Extracurricular activities, screen media activity, and sleep may be modifiable factors influencing children's cognitive functioning: Evidence from the ABCD study

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ABSTRACT

This study used a machine learning framework in conjunction with a large battery of measures from 9,718 children from the Adolescent Brain Cognitive Development (ABCD) study to identify factors associated with fluid cognitive functioning (FCF). The identified algorithm explained 14.74% of variance in FCF. Among the most important factors were those that replicated previous research (socioeconomic and mental health factors), and novel, potentially modifiable factors, including extracurricular involvement and screen media activity. Pragmatic interventions targeting these behaviors may enhance cognitive performance and also protect against the negative impact of a range of factors on cognitive performance in at-risk children. The longitudinal data from ABCD will be able to assess causality by examining how changes in these factors affect subsequent performance.

Keywords: children, socioeconomic status, fluid cognitive functioning, ABCD, screen media activity, extracurricular activities, sleep

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 intervene and assert meaningful improvements in these domains. Therefore, research identifying factors contributing to FCF in childhood is essential for developing meaningful interventions to promote positive long-term outcomes.

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. It is understood that FCF reaches its peak in early adulthood and declines across the remainder of the lifespan. However, a large number of factors influences performance on FCF measures, some of which are difficult to modify (e.g., parental education), while others lend themselves well to personal and/or systemic interventions (e.g., exercise).

Among the most robust contributors of poor FCF function 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 and Schamberg, 2009). On the other hand, higher FCF can act as a protective factor in socioeconomic disparity as it is often a mediator between SES and individual outcomes (Lawson *et al*, 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 lead to increased levels of stress during childhood and result in FCF deficits, even when controlling for the effects of poverty (Vernon-Feagans, Willoughby, & Garrett-Peters, 2016). Furthermore, early life stress (e.g., childhood maltreatment, parental psychopathology, and family dysfunction) in particular can have detrimental effects on cognitive and executive function across the lifespan (Irigaray et al., 2013).

Factors related to mental and physical health are also frequently implicated in studies of childhood FCF. FCF deficits are commonly seen in neurodevelopmental [e.g., ADHD; (Biederman et al., 2004)] and mood and anxiety disorders (Goodall et al., 2018; Kavanaugh & Holler, 2014). Furthermore, children who receive insufficient sleep (i.e., fewer than the recommended number of hours for their age) are more likely to receive poorer scores on mother- and teacher-reported measures of FCF (Taveras, Rifas-Shiman, Bub, Gillman, & Oken, 2017). Finally, obese children and adolescents exhibit significantly poorer inhibitory control than those with healthy weight (Reinert, Po'e, & Barkin, 2013), suggesting that there is a relation between physical health and FCF. Taken together, these data show the multitude of environmental and behavioral factors that demonstrate a relation with FCF during development. Further, they emphasize the need to identify factors that may impact FCF in order to guide potential 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, sophisticated multivariate statistical models employing large datasets are necessary to identify generalizable associations with FCF and factors of adequate prospective clinical utility. Machine learning (ML) approaches address these issues across a number of different fields as they allow for the simultaneous testing of numerous factors and their complex interactions, and for non-linearity in producing predictive models (McArdle & Ritschard, 2013). Although ML approaches with cross-sectional data cannot infer causation, 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.

With a large, diverse dataset of children and variables across a number of broad domains relevant to cognitive function, the Adolescent Brain Cognitive Development (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 variables associated with baseline FCF across demographic/environmental, mental and physical health, and behavioral domains. The aims were to identify whether algorithms developed based on these measures may identify important factors associated with FCF, and to identify factors that could potentially be targeted with scalable prevention and intervention efforts and explored in longitudinal analyses.

METHODS

Participants

The ABCD study is large multi-site, longitudinal study following 9-10-year-old children 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, 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.

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.

Measures

Fluid Cognitive Functioning. FCF was measured using the NIH Toolbox Neurocognitive Battery specified for ages 7-17 (Luciana et al., 2018). The age-corrected composite FCF score consists of 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 processing ability of new information within a certain amount of time.

Demographic and Environmental Information. Parents reported demographic information regarding household and immediate family members using the PhenX survey toolkit (Barch et al., 2018). SES was measured using the relative income disparity, or the area deprivation index

(Singh, 2003), and a subscale for basic needs unaffordability (Diemer, Mistry, Wadsworth, Lopez, & Reimers, 2012). Neighborhood crime rates based on US 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) were provided. Child trauma exposure was measured from a subscale of the Kiddie Schedule for Affective Disorders and Schizophrenia for DSM-5 (Barch et al., 2018).

