, Prill RJ, Camacho DM, … Stolovitzky G (2012). Wisdom of crowds for robust gene network inference. Nature Methods, 9, 796. 10.1038/nmeth.2016 [PubMed: 22796662]

Marsh H (1992). Extracurricular activities: Beneficial extension of the traditional curriculum or subversion of academic goals? Journal of Educational Psychology, 84, 553. 10.1037/0022-0663.84.4.553

Marsh H, & Kleitman S (2002). Extracurricular school activities: The good, the bad, and the nonlinear. Harvard Educational Review, 72, 464–515. 10.17763/haer.72.4.051388703v7v7736

McArdle JJ, & Ritschard G (2013). Contemporary issues in exploratory data mining in the behavioral sciences. New York, NY: Routledge.

McClelland MM, Acock AC, Piccinin A, Rhea SA, & Stallings MC (2013). Relations between preschool attention span-persistence and age 25 educational outcomes. Early Childhood Research Quarterly, 28, 314–324. 10.1016/j.ecresq.2012.07.008 [PubMed: 23543916]

McClelland MM, & Cameron CE (2012). Self-regulation in early childhood: Improving conceptual clarity and developing ecologically valid measures. Child Development Perspectives, 6, 136–142. 10.1111/j.1750-8606.2011.00191.x

Mezzacappa E, Kindlon D, & Earls F (1999). Relations of age to cognitive and motivational elements of impulse control in boys with and without externalizing behavior problems. Journal of Abnormal Child Psychology, 27, 473–483. 10.1023/a:1021936210844 [PubMed: 10821629]

Miller KL, Alfaro-Almagro F, Bangerter NK, Thomas DL, Yacoub E, Xu J, … Smith SM (2016). Multimodal population brain imaging in the UK Biobank prospective epidemiological study. Nature Neuroscience, 19, 1523–1536. 10.1038/nn.4393 [PubMed: 27643430]

Moos RH, & Moos BS (1994). Family environment scale manual. Palo Alto, CA: Consulting Psychologists Press.

Nigg JT (2017). Annual research review: On the relations among self-regulation, self-control, executive functioning, effortful control, cognitive control, impulsivity, risk-taking, and inhibition for developmental psychopathology. Journal of Child Psychology and Psychiatry, 58, 361–383. 10.1111/jcpp.12675 [PubMed: 28035675]

Noble KG, Norman MF, & Farah MJ (2005). Neurocognitive correlates of socioeconomic status in kindergarten children. Developmental Science, 8, 74–87. 10.1111/j.1467-7687.2005.00394.x [PubMed: 15647068]

Parvandeh S, Yeh H-W, Paulus MP, & McKinney BA (2020). Consensus features nested cross-validation. Bioinformatics, 36, 3093–3098. 10.1093/bioinformatics/btaa046 [PubMed: 31985777]

Paulus MP, Squeglia LM, Bagot K, Jacobus J, Kuplicki R, Breslin FJ, … Tapert SF (2019). Screen media activity and brain structure in youth: Evidence for diverse structural correlation networks from the ABCD study. NeuroImage, 185, 140–153. 10.1016/j.neuroimage.2018.10.040 [PubMed: 30339913]

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Peck SC, Roeser RW, Zarrett N, & Eccles JS (2008). Exploring the roles of extracurricular activity quantity and quality in the educational resilience of vulnerable adolescents: Variable-and pattern-centered approaches. Journal of Social Issues, 64, 135–156. 10.1111/j.1540-4560.2008.00552.x

Pessoa L (2009). How do emotion and motivation direct executive control? Trends in Cognitive Sciences, 13, 160–166. 10.1016/j.tics.2009.01.006 [PubMed: 19285913]

Piccolo LDR, Sbicigo JB, Grassi-Oliveira R, & Fumagalli de Salles J (2014). Do socioeconomic status and stress reactivity really impact neurocognitive performance? Psychology & Neuroscience, 7, 567. 10.3922/j.psns.2014.4.16

Piché G, Fitzpatrick C, & Pagani LS (2015). Associations between extracurricular activity and self-regulation: A longitudinal study from 5 to 10 years of age. American Journal of Health Promotion, 30, e32–e40. 10.4278/ajhp.131021-QUAN-537. [PubMed: 25372230]

