Psychological Medicine

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Original Article

Cite this article: Gray JC, Schvey NA, Tanofsky-Kraff M (2020). Demographic, psychological, behavioral, and cognitive correlates of BMI in youth: Findings from the Adolescent Brain Cognitive Development (ABCD) study. *Psychological Medicine* **50**, 1539–1547. https://doi.org/10.1017/S0033291719001545

Received: 7 February 2019
Revised: 1 May 2019
Accepted: 4 June 2019
First published online: 10 July 2019

Key words:
Adolescent; BMI; obesity; pediatric; youth

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Demographic, psychological, behavioral, and cognitive correlates of BMI in youth: Findings from the Adolescent Brain Cognitive Development (ABCD) study

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Abstract

Background. Previous research has implicated demographic, psychological, behavioral, and cognitive variables in the onset and maintenance of pediatric overweight/obesity. No adequately-powered study has simultaneously modeled these variables to assess their relative associations with body mass index (BMI; kg/m^2) in a nationally representative sample of youth.
Methods. Multiple machine learning regression approaches were employed to estimate the relative importance of 43 demographic, psychological, behavioral, and cognitive variables previously associated with BMI in youth to elucidate the associations of both fixed (e.g. demographics) and potentially modifiable (e.g. psychological/behavioral) variables with BMI in a diverse representative sample of youth. The primary analyses consisted of 9–10 year olds divided into a training ($n = 2724$) and test ($n = 1123$) sets. Secondary analyses were conducted by sex, ethnicity, and race.
Results. The full sample model captured 12% of the variance in both the training and test sets, suggesting good generalizability. Stimulant medications and demographic factors were most strongly associated with BMI. Lower attention problems and matrix reasoning (i.e. nonverbal abstract problem solving and inductive reasoning) and higher social problems and screen time were robust positive correlates in the primary analyses and in analyses separated by sex.
Conclusions. Beyond demographics and stimulant use, this study highlights abstract reasoning as an important cognitive variable and reaffirms social problems and screen time as significant correlates of BMI and as modifiable therapeutic targets. Prospective data are needed to understand the predictive power of these variables for BMI gain.

Introduction

Almost 20% of American youth are classified as having obesity (body mass index (BMI) ≥95th %ile) (Hales *et al.*, 2018). Children with high weight are vulnerable to a host of adverse medical complications, previously thought to only affect adults, including type 2 diabetes (Dabelea *et al.*, 2014), sleep apnea (Muzumdar and Rao, 2006), nonalcoholic steatohepatitis, and resultant cirrhosis (Dietz, 1998). Given that overweight and obesity in youth tend to persist into adulthood and the health effects of chronic obesity are well-documented (Kopelman, 2007), identifying correlates and predictors of BMI in youth is imperative. Current treatment approaches to pediatric overweight and obesity are typically unsuccessful (Kobes *et al.*, 2018), warranting a need for prevention and the identification of modifiable risk factors that can be targeted on a broad level.

Previous research has implicated a number of demographic, psychological, behavioral, and cognitive variables, in the onset and maintenance of pediatric overweight/obesity (Hu *et al.*, 2004; Wang and Zhang, 2006; Chandola *et al.*, 2006; Zeller *et al.*, 2007; Davis *et al.*, 2007; Cappuccio *et al.*, 2008; Kandula *et al.*, 2008; Puder and Munsch, 2010; Tsukayama *et al.*, 2010; Delgado-Rico *et al.*, 2012; Carroll-Scott *et al.*, 2013; Mitchell *et al.*, 2013; Ogden *et al.*, 2016; Guerrero *et al.*, 2016; Sweat *et al.*, 2017; Pearce *et al.*, 2018; Nghiem *et al.*, 2018). However, to our knowledge, no adequately-powered study has simultaneously modeled these candidate variables to assess their relative associations with BMI in childhood. Additionally, given the replication rate of about 50% in psychological research (Open Science Collaboration, 2015), it is important to verify findings in additional well-powered samples. To address this gap, we utilized data from the first wave of the Adolescent Brain Cognitive Development (ABCD) study, a large representative US sample of 9–10 year olds to elucidate and replicate the relative associations of both fixed and modifiable variables with BMI in a diverse, representative sample of youth, employing multiple machine learning regression approaches. Exploratory analyses were conducted stratified by sex, race, and ethnicity. Based on previous research, we hypothesized BMI would be associated with key demographic variables (e.g. male sex, non-White race, Hispanic ethnicity, lower household income), cognitive task performance (e.g. poorer performance on executive functioning tasks), and psychological and behavioral variables (e.g. social problems, lower sleep duration, screen time).