Mental Health and Familial Variables. The Achenbach Adult Self-Report Questionnaire (Barch et al., 2018) provided parental psychopathology and adaptive functioning scores. The Family History Assessment Module Screener (Barch et al., 2018) reported history of psychopathology among first- and second-degree relatives, and the Family Environment Scale (Zucker et al., 2018) assessed family conflict. Family conflict was also assessed via child report with the FES. Child perception of parental monitoring and parental acceptance were measured with the Parental Monitoring Scale (Zucker et al., 2018) and the Acceptance Subscale of the Child Report of Behavior Inventory (Zucker et al., 2018).

Child Mental Health Symptoms and Behaviors. Parents reported child dimensional psychopathology using the Achenbach Child Behavior Checklist (Barch et al., 2018), while Parent General Behavior Inventory for Children and Adolescents (Barch et al., 2018) assessed mania symptoms. Sleep Disturbances Scale for Children (Bruni et al., 1996) provided sleep behaviors, and extracurricular activities and physical exercise was assessed with the Sports and Activities Involvement Questionnaire (Huppertz et al., 2016).

Child self-reports included the four subscales of the Behavioral Inhibition & 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). Estimated amounts of time typically spent engaging in various screen media activity (Bagot et al., 2018) were reported. Physical exercise was assessed using the Youth Risk Behavior Survey (CDC, 2016). 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). For additional information, see the supplemental information.

Analysis

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

Machine learning. In order to build a model that would best characterize the age-corrected FCF composite scores, 52 unique variables 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 performance of stack ensembles in independent, unseen datasets. The nCV procedure was repeated five times to quantify the variability of prediction accuracy and variable importance.

We applied four base learners in the inner loop for each training set, including elastic net (Barsaglini, Sartori, Benetti, Pettersson-Yeo, & Mechelli), support vector regression (SVR) (Suykens & Vandewalle, 1999), conditional random forest (CRF) (Hothorn, Hornik, & Zeileis, 2006), and k-Nearest Neighbors (knn) (Keller, Gray, & Givens, 1985). For each base learner, the tuning parameter(s) were optimized by 5-fold cross validation. Specifically, each training set was partitioned into five distinct subsets, where four subsets were used for the training process to evaluate different hyper parameter values; as a pre-process procedure, predictors with lower than 10% variability were removed and the remaining variables were standardized to 0 mean and unit variance. Optimal hyper-parameter 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 hyper-parameter 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 variable importance (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 elastic net, an “out-of-bag” mean square error obtained by permutation for CRF, 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 variable importance. 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 model described above. 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 purpose (Table S2). 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, see the Supplementary methods.

Follow-up analyses. We conducted follow-up analyses using linear mixed effects [LME; R-package 'lme4' (Bates, Maechler, Bolker, & Walker, 2014)] models on variables constituting potentially modifiable behaviors, including weekday screen media activity and extracurricular involvement, to further delineate their effects on FCF. Regarding weekday screen media, type of activities were entered as fixed effects with ABCD site entered as random effect. 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 entered as a random effect. Given the large sample size, the analysis focused on effect sizes rather than statistically significant relations.

RESULTS

Table 1 presents demographic and clinical characteristics of the final sample. On average, participants evidenced FCF in the normal range (mean=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 (1) socioeconomic: family income less than \$50,000, relative income disparity, racial minority status, and unaffordability of basic needs; and (2) 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 (1) demographic/environmental: parents married, parents living together, and increased neighborhood safety; and (2) child-specific: extracurricular involvement and sleep duration. Figure 2 shows the partial dependence (PD) plots of marginal effect each variable with the highest importance has on FCF. PD plots indicated a non-linear relation between FCF and extracurricular involvement, weekday screen time, neighborhood safety and crime, and basic needs unaffordability.

Follow-up analyses

LME analysis revealed a small positive relation between FCF and art-related ($F(1,9490)=75.90, p<.001$; Cohen's $d=.18$) and team ($F(1,9494)=42.32, p<.001$; Cohen's $d=.13$) and individual sport ($F(1,9492)=30.24, p<.001$; Cohen's $d=.11$) activities (Figure S5).

LME analysis revealed a small negative relation between FCF and weekday time spent watching internet videos ($F(1,9673)=59.95, p<.001$; Cohen's $d=.16$), playing mature-rated video

games ($F(1,9673)=33.51$, $p<.001$; Cohen's $d=.12$), watching TV shows and movies ($F(1,9672)=29.28$, $p<.001$; Cohen's $d=.11$), video chatting ($F(1,9670)=27.18$, $p<.001$; Cohen's $d=.11$), watching mature-rated movies FCF ($F(1,9670)=12.69$, $p<.001$; Cohen's $d=.07$), and using social media ($F(1,9664)=6.79$, $p<.01$; Cohen's $d=.05$), whereas time spent playing video games ($F(1,9669)=0.13$, $p=.72$; Cohen's $d=.01$) and texting ($F(1,9669)=0.10$, $p=.75$; Cohen's $d=.01$) did not show a relation with FCF (Figure S5).