Platt JM, McLaughlin KA, Luedtke AR, Ahern J, Kaufman AS, & Keyes KM (2018). Targeted estimation of the relationship between childhood adversity and fluid intelligence in a US population sample of adolescents. American Journal of Epidemiology, 187, 1456–1466. 10.1093/aje/kwy006 [PubMed: 29982374]

Rauscher FH, Shaw GL, & Ky CN (1993). Music and spatial task performance. Nature, 365, 611. 10.1038/365611a0

Reinert KRS, Po'e EK, & Barkin SL (2013). The relationship between executive function and obesity in children and adolescents: A systematic literature review. Journal of Obesity, 2013, 1–10. 10.1155/2013/820956

Revelle WR (2017). psych: Procedures for personality and psychological research. Retrieved from https://www.scholars.northwestern.edu/en/publications/psych-procedures-for-personality-and-psychological-research

Rey AE, Guignard-Perret A, Imler-Weber F, Garcia-Larrea L, & Mazza S (2020). Improving sleep, cognitive functioning and academic performance with sleep education at school in children. Learning and Instruction, 65, 101270. 10.1016/j.learninstruc.2019.101270

Rothman KJ, Greenland S, & Lash TL (2008). Modern epidemiology. Philadelphia, PA: Lippincott Williams & Wilkins.

RStudio Team. (2015). RStudio: Integrated development for R. Boston, MA: Rstudio.

Schaefer ES (1965). A configurational analysis of children's reports of parent behavior. Journal of Consulting Psychology, 29, 552–557. 10.1037/h0022702 [PubMed: 5846126]

Schellenberg EG (2004). Music lessons enhance IQ. Psychological Science, 15, 511–514. 10.1111/j.0956-7976.2004.00711.x [PubMed: 15270994]

Short MA, & Chee MW (2019). Adolescent sleep restriction effects on cognition and mood. Progress in Brain Research, 246, 55–71. [PubMed: 31072563]

Singh GK (2003). Area deprivation and widening inequalities in US mortality, 1969–1998. American Journal of Public Health, 93, 1137–1143. 10.2105/AJPH.93.7.1137 [PubMed: 12835199]

Stautz K, Pechey R, Couturier D-L, Deary IJ, & Marteau TM (2016). Do executive function and impulsivity predict adolescent health behaviour after accounting for intelligence? Findings from the ALSPAC cohort. PLoS One, 11, e0160512. 10.1371/journal.pone.0160512 [PubMed: 27479488]

Suykens JA, & Vandewalle J (1999). Least squares support vector machine classifiers. Neural Processing Letters, 9, 293–300. 10.1023/A:1018628609742

Taveras EM, Rifas-Shiman SL, Bub KL, Gillman MW, & Oken E (2017). Prospective study of insufficient sleep and neurobehavioral functioning among school-age children. Academic Pediatrics, 17, 625–632. 10.1016/j.acap.2017.02.001 [PubMed: 28189692]

Van der Laan MJ, Polley EC, & Hubbard AE (2007). Super learner. Statistical Applications in Genetics and Molecular Biology, 6. 10.2202/1544-6115.1309

Vernon-Feagans L, Willoughby M, & Garrett-Peters P (2016). Predictors of behavioral regulation in kindergarten: Household chaos, parenting, and early executive functions. Developmental Psychology, 52, 430. 10.1037/dev0000087 [PubMed: 26751500]

Williamson AA, & Mindell JA (2019). Cumulative socio-demographic risk factors and sleep outcomes in early childhood. Sleep, 43. 10.1093/sleep/zsz233

Winsler A, Gara TV, Alegrado A, Castro S, & Tavassolie T (2020). Selection into, and academic benefits from, arts-related courses in middle school among low-income, ethnically diverse youth. Psychology of Aesthetics, Creativity, and the Arts, 14, 415–432. 10.1037/aca0000222

Wolpert DH (1992). Stacked generalization. Neural Networks, 5, 241–259. 10.1016/S0893-6080(05)80023-1