Methods

Participants

Participants were derived from the first wave of the ABCD study (Garavan *et al.*, 2018), an ongoing project seeking to recruit 11,500 9–10 year olds to assess longitudinally for 10 years. The first wave of data was released in 2018 and included 4524 participants. This wave included a 6–7 h assessment and comprised physiological and psychological measures. For more information on the recruitment of subjects and study procedures see https://abcdstudy.org/study-procedures.html (Garavan *et al.*, 2018). Child- and parent-report and assessments of demographic, psychological, behavioral, and cognitive variables that have been associated with pediatric obesity in prior studies were selected *a priori* for inclusion in the present analyses.

Demographics variables

Parent-report

Demographics variables included sex (biological sex at birth), race (0 = male, 1 = female and 0 = non-White, 1 = White, respectively), Hispanic ethnicity (0 = non-Hispanic, 1 = Hispanic), combined family income (1 ≤ \$5000; 2 = \$5000–11 999; 3 = \$12 000–15 999, 4 = \$ 16 000–24 999, 5 = \$ 25 000–34 999, 6 = \$ 35 000–49 999, 7 = \$50 000–74 999, 8 = \$ 75 000–99 999, 9 = \$ 100 000–199 999, 10 ≥ \$200 000), parental years of education, marital status (0 = married, 1 = not married), and single parent home (0 = no, 1 = yes).

Additionally, we included the Neighborhood Safety/Crime Survey that comprised the sum total of three items assessing feelings about safety and the presence of crime in the respondent's neighborhood ($\alpha = 0.87$).

Finally, stimulant medication variable was generated [1 = on stimulant(s); 0 = no stimulant(s)] based on parent reports of any prescription medications the child took within the past 2 weeks. The medications classified as stimulants in this study were methylphenidate, dextroamphetamine, dexmethylphenidate, amphetamine, Evekeo®, Adderall®, Vyvanse®, Concerta®, Focalin®, Quillivant®, Ritalin®, and Metadate®.

Parent- and child-report

The conflict subscale (nine items) of the Family Environment Scale (FES) was administered to both parents and children and summed into separate subscale total scores ($\alpha = 0.64$, 0.67, respectively).

Psychological and behavioral variables

Parent-report

The eight empirically based syndrome scales of the Child Behavior Checklist (CBCL) were used: aggressive behavior, anxious/depressed, attention problems, rule-breaking behavior, somatic complaints, social problems, thought problems, and withdrawn/depressed.

The sleep initiation subscale of the Sleep Disturbances Scale was utilized (i.e. duration and disorders of initiating and maintaining sleep).

Child-report

The 20-item Urgency, Premeditation, Perseverance, Sensation Seeking, Positive Urgency, Impulsive Behavior Scale for Children-Short Form (UPPS-P) was utilized which assesses five facets of impulsivity ($\alpha = 0.63$, 0.73, 0.69, 0.50, 0.78, respectively).

The following subscales of the Behavioral Avoidance/Inhibition Scales (BIS/BAS) were utilized: BIS, BAS drive, BAS reward responsiveness, and BAS fun seeking ($\alpha = 0.63$, 0.73, 0.78, and 0.65, respectively).

The single item Cash Choice Task measure of delayed reward discounting asked children,'Let's pretend a kind person wanted to give you some money. Would you rather have \$75 in three days or \$115 in 3 months?' (0 = \$75 in 3 days, 1 = \$115 in 3 months).

The first item of the Youth Risk Behavior: Exercise measure ('During the past 7 days, on how many days were you physically active for a total of at least 60 min per day?') was utilized to capture a typical level of physical activity.

Screen time was defined as the average minutes per week a child typically spends on a computer, cellphone, tablet, or other electronic device.

Cognitive variables

Child-report

The following NIH Toolbox (TB) Tasks were utilized: Picture Vocabulary, Reading Recognition, Picture Sequence Memory, Dimensional Change Card Sort, Flanker Inhibitory Control & Attention, List Sorting Working Memory, Pattern Comparison Processing Speed, Crystalized Composite, and Fluid Comprehension Composite. All scores were age-corrected standard scores.

Wechsler Intelligence Scale for Children-V (WISC-V) matrix reasoning assessed as a measure of nonverbal abstract problem solving and inductive reasoning. Scaled scores were utilized for the analyses.