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 and FCF in a large prepubertal group of youth. This is an important task given that FCF is associated with long-term psychological, academic, and occupational outcomes. We observed a normally distributed range of FCF scores in this large sample of 9,718 children from across the U.S. Notably, a significant percentage (6.3%) performed in the extremely low range, while an additional 11.8% performed in the borderline range.

Fifteen variables with highest importance associated with FCF that were identified by the ML analysis fell into two broad categories: socioeconomic and child-specific. First, the findings confirm previous reports (Lawson, Hook, & Farah, 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 lifespan (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 support previous work indicating that impairment in processes underlying irritability, changes in mood, and aggressive and rule-breaking behavior, such as effortful control, self-regulation, and impulse control relate to impairments in FCF (Gartstein & Fagot, 2003; Horn, Roessner, & Holtmann, 2011; Mezzacappa, Kindlon, & Earls, 1999). 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, child with insufficient sleep evidence deficits in inhibitory responses, working memory, executive function, and emotional control (Taveras et al., 2017). Together, co-occurring socioeconomic disadvantages, adverse environments, and mental health problems may have a significant adverse effect on the neurobiological development and functioning in developing children.

Conversely, there is converging evidence that involvement in constructive, non-academic 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 non-linear relation between these variables and suggest that there may be a point of diminishing returns. 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), while 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). Extracurricular enrichment may promote new learning and skill acquisition, creativity, self-efficacy, formation of strong social bonds with non-familial adults and peers, identity development, and physical health (Eccles et al., 2003; Etnier & Chang, 2009), which may translate into improved 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 generally has a negative impact on sleep quality and duration, which in turn affects problem behaviors (Guerrero, Barnes, Chaput, & Tremblay, 2019), and both are known to be negatively associated with FCF (Short & Chee, 2019; Taveras et al., 2017). A recent study with the first half of the ABCD sample examining the direct relation between FCF and screen media activity found that gaming activities had a positive relation with FCF, while 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.

Although contributors of FCF are multifaceted, 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). Further, schools could increase participation in extracurricular activities among children by making them widely available and accessible. 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 bi-directional relations between FCF and associated factors are possible. Although we employed repeated nCV to reduce the risk of over-estimation 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.

Conclusions

We used a machine learning framework to identify variables associated with cognitive functioning in a large sample of 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 ABCD will be able to begin to assess causality by examining how changes in these factors affect subsequent cognitive performance.

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TABLES

Table 1. Sample characteristics.

Demographics (parent report)	n = 9718	Range
Age, Mean (SD)	9.89 (0.62)	9.00 – 10.92
Gender, N (%)		-
Male	5125 (52.8)	
Female	4590 (47.2)	
Race, N (%)		-
White	4937 (50.9)	
Black or African American	1459 (15.0)	
Hispanic	2066 (21.3)	
Asian	225 (2.3)	
Other/Mixed	1019 (10.5)	
Twin Status, N (%)		-
Yes	856 (8.8)	
No	8862 (91.2)	
Siblings in Household, N (%)		-
Yes	1835 (18.9)	
No	7883 (81.1)	
Parent Age, Mean (SD)	39.92 (6.39)	23.00 - 80.00
Parent Marital Status, N (%)		-
Married	6482 (67.3)	
Not Married	3154 (32.7)	
Parents Living Together, N (%)		-
Yes	7064 (73.3)	
No	2572 (26.7)	
Parent Education		-
< High School Diploma	492 (5.1)	
High School Diploma or Equivalent	946 (9.7)	
Some College	2539 (26.2)	
Bachelor's Degree	2408 (24.8)	
Graduate Degree	3323 (34.2)	
Income, N (%)		-
< \$50,000	2695 (30.4)	
\$50,000 - \$100,000	3664 (41.3)	
> \$100,000	2515 (28.3)	
Environment (parent report), M (SD)		