Zucker RA, Gonzalez R, Feldstein Ewing SW, Paulus MP, Arroyo J, Fuligni A, … Wills T (2018). Assessment of culture and environment in the Adolescent Brain and Cognitive Development Study: Rationale, description of measures, and early data. Developmental Cognitive Neuroscience, 32, 107–120. 10.1016/j.dcn.2018.03.004 [PubMed: 29627333]

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript
Author Manuscript
Author Manuscript
Author Manuscript

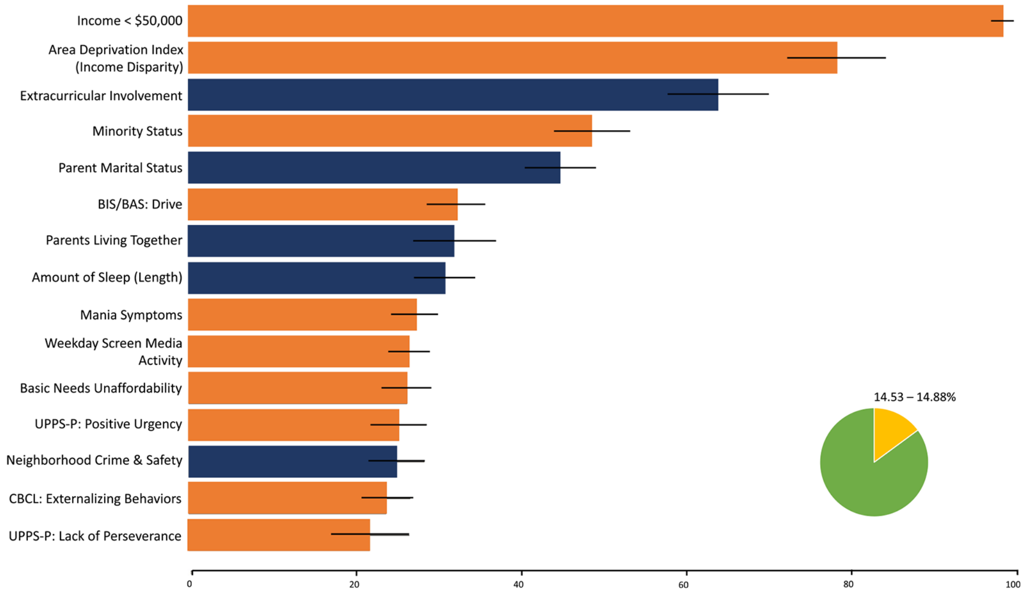

Figure 1.

Variable importance (VI) for models predicting fluid cognitive functioning in the ABCD Study® cohort (*n* = 9,718). VI is based on the stacked ensemble. Variables with orange or blue coloring have a negative or positive univariate correlation with fluid cognitive functioning, respectively. Error bars represent the 95% confidence interval, taken across partitions. The accompanying pie chart depicts percent of variance explained by the model and its 95% confidence interval.

Note. BIS/BAS = Behavioral Avoidance/Inhibition Scales; CBCL = Child Behavior Checklist; UPPS-P = Impulsive Behavior Scale.