Data analysis

BMIz

Height and weight were measured twice consecutively and the average of the two measurements was used. BMI (kg/m^2) was calculated according to convention and converted to a *z*-score using the CDC 2000 Growth Chart SAS (SAS Institute, Inc, Cary, NC) software. Per the CDC guidelines, we excluded 12 children for BMIz less than the recommended cutoff of −4. Given the known issues in using BMIz scores for children with severe obesity (Freedman *et al.*, 2017), we converted these scores to the percentage of the sex- and age-specific 95th BMI percentile (the cutoff for obesity). This metric is referred to as %BMI$_{p95}$ (Freedman *et al.*, 2017).

Analytic approach

Data were randomly partitioned to 70% training sample (for building the models) and a 30% test sample (for validating the models) accounting for familial structure. Specifically, participants with sibling(s) in the study were all included in either the training or the test set in order to avoid dependencies across the training and test sets. Multiple analytical approaches were

https://doi.org/10.1017/S0033291719001545 Published online by Cambridge University Press

utilized to attempt the best model prediction of $\%BMI_{p95}$. These approaches, all implemented using the R packages 'glmnet' and 'caret', included ridge regression, least absolute shrinkage and selection operator (LASSO) regression, elastic net regression, and linear regression (for an overview of these approaches see (James *et al.*, 2013)). The former three approaches include penalty term(s) that reduce coefficients and, in the case of LASSO and elastic net, can select out variables, simplifying the model. This offers benefits over conventional approaches (e.g. linear regression, stepwise-regression) that often lead to inflated coefficients and R^2 which limit generalizability of findings. In ridge regression, $\alpha = 0$ and a range of lambda values are implemented, enabling continuous shrinkage of coefficients but no variable selection. In LASSO, $\alpha = 1$ and a range of lambda values are implemented, enabling continuous shrinkage of coefficients and variable selection. Elastic net regularized regression uses a linear combination of two regularization techniques, L2 regularization (ridge) and L1 regularization (LASSO), by simultaneously implementing variable selection and continuous shrinkage of coefficients across a range of alpha and lambda values (Zou and Hastie, 2005). In all three penalized approaches, lambda was tested at five different levels ranging from 0.00001 to 1. Additionally, elastic net allowed alpha to range at 10 levels from 0 to 1. All models, including linear regression, employed 10-fold cross-validation repeated 5 times on the training sample. Subsequently, the best models from each approach (i.e. where root-mean-square error (RMSE) was minimized) were applied to a test set that comprised 30% of the data to test for generalizability. To fully utilize the data and explore how more traditional analyses would perform, we also conducted a linear regression on the full sample ($N = 3847$) with false-discovery rate (FDR) correction of the 43 predictors (Benjamini and Hochberg, 1995). Finally, to explore potential interactions we utilized a LASSO in the full sample to assess all potential 2-way interactions among the 43 independent variables (i.e. 903 interactions) as well as all 2-way interactions with a subset of 7 demographic variables (i.e. sex, race, ethnicity, combined family income, parental years of education, marital status, and single-parent home; 273 interactions).

Following the full sample analyses, sex-specific analyses were conducted in a parallel fashion (i.e. testing all four analytical approaches on a 70% training sample followed by validation on a 30% test set, all conducted separately for boys and girls). To increase comparability to the full sample models, the training and test sets for sex-based analyses were the same as for the full sample. In other words, only full sample subjects from the training set were used to develop the training sets for the separate boys and girls models.

For exploratory analyses of model performance on Hispanic and Black non-Hispanic participants, we constructed the models on all available participants in order to maximize power. For comparison, we constructed models on matching numbers of White non-Hispanic participants.

Preliminary analyses and missing data

From the 4524 participants who completed the baseline assessment, 3847 survived quality control procedures (see online Supplementary Materials for more details). We believe this sample size was sufficient for our analyses because it has thousands of more subjects than many previous studies that explored similar variables and it employed several machine learning techniques detailed above (e.g. penalized regression, cross-validation, evaluating models on a partitioned test dataset which was not used in building the original model) to increase the likelihood for good generalizability to independent samples.

Given only 3108 participants from the original 4524 had valid Stop Signal Task performance (exclusion criteria described in detail in the ABCD Release Notes 1.0; https://ndar.nih.gov/edit_collection.html?id=2573), we first ran a bivariate correlation in all subjects with valid Stop Signal Reaction Time (SSRT; i.e. the primary SST measure of inhibition) and $\%BMI_{p95}$ data ($n = 3098$) to assess if SSRT is a relevant variable to include in the models. The correlation between SSRT and $\%BMI_{p95}$ was not significant ($r = 0.03$, $p = 0.10$), thus we did not include SSRT in the primary analyses. Imputation of missing values was conducted for the final sample utilizing multivariate imputation by chained equations implemented in the R package 'mice'. Given the possibility that some variables, particularly combined family income, are not missing completely at random, the 'MNAR' (i.e. missing not at random) mechanism was utilized (see online Supplementary Materials for the proportion of imputed values per variable). The final sample compared to the excluded sample had significantly higher $\%BMI_{p95}$ and lower parent education and income and had higher frequencies of White race, non-Hispanic ethnicity, and married parents (online Supplementary Table S1).