Area Deprivation Index (Income Disparity)	2.17 (1.35)	-1.13 - 8.16
Basic Needs Unaffordability (PhenX)	0.48 (1.10)	0.00 - 7.00
Area Number of Crimes	54512.12 (87439.22)	0.00 - 348049.30
Neighborhood Crime and Safety (PhenX)	3.87 (0.98)	1.00 - 5.00
Youth Access to Substances (CRPF)	9.52 (3.14)	1.00 - 30.00
Trauma Exposure (KSADs)	0.53 (1.10)	0.00 - 17.00
Parent Mental Health and Familial Variables, M (SD)		
<i>Parent Report</i>		
ASR		
Externalizing Behaviors	45.94 (9.67)	30.00 - 90.00
Internalizing Symptoms	48.21 (10.57)	30.00 - 95.00
Personal Strength	47.87 (9.37)	20.00 - 60.00
Parent Alcohol Use, days intoxicated in past 6 months	1.37 (6.34)	0.00 - 180.00
Parent Nicotine Use, times per day in past 6 months	1.01 (4.50)	0.00 - 100.00
Parent Drug Use, days in past 6 months	1.97 (14.85)	0.00 - 180.00
Family History (FHAM-S)	2.36 (2.02)	0.00 - 8.00
Family Conflict (FES)	2.52 (1.95)	0.00 - 9.00
<i>Youth Report</i>		
Family Conflict (FES)	2.02 (1.96)	0.00 - 9.00
Parental Monitoring (PMQ)	4.39 (0.51)	1.00 - 5.00
Study Caregiver Acceptance (CRPBI)	2.78 (0.30)	1.00 - 3.00
Secondary Caregiver Acceptance (CRPBI)	2.69 (0.38)	1.00 - 3.00
Youth Mental Health Symptoms and Behaviors, M (SD)		
<i>Parent Report</i>		
CBCL		
Externalizing Behaviors	45.89 (10.36)	33.00 - 84.00
Internalizing Symptoms	48.75 (10.68)	33.00 - 93.00
Mania Symptoms (PGBI)	1.37 (2.84)	0.00 - 28.00
<i>Youth Report</i>		
BIS/BAS		
Drive	4.18 (3.08)	0.00 - 12.00
Fun Seeking	5.74 (2.66)	0.00 - 12.00

Reward Responsiveness	8.85 (2.38)	0.00 - 12.00
Inhibition	5.53 (2.85)	0.00 - 12.00
UPPS-P		
Lack of Perseverance	7.06 (2.26)	4.00 - 16.00
Lack of Planning	7.73 (2.37)	4.00 - 16.00
Negative Urgency	8.50 (2.65)	4.00 - 16.00
Positive Urgency	7.98 (2.95)	4.00 - 16.00
Sensation Seeking	9.79 (2.68)	4.00 - 16.00
Modifiable Risks, M (SD)		
Body Mass Index	18.81 (4.00)	11.10 - 35.87
Waist Circumference, Inches	26.68 (4.95)	0.00 - 90.00
<i>Parent Report</i>		
Extracurricular Involvement, hours	17.99 (13.84)	0.00 - 170.00
per week (SAIQ)		
Art	5.07 (6.32)	0.00 – 54.00
Individual Sports	4.93 (5.7)	0.00 – 70.00
Team Sports	8.06 (7.65)	0.00 – 54.00
Sleep (SDSC)		
Amount, Hours, N (%)		-
< 5	24 (0.25)	
5 - 7	305 (3.14)	
7 - 8	1197 (12.32)	
8 - 9	3615 (37.21)	
9 - 11	4575 (47.09)	
Initiation, Minutes, N (%)		-
< 15	3760 (38.70)	
15 - 30	3950 (40.65)	
30 - 45	1209 (12.44)	
45 - 60	534 (5.50)	
> 60	263 (2.71)	
<i>Youth Report</i>		
Physical Activity, Days per Week	3.49 (2.32)	0.00 - 7.00
Screen Media Activity, Hours (STQ)		
Weekday	2.57 (2.61)	0.00 - 24.00
Social Network Sites	0.11 (0.42)	0.00 - 4.00
Text and Instant Messages	0.22 (0.56)	0.00 - 4.00
TV shows or Movies	1.11 (1.10)	0.00 - 4.00

R-rated Movies	0.40 (0.73)	0.00 - 4.00
Videos (e.g, YouTube)	0.93 (1.17)	0.00 - 4.00
Video Games	0.92 (1.14)	0.00 - 4.00
Mature-rated Games	0.63 (1.06)	0.00 - 4.00
Video Chat	0.18 (0.50)	0.00 - 4.00
Weekend	4.00 (2.65)	0.00 - 24.00
Social Network Sites	0.13 (0.54)	0.00 - 4.00
Text and Instant Messages	0.26 (0.71)	0.00 - 4.00
TV shows or Movies	1.75 (1.27)	0.00 - 4.00
Videos (e.g, YouTube)	1.31 (1.38)	0.00 - 4.00
Video Games	1.40 (1.35)	0.00 - 4.00
Video Chat	0.23 (0.67)	0.00 - 4.00
R-rated Movies	0.40 (0.73)	0.00 - 4.00
Mature-rated Games	0.63 (1.06)	0.00 - 4.00

Abbreviations: 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.

Table 2. Variables with univariate correlation (Spearman r and P-value FDR corrected) with age-corrected fluid cognitive functioning and variable importance (VI) in the stacked model. Order of variables are in alphabetic order.