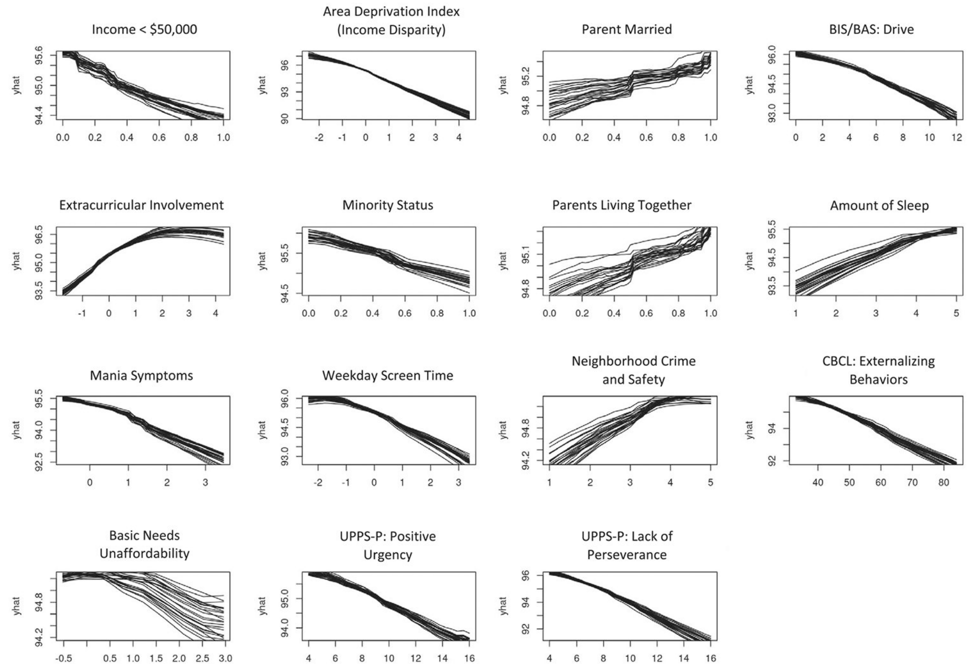

Figure 2.

Partial dependence plots showing the marginal effect each of the 15 variables with the highest importance has on age corrected fluid cognitive functioning scores.

Notes. BIS/BAS = Behavioral Avoidance/Inhibition Scales; CBCL = Child Behavior Checklist; UPPS-P = Impulsive Behavior Scale.

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Table 1

Sample Characteristics

	n = 9,718	Range
Demographics (parent report)		
Age, *M* (*SD*)	9.89 (0.62)	9.00 to 10.92
Gender, *N* (%)		—
Male	5,125 (52.8)	
Female	4,590 (47.2)	
Race, *N* (%)		—
White	4,937 (50.9)	
Black or African American	1,459 (15.0)	
Hispanic	2,066 (21.3)	
Asian	225 (2.3)	
Other/mixed	1,019 (10.5)	
Twin status, *N* (%)		—
Yes	856 (8.8)	
No	8,862 (91.2)	
Siblings in household, *N* (%)		—
Yes	1,835 (18.9)	
No	7,883 (81.1)	
Parent age, *M* (*SD*)	39.92 (6.39)	23.00 to 80.00
Parent marital status, *N* (%)		—
Married	6,482 (67.3)	
Not married	3,154 (32.7)	
Parents living together, *N* (%)		—
Yes	7,064 (73.3)	
No	2,572 (26.7)	
Parent education		—
<High school diploma	492 (5.1)	
High school diploma or equivalent	946 (9.7)	
Some college	2,539 (26.2)	

	n = 9,718	Range
Bachelor's degree	2,408 (24.8)	
Graduate degree	3,323 (34.2)	
Income, *N* (%)		—
< $50,000	2,695 (30.4)	
$50,000–$100,000	3,664 (41.3)	
> $100,000	2,515 (28.3)	
Environment (parent report), *M* (*SD*)		
Area Deprivation Index (income disparity)	2.17 (1.35)	−1.13 to 8.16
Basic needs unaffordability (PhenX)	0.48 (1.10)	0.00 to 7.00
Area number of crimes	54,512.12 (87,439.22)	0.00 to 348,049.30
Neighborhood crime and safety (PhenX)	3.87 (0.98)	1.00 to 5.00
Youth access to substances (CRPF)	9.52 (3.14)	1.00 to 30.00
Trauma exposure (KSADs)	0.53 (1.10)	0.00 to 17.00
Parent mental health and familial variables, *M* (*SD*)		
Parent report		
ASR		
Externalizing behaviors	45.94 (9.67)	30.00 to 90.00
Internalizing symptoms	48.21 (10.57)	30.00 to 95.00
Personal strength	47.87 (9.37)	20.00 to 60.00
Parent alcohol use, days intoxicated in past 6 months	1.37 (6.34)	0.00 to 180.00
Parent nicotine use, times per day in past 6 months	1.01 (4.50)	0.00 to 100.00
Parent drug use, days in past 6 months	1.97 (14.85)	0.00 to 180.00
Family history (FHAM-S)	2.36 (2.02)	0.00 to 8.00
Family conflict (FES)	2.52 (1.95)	0.00 to 9.00
Youth report		
Family conflict (FES)	2.02 (1.96)	0.00 to 9.00
Parental monitoring (PMQ)	4.39 (0.51)	1.00 to 5.00
Study caregiver acceptance (CRPBI)	2.78 (0.30)	1.00 to 3.00
Secondary caregiver acceptance (CRPBI)	2.69 (0.38)	1.00 to 3.00
Youth mental health symptoms and behaviors, *M* (*SD*)		
Parent report		