Variables that were $> \pm 2$ skew and kurtosis were log or square root transformed (whichever improved the distribution most was used). Variables for which log transformation improved the distribution included all CBCL subscales except for somatic complaints. Screen time was square root transformed.

Results

Full group analysis

The initial variable set comprised 43 demographic, psychological, behavioral, and cognitive variables. The training set comprised 70% of the subjects ($n = 2724$) and the test set comprised 30% ($n = 1123$) (online Supplementary Table S2). The LASSO model exhibited the lowest RMSE on the training set (RMSE = 15.97, $R^2 = 0.12$), generalized well to the test set (RMSE = 17.34, $R^2 =$ 0.12), and offered the solution with the fewest variables ($N =$ 25). Coefficients of variable importance are illustrated in Fig. 1. The most strongly associated variable was stimulant medications, associated with lower $\%BMI_{p95}$. In terms of demographics: Hispanic ethnicity, non-White race, male sex, low income, and unmarried primary caregiver were most strongly associated with higher $\%BMI_{p95}$. The next five variables of importance were: attention problems and matrix reasoning (inversely associated with $\%BMI_{p95}$); and social problems, screen time, and reward responsiveness (positively associated with $\%BMI_{p95}$). The linear regression on the full sample ($N = 3847$) is broadly consistent with the findings from the LASSO model, with 11 variables surviving FDR-correction, including screen time as the second most significant variable ($p = 7.5 \times 10^{-8}$) after Hispanic ethnicity (online Supplementary Fig. S1). The interaction analyses did not yield improvements in model performance despite the inclusion of hundreds of additional variables.

Sex-based analysis

The same variables were tested in models stratified by sex. For girls, the LASSO model performed best in the training set ($n =$ 1271; RMSE = 15.92, $R^2 = .12$) and captured similar levels of variance in the test set ($n = 535$; RMSE = 17.18, $R^2 = 0.10$). The boys