Variable	Baseline		VI
	r	pFDR	
ABCD Site	0.018	0.09	2.960
Area Deprivation Index (Income Disparity)	-0.242	<0.001	78.541
Area Number of Crimes	-0.003	0.78	3.301
ASR: Externalizing Behaviors	-0.019	0.07	2.909
ASR: Internalizing Symptoms	-0.039	<0.001	3.694
ASR: Parent Alcohol Use	0.020	0.06	0.963
ASR: Personal Strength	0.118	<0.001	17.292
Basic Needs Unaffordability (PhenX)	-0.163	<0.001	26.448
BIS/BAS: Drive	-0.144	<0.001	32.518
BIS/BAS: Fun Seeking	-0.067	<0.001	5.085
BIS/BAS: Inhibition	-0.024	0.03	1.926
BIS/BAS: Reward Responsiveness	-0.052	<0.001	4.713
Body Mass Index	-0.111	<0.001	17.485
CBCL: Externalizing Behaviors	-0.126	<0.001	23.911
CBCL: Internalizing Symptoms	-0.050	<0.001	4.332
Extracurricular Involvement (SAIQ)	0.212	<0.001	64.142
Family Conflict (FES)	-0.105	<0.001	14.686
Family History (FHAM-S)	0.012	0.25	2.398
Family Relationships (FES)	0.013	0.23	0.766
Gender	0.039	<0.001	4.818
Income < \$50,000	-0.260	<0.001	98.740
Income \$50,000 - \$100,000	0.030	0.004	3.929
Mania Symptoms (PGBI)	-0.147	<0.001	27.484
Neighborhood Crime and Safety (PhenX)	0.157	<0.001	25.169
Parent Age	0.118	<0.001	14.430
Parent Education: Bachelor's Degree	0.066	<0.001	6.928
Parent Education: Some College	-0.129	<0.001	21.737
Parent Marital Status	0.201	<0.001	45.079
Parental Conflict (FES)	-0.049	<0.001	3.331
Parental Monitoring (PMQ)	0.067	<0.001	6.884
Parents Living Together	0.176	<0.001	32.177
Physical Activity (SAIQ)	0.093	<0.001	10.502

Racial Minority Status	-0.196	<0.001	48.963
Screen Media Activity: Weekday (STQ)	-0.148	<0.001	26.642
Screen Media Activity: Weekend (STQ)	-0.089	<0.001	9.183
Secondary Caregiver Acceptance (CRPBI)	0.005	0.67	0.866
Sleep Amount (SDSC)	0.168	<0.001	31.073
Sleep Initiation (SDSC)	-0.045	0.000	2.968
Study Caregiver Acceptance (CRPBI)	0.019	0.07	2.378
Trauma Exposure (KSADs)	-0.054	<0.001	3.591
UPPS: Lack of Perseverance	-0.092	<0.001	21.918
UPPS: Lack of Planning	0.002	0.85	4.000
UPPS: Negative Urgency	-0.068	<0.001	5.669
UPPS: Positive Urgency	-0.133	<0.001	25.419
UPPS: Sensation Seeking	0.023	0.03	2.103
Waist Circumference	-0.084	<0.001	7.706
Youth Access to Substances (CRPF)	0.073	<0.001	8.670

Abbreviations: 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.

FIGURES

Figure 1. Variable importance (VI) for models predicting Fluid Cognitive Functioning in the ABCD cohort (n = 9,718). Variable importance (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. Abbreviations: BIS/BAS, Behavioral Inhibition/Behavioral Activation Scale; CBCL, Child Behavior Checklist UPPS-P, Impulsive Behavior Scale.

Variable importance (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. Abbreviations: BIS/BAS, Behavioral Inhibition/Behavioral Activation Scale; 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. Abbreviations: BIS/BAS, Behavioral Avoidance/Inhibition Scales; CBCL, Child Behavior Checklist.

Abbreviations: BIS/BAS, Behavioral Avoidance/Inhibition Scales; CBCL, Child Behavior Checklist.

Supplementary Information

Title: Extracurricular activities, screen media activity, and sleep may be modifiable factors influencing children's cognitive functioning: Evidence from the ABCD study

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Supplementary Materials

Overview

1. Supplementary methods
  - a. Measures
  - b. Machine learning methods
2. Supplementary tables
  - a. Table S1. Variables included in the machine learning analysis.
3. Supplementary figures
  - a. Figure S1. The process of repeated nested CV.
  - b. Figure S2. The inner-loop of repeated nested CV
  - c. Figure S3. Distribution of age-corrected Fluid Cognitive Functioning (FCF) composite scores.
  - d. Figure S4. Percent of variance explained for age corrected fluid cognitive functioning score by 47 demographic, psychological, and environmental predictors (n = 9,719).
  - e. Figure S5. Scatter plots between potentially modifiable variables and Fluid Cognitive Functioning composite scores.

1. Supplementary methods

a. Measures

Family Demographics. Primary caregivers provided demographic information regarding the parent/guardian, their partner, the youth's grandparents, and the youth using the PhenX survey toolkit (D. M. Barch et al., 2018; P. J. Stover, W. R. Harlan, J. A. Hammond, T. Hendershot, & C. M. Hamilton, 2010).