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

	n = 9,718	Range
CBCL		
Externalizing Behaviors	45.89 (10.36)	33.00 to 84.00
Internalizing Symptoms	48.75 (10.68)	33.00 to 93.00
Mania symptoms (PGBI)	1.37 (2.84)	0.00 to 28.00
Youth report		
BIS/BAS		
Drive	4.18 (3.08)	0.00 to 12.00
Fun seeking	5.74 (2.66)	0.00 to 12.00
Reward responsiveness	8.85 (2.38)	0.00 to 12.00
Inhibition	5.53 (2.85)	0.00 to 12.00
UPPS-P		
Lack of perseverance	7.06 (2.26)	4.00 to 16.00
Lack of planning	7.73 (2.37)	4.00 to 16.00
Negative urgency	8.50 (2.65)	4.00 to 16.00
Positive urgency	7.98 (2.95)	4.00 to 16.00
Sensation seeking	9.79 (2.68)	4.00 to 16.00
Modifiable risks, *M* (*SD*)		
Body mass index	18.81 (4.00)	11.10 to 35.87
Waist circumference, in.	26.68 (4.95)	0.00 to 90.00
Parent report		
Extracurricular involvement, hours per week (SAIQ)	17.99 (13.84)	0.00 to 170.00
Art	5.07 (6.32)	0.00 to 54.00
Individual sports	4.93 (5.7)	0.00 to 70.00
Team sports	8.06 (7.65)	0.00 to 54.00
Sleep (SDSC)		
Amount, hr, *N* (%)		—
< 5	24 (0.25)	
5–7	305 (3.14)	
7–8	1,197 (12.32)	
8–9	3,615 (37.21)	
9–11	4,575 (47.09)	

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

	n = 9,718	Range
Initiation, min, *N* (%)		—
< 15	3,760 (38.70)	
15–30	3,950 (40.65)	
30–45	1,209 (12.44)	
45–60	534 (5.50)	
> 60	263 (2.71)	
Youth report		
Physical activity, days per week	3.49 (2.32)	0.00 to 7.00
Screen media activity, hr (STQ)		
Weekday	2.57 (2.61)	0.00 to 24.00
Social network sites	0.11 (0.42)	0.00 to 4.00
Text and instant messages	0.22 (0.56)	0.00 to 4.00
TV shows or movies	1.11 (1.10)	0.00 to 4.00
R-rated movies	0.40 (0.73)	0.00 to 4.00
Videos (e.g., YouTube)	0.93 (1.17)	0.00 to 4.00
Video games	0.92 (1.14)	0.00 to 4.00
Mature-rated games	0.63 (1.06)	0.00 to 4.00
Video chat	0.18 (0.50)	0.00 to 4.00
Weekend	4.00 (2.65)	0.00 to 24.00
Social network sites	0.13 (0.54)	0.00 to 4.00
Text and instant messages	0.26 (0.71)	0.00 to 4.00
TV shows or movies	1.75 (1.27)	0.00 to 4.00
Videos (e.g., YouTube)	1.31 (1.38)	0.00 to 4.00
Video games	1.40 (1.35)	0.00 to 4.00
Video chat	0.23 (0.67)	0.00 to 4.00
R-rated movies	0.40 (0.73)	0.00 to 4.00
Mature-rated games	0.63 (1.06)	0.00 to 4.00

Note. ASR = Adult Self-Report; BIS/BAS = Behavioral Inhibition/Behavioral Activation Scale; CBCL = Child Behavior Checklist; CRPBI = Child’s Report of Parental Behavior Inventory—Acceptance subscale; CRPF = Community Risk and Protective Factors; FES = Family Environment Scale—Family Conflict subscale; FHAM-S = Family History Assessment Module Screener; KSADS = Kiddie Schedule for Affective Disorders and Schizophrenia; PGBI = Parent General Behavior Inventory for Children and Adolescents—Mania subscale; PMQ = Parental Monitoring Questionnaire; SAIQ = Sports and Activities Involvement Questionnaire; SDSC = Sleep Disturbance Scale for Children; STQ = Screen Time Questionnaire; UPPS-P = Impulsive Behavior Scale.