Mental Health and Psychopathology. Behavioral inhibition and activation were assessed using the Behavioral Inhibition & Behavioral Activation Scales (BIS/BAS) from PhenX (D. M. Barch et al., 2018; Pagliaccio et al., 2016) with subscales for drive (intensity of goal-directed behavior), fun seeking (enjoyment for its own sake; spontaneity), and reward responsiveness (excitement over reinforcing outcomes), as well as inhibition (worry, fearfulness). Impulsivity was measured via the UPPS-P for Children from PhenX (D. M. Barch et al., 2018; Lynam, 2013; Zapolski, Stairs, Settles, Combs, & Smith, 2010), with four subscales including lack of premeditation, positive and negative urgency (difficulty controlling emotions), sensation seeking, and lack of perseverance.

Dimensional psychopathology and adaptive functioning were measured using the Achenbach Child Behavior Checklist (CBCL; T.M. Achenbach, 2009; D. M. Barch et al., 2018), normed for sex, age, and ethnicity. We utilized the broader syndrome subscale scores for internalizing and externalizing symptoms. Mania symptoms were measured using a sum score from the mania subscale of the Parent General Behavior Inventory for Children and Adolescents (D. M. Barch et al., 2018; E. A. Youngstrom, T. W. Frazier, C. Demeter, J. R. Calabrese, & R. L.

Findling, 2008). Finally, exposure to traumatic events, including the death of a loved one, or the youth witnessing or experiencing physical or sexual assault, domestic violence, or other violent acts was assessed with questions from the Kiddie Schedule for Affective Disorders and Schizophrenia for DSM-5 (KSADS-5; D. M. Barch et al., 2018; Kobak & Kaufman, 2015).

Physical Health and Extracurricular Engagement. Youth standardized measures of height, weight, body mass index (BMI), and waist circumference were measured using the National Health and Nutrition Examination Survey (CDC (Division of Nutrition, 2016). Parents reported on the past and current involvement of youth in sports, activities, music, or hobbies using the Sports and Activities Involvement Questionnaire (modified from the Vermont Health Behavior Questionnaire; Huppertz et al., 2016). Youth also self-reported their level of physical exercise via items from the Youth Risk Behavior Survey (YBR; CDC, 2016b). Youth sleep initiation delays and average total sleep length were assessed using the parent-report Sleep Disturbances Scale for Children (O. Bruni et al., 1996). Finally, youth self-reported the estimated amount of time typically spent on multiple types of screen media activity (e.g., watching TV, movies, or internet videos and active/social use such as playing video games, texting, or visiting social media sites) on a typical day week or weekend day (K. S. Bagot et al., 2018). Questions were also asked relating to time spent engaging with mature rated movies and video games.

Environmental Adversity. To address influences on socioeconomic status other than income alone, we used a measure of relative income disparity based on residential histories and measures of economic insecurity and neighborhood safety. For relative income disparity, we used the area deprivation index (ADI; Singh (2003)), a composite measure of neighborhood socioeconomic

disadvantage. ADI uses US Census data related to poverty, education, housing, and employment within a given zip code to create census-based regions for neighborhood risk. A grand total of neighborhood crime rates was also included with various forms of violent and non-violent reported crimes based on US Census data (K. S. Bagot et al., 2018). Economic insecurity was measured using the best practices for conceptualizing and measuring social class in psychological research outlined in Diemer et al. (2012). One's ability to pay for basic needs such as medical care, phone service, utilities, or food were summed and used in analyses. Finally, a sum score of parent-reported questions relating to the perceived safety of and presence of crime in one's neighborhood including feeling safe walking alone and level of violence and crime (ranging from "strongly agree" to "strongly disagree") was derived from the Safety from Crime subscale of the PhenX Toolkit (Toolkit, 2016; R. A. Zucker et al., 2018).

In addition to markers of environmental adversity, we also included measures addressing the family environment. The Family Conflict subscale of the Family Environment Scale (Moos & Moos, 1994; R. A. Zucker et al., 2018) was completed by both the parent and the youth. Items included questions regarding family members losing their temper, arguing, or acting violent with higher scores indicating more conflict. Parents self-reported dimensional psychopathology and adaptive functioning using the Achenbach Adult Self Report Questionnaire (ASR; T.M. Achenbach, 2009; D. M. Barch et al., 2018), from which items regarding parent substance use, personal strength, and internalizing and externalizing symptoms were used. Finally, we included questions relating to history of psychopathology among first- and second-degree relatives (i.e., substance use, depression, mania, psychosis, and antisocial personality disorder) from the Family History Assessment Module Screener (FHAM-S; D. M. Barch et al., 2018; J. P. Rice et al., 1995). Youth also reported on their perception of parental monitoring using the Parental

Monitoring Scale, including parent/child contact, frequency of family dinners, parents knowing child's whereabouts, and child disclosure to parents (H. D. Chilcoat & J. C. Anthony, 1996; R. A. Zucker et al., 2018) and their perception of parental warmth, acceptance, and responsiveness via the Acceptance Subscale of the Child Report of Behavior Inventory modified for ABCD to address primary and secondary caregivers' behaviors (Schaefer, 1965; R. A. Zucker et al., 2018). Finally, parent-reported youth accessibility to substances was measured using the Community Risk and Protective Factors scale from the PhenX toolkit (Arthur et al., 2007; K. M. Lisdahl et al., 2018).

b. Machine learning methods

Selection of algorithms. In this work, we implemented four algorithms: elastic net (ENET) (Barsaglini, Sartori, Benetti, Pettersson-Yeo, & Mechelli), support vector regression (SVR) (Suykens & Vandewalle, 1999), conditional random forest (CRF) (Hothorn, Hornik, & Zeileis, 2006), and k-Nearest Neighbors (knn) (Keller, Gray, & Givens, 1985).

Repeated nested cross-validation. It is well known that using the same dataset to build a prediction model and evaluate its performance can cause overestimation in the model performance (Varma & Simon, 2006). If we have two datasets, one of them can be used to train a prediction model, and the other to evaluate the model performance. Because we had only one dataset, one possibility was to split the data into a training set for model building and a validation

set for model evaluation. Alternatively, the whole dataset could be partitioned to “ K ” parts, where one part served as a validation set and the other parts were combined to serve as a training set, and the process iterated so that each part served as a validation set exactly once (Outer loop). For a given machine learning method, a training set could be partitioned into K parts and the optimal tuning parameters could be determined by K -fold cross validation (Inner loop). The trained model was then applied to make predictions in the corresponding validation set. Iterating across the “ K ” parts, the “ K ” sets of predicted values were combined to compare with the observed values to evaluate model performance. The whole procedure is known as nested or double cross-validation (Stone, 1974; Varma & Simon, 2006) and was repeated by different partition indices to assess the variability of the results (Filzmoser, Liebmann, & Varmuza, 2009). We chose to repeat 100 times nested cross-validation (CV), with 5-fold CV for both the outer and the inner loops.

Stacked regression/Super learner (the inner loop)

In the inner loop, we applied four machine learning methods and then combined their predictions by stack ensemble. Suppose a training set $\mathbf{D}$ was expressed as a matrix, concatenated in columns by a response vector $\mathbf{y}$ and a predictor matrix $\mathbf{X}$, with $n \times (K_1 - 1)/K_1$ observations.

Step 1: Building base learners. Each base learner was built by K_2 -fold CV, which consisted of data partition and parameter optimization.

Data partition: A training set D was partitioned into K_2 non-overlapped parts where $(K_2 - 1)$ parts were used to train a model with hyper-parameter θ_j , which was then used to

predict the held-out part and to compute the corresponding model performance metric (R^2 here); this process was repeated so that this step would give K_2 values of R^2 .

Optimization: For a grid of J hyper-parameter combinations, denoted as $\theta_j, j = 1, \dots, J$, the same partition indices of K_2 -fold CV were applied to each θ_j . Note θ_j was either a vector (two parameters for eNet) or a scalar (other methods). The optimal hyperparameter θ_{Opt} were determined by the “one-standard-error” (1-SE) rule: among the θ_j ’s whose mean R^2 (averaged across K_1 test sets) fell within one SE of the maximal mean R^2 , the θ_j that corresponded to the most parsimonious model was θ_{Opt} . Note that SE of the metric is defined as

$$SE = \frac{SD}{\sqrt{K_2}}$$

Should θ_{Opt} be identified, the predicted values of the held-out sets at θ_{Opt} , denoted as $\hat{\mathbf{y}}(\theta_{\text{Opt}})$ were extracted for stack ensemble.

Step 2: Building a stack ensemble model. The predicted values of the optimal hyperparameter θ_{Opt} from L base learners (Step 1) were then combined with the observed response values into a matrix $\hat{\mathbf{D}}$ with $(L + 1)$ columns. The observed response could be regressed on the m variables to obtain a stack ensemble model M^S . We chose to average predicted values of base learners weighted by their mean R^2 values from Step 1.

Hyper-parameter selection. Elastic net had two tuning parameters α and λ . CRF was tuned on a single parameter “mtry” for the number of predictors randomly selected to grow a tree; the

number of trees was set at 500 and not tuned. Although in theory SVR may have three parameters: cost, ϵ , and σ , the scale parameter σ (“sigma”) for radial basis function was estimated by the midpoint of the 10th and 90th percentiles of Euclidean distance between all training points (Caputo, Sim, Furesjo, & Smola, 2002); also, the cost and ϵ parameters have some relationship and Kuhn (2014) suggests using cost (“C”) as the only tuning parameter. The knn algorithm had a single tuning parameter k , the number of nearest neighbors. To alleviate computation burden, we used random search (Bergstra & Bengio, 2012) with adaptive resampling algorithm (Kuhn, 2014) for no more than 15 parameter combinations, so the actually used parameter combinations and values varied with replications and training sets.