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

Table 2

Variables With Univariate Correlation (Spearman r *and* p-*Value FDR Corrected) With Age-Corrected Fluid Cognitive Functioning and VI in the Stacked Model. Order of Variables Are in Alphabetic Order*

	Baseline		
Variable	***r***	***p*FDR**	**VI**
ABCD site	.018	.09	2.960
Area Deprivation Index (income disparity)*	−.242	< .001	78.541
Area number of crimes	−.003	.78	3.301
ASR: externalizing behaviors	−.019	.07	2.909
ASR: internalizing symptoms	−.039	< .001	3.694
ASR: parent alcohol use	.020	.06	0.963
ASR: personal strength	.118	< .001	17.292
Basic needs unaffordability (PhenX)*	−.163	< .001	26.448
BIS/BAS: drive*	−.144	< .001	32.518
BIS/BAS: fun seeking	−.067	< .001	5.085
BIS/BAS: inhibition	−.024	.03	1.926
BIS/BAS: reward responsiveness	−.052	< .001	4.713
Body mass index	−.111	< .001	17.485
CBCL: externalizing behaviors*	−.126	< .001	23.911
CBCL: internalizing symptoms	−.050	< .001	4.332
Extracurricular involvement (SAIQ)*	.212	< .001	64.142
Family conflict (FES)	−.105	< .001	14.686
Family history (FHAM-S)	.012	.25	2.398
Family relationships (FES)	.013	.23	0.766
Gender	.039	< .001	4.818
Income < $50,000*	−.260	< .001	98.740
Income $50,000–$100,000	.030	.004	3.929
Mania symptoms (PGBI)*	−.147	< .001	27.484
Neighborhood crime and safety (PhenX)*	.157	< .001	25.169
Parent age	.118	< .001	14.430
Parent education: bachelor's degree	.066	< .001	6.928
Parent education: some college	−.129	< .001	21.737
Parent marital status*	.201	< .001	45.079
Parental conflict (FES)	−.049	< .001	3.331
Parental monitoring (PMQ)	.067	< .001	6.884
Parents living together*	.176	< .001	32.177
Physical activity (SAIQ)	.093	< .001	10.502
Racial minority status*	−.196	< .001	48.963
Screen media activity: weekday (STQ)*	−.148	< .001	26.642
Screen media activity: weekend (STQ)	−.089	< .001	9.183

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

	Baseline		
Variable	***r***	***p*FDR**	**VI**
Secondary caregiver acceptance (CRPBI)	.005	.67	0.866
Sleep amount (SDSC) *	.168	< .001	31.073
Sleep initiation (SDSC)	−.045	.000	2.968
Study caregiver acceptance (CRPBI)	.019	.07	2.378
Trauma exposure (KSADs)	−.054	< .001	3.591
UPPS: lack of perseverance *	−.092	< .001	21.918
UPPS: lack of planning	.002	.85	4.000
UPPS: negative urgency	−.068	< .001	5.669
UPPS: positive urgency *	−.133	< .001	25.419
UPPS: sensation seeking	.023	.03	2.103
Waist circumference	−.084	< .001	7.706
Youth access to substances (CRPF)	.073	< .001	8.670

* *Note*. Top 15 most important variables are denoted by an.

ABCD = Adolescent Brain Cognitive Development; ASR = Adult Self-Report; BIS/BAS = Behavioral Avoidance/Inhibition Scales; CBCL = Child Behavior Checklist; CRPBI = Child’s Report of Parental Behavior Inventory—Acceptance subscale; CRPF = Community Risk and Protective Factors; FES = Family Environment Scale; FHAM-S = Family History Assessment Module Screener; KSADs = Kiddie Schedule for Affective Disorders and Schizophrenia; PGBI = Parent General Behavior Inventory for Children and Adolescents—Mania subscale; PMQ = Parental Monitoring Scale; SAIQ = Sports and Activities Involvement Questionnaire; SDSC = Sleep Disturbance Scale for Children; STQ = Screen Time Questionnaire; UPPS-P = Impulsive Behavior Scale; VI = variable importance.