2. Supplementary tables

Table S1. Variables included in the machine learning analysis.

Demographics (Deanna M Barch et al., 2018; Patrick J Stover, William R Harlan, Jane A Hammond, Tabitha Hendershot, & Carol M Hamilton, 2010)	
· Age	· Parent Age
· Gender	· Parent Marital and Household Status
· Racial Minority Status	· Parent Education
· Twin and Sibling Status	· Parent Age
Environment	
· Income Disparity and Affordability (Patrick J Stover et al., 2010)	· Neighborhood Crime and Safety (Deanna M Barch et al., 2018)
· Youth Access to Substances – CRPF (Arthur et al., 2007; Krista M Lisdahl et al., 2018)	· Trauma – KSADs (Puig-Antich & Ryan, 1986)
Parent Mental Health and Familial Variables	
· Psychopathology and Substance Use – ASR (Thomas M Achenbach, 1997)	· Parental Monitoring – PMQ (Howard D Chilcoat & James C Anthony, 1996) and Family Conflict – FES (Moos & Moos, 1994; Robert A Zucker et al., 2018)
· Caregiver Acceptance – CRBPI (Schaefer, 1965; Robert A Zucker et al., 2018)	· Family History – FHAM-S (John P Rice et al., 1995)
Youth Mental Health Symptoms and Behaviors	

· Pscyhopathology – CBCL (Thomas M Achenbach & Ruffle, 2000)	· Mania Symptoms – PGBI (Eric A Youngstrom, Thomas W Frazier, Christine Demeter, Joseph R Calabrese, & Robert L Findling, 2008)
· Behavioral Avoidance and Inhibition – BIS/BAS (Carver & White, 1994)	· Impulsivity – UPPS-P (Whiteside, Lynam, Miller, & Reynolds, 2005)
Modifiable Risks	
· BMI And Waist Circumference (CDC (Division of Nutrition, 2016)	· Sleep Quality – SDSC (Oliviero Bruni et al., 1996)
· Extracurricuar Involvement – SAIQ (Huppertz et al., 2016)	· Physical Activity – YRB (CDC, 2016a)
· Screen Media Activity – STQ (K. Bagot et al., 2018)	

Abbreviations: ASR, Adult Self-Report; BIS/BAS, Behavioral Avoidance/Inhibition Scales; BMI, Body Mass Index; 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 for DSM-5; 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; YRB, Youth Risk Behavior Survey.

3. Supplementary figures

Figure S1. The process of repeated nested CV. This figure illustrates the process of nested CV repeated 100 times indexed by ρ . In the outer loop, the original data of n subjects were partitioned into K_1 parts indexed by τ . For each iterate, $(K_1 - 1)$ parts served as a training set to optimize tuning parameters in the inner loop (see Supplementary Figure S1b.). The stack model $M^S_{\rho, \tau}$ from the inner loop was then used to predict the held-out set of the outer loop. Predicted values $\hat{y}(\rho)$ were combined across held-out sets to evaluate the performance of the stack models.

Inner loop

Figure S2. The inner-loop of repeated nested CV. In the inner loop, each training set from the outer loop was further partitioned into K_2 parts indexed by κ . A model with a tuning parameter combination θ_j was trained on $(K_2 - 1)$ parts, and then this model was applied to

predict the held-out set. The predicted values were then compared to the observed values by R-square. Iterating across K_2 folds led to K_2 values of R-square. The process was repeated for all parameter combinations, and the optimal tuning parameter combination (θ_{Opt}) was determined by the "one-SE" rule. This optimal parameter combination was applied to the whole training set and gave the predicted values as $\hat{y}(\theta_{\text{Opt}})$. This process was then repeated for all machine learning methods. The predicted values across machine learning methods were then combined with observed values to build a stack model M^S .

Figure S3. Distribution of age-corrected Fluid Cognitive Functioning (FCF) composite scores.

Figure S4. Percent of variance explained for age corrected fluid cognitive functioning scores by 47 demographic, psychological, and environmental predictors ($n = 9,719$). glmnet: Elastic net; cforest: conditional random forest; knn: k-nearest neighbors; svmRadial: support vector machine; StackClscR2: combined (stacked) method. Error bars represent 95% confidence intervals.

Figure S5. Scatter plots showing the relationship between potentially modifiable variables and Fluid Cognitive Functioning (FCF) composite scores. Abbreviations: SMA, screen media activity.

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