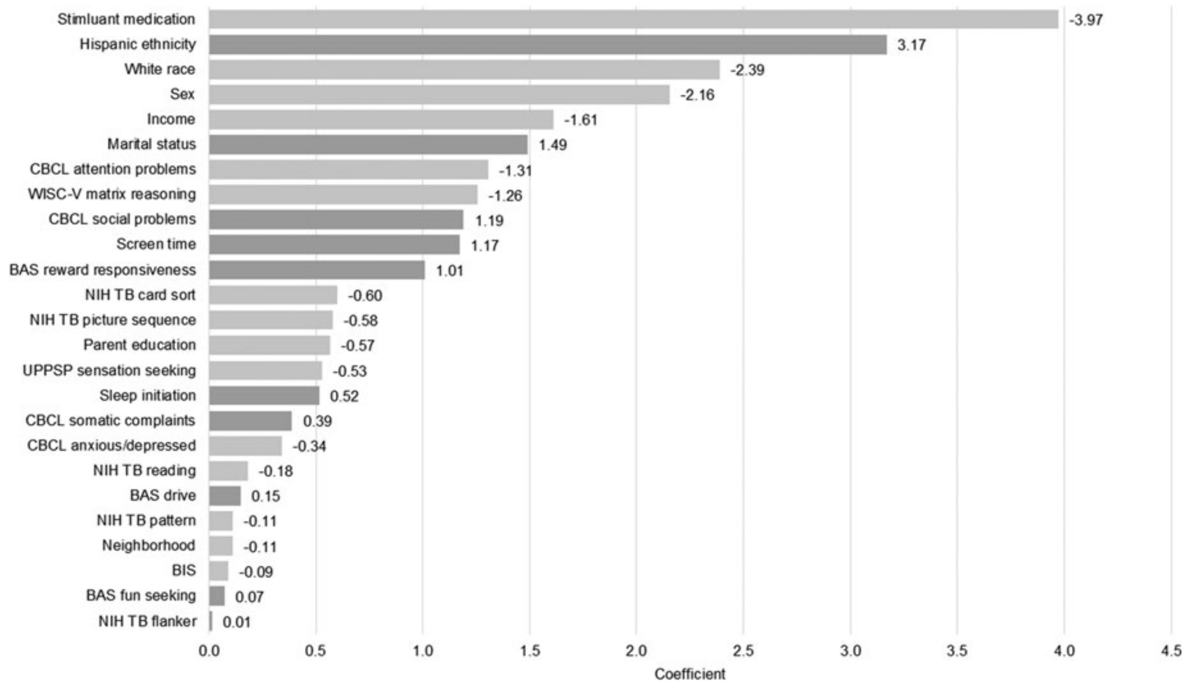

Fig. 1. Variable importance for LASSO in the full sample training set ($n = 2724$). BIS/BAS, Behavioral Avoidance/Inhibition Scales; CBCL, Child Behavior Checklist; LASSO, least absolute shrinkage, and selection operator; NIHTB, NIH Toolbox; UPPSP, Urgency, Premeditation, Perseverance, Sensation Seeking, Positive Urgency, Impulsive Behavior Scale for Children-Short Form; WISC-V, Wechsler Intelligence Scale for Children-V.

dataset was similarly divided into a 70% training ($n = 1453$) and 30% test dataset ($n = 588$). For boys, the elastic net exhibited the lowest RMSE on the training set (RMSE = 16.11, $R^2 = 0.10$) and captured similar levels of variance in the test set (RMSE = 17.44, $R^2 = 0.14$). The girls and boys models were similar with 3 of the top 5 variables shared across models (Fig. 2). Social problems and reward responsiveness exhibited particularly strong positive associations with $\%BMI_{p95}$ in the girls' model. Among the non-demographic variables, attention problems and matrix reasoning (negatively associated with $\%BMI_{p95}$), and screen time (positively associated with $\%BMI_{p95}$) again exhibited among the strongest associations with $\%BMI_{p95}$ in both models.

Exploratory minority analyses

We conducted exploratory analyses on the full samples of Hispanic ($n = 727$) and Black non-Hispanic ($n = 366$) participants as well as matching numbers of White non-Hispanic participants sampled from the training dataset. In independent *t*tests, the White non-Hispanic participants had significantly lower $\%BMI_{p95}$ than Hispanic and Black non-Hispanic participants (M $\%BMI_{p95} = 79.5$, 88.7, 91.7, respectively; $p\text{s} < 0.001$), and Hispanic participants had significantly lower $\%BMI_{p95}$ than Black non-Hispanic participants ($p < 0.05$).

The elastic net model was best in Hispanic participants, but despite a sizable sample, the model did not perform well (RMSE = 19.14, $R^2 = 0.04$), indicating that less variance was captured by the variables of interest in this group as compared to the 727 randomly selected, White, non-Hispanic participants (RMSE = 14.54, $R^2 = 0.08$). Although different levels of variance were captured across these groups, similar variables were identified as most important. In particular, stimulant medications, female sex, and matrix reasoning (negatively associated with $\%BMI_{p95}$); and unmarried primary caregiver and screen time (positively associated with $\%BMI_{p95}$), exhibited among the strongest associations in both the full sample and the Hispanic subsample (Fig. 3).

In the Black, non-Hispanic participants, the elastic net exhibited the minimum RMSE, but it captured minimal variance (RMSE = 22.30, $R^2 = 0.03$). In the model of 366 randomly selected, White, non-Hispanic participants, elastic net captured more variance (RMSE = 13.67, $R^2 = 0.08$). Nonetheless, the top most influential variables for the Black, non-Hispanic participants were stimulant medications associated with lower $\%BMI_{p95}$, Behavioral Inhibition Scale scores, and sleep initiation associated with higher $\%BMI_{p95}$, followed by matrix reasoning associated with lower $\%BMI_{p95}$ (Fig.3).

Discussion

This study used robust machine learning models on data from the first wave of the ABCD study to assess the relative importance of demographic, psychological, behavioral, and cognitive variables in simultaneous models assessing $\%BMI_{p95}$. The most strongly associated variables with $\%BMI_{p95}$ were stimulant medications (inversely associated), Hispanic ethnicity, non-White race, male sex, lower income, and unmarried caregiver. Our findings corroborate previous research indicating that Hispanic and Black youth experience the highest rates of overweight and obesity (Ogden *et al*., 2016). Beyond demographic factors, attention problems, matrix (abstract) reasoning, social problems and screen time were among the most significant correlates of $\%BMI_{p95}$ in primary analyses as well as analyses separated by sex.

The robust inverse association of stimulant medications with $\%BMI_{p95}$ suggests a protective effect of stimulants against overweight/obesity in children for whom they are indicated (i.e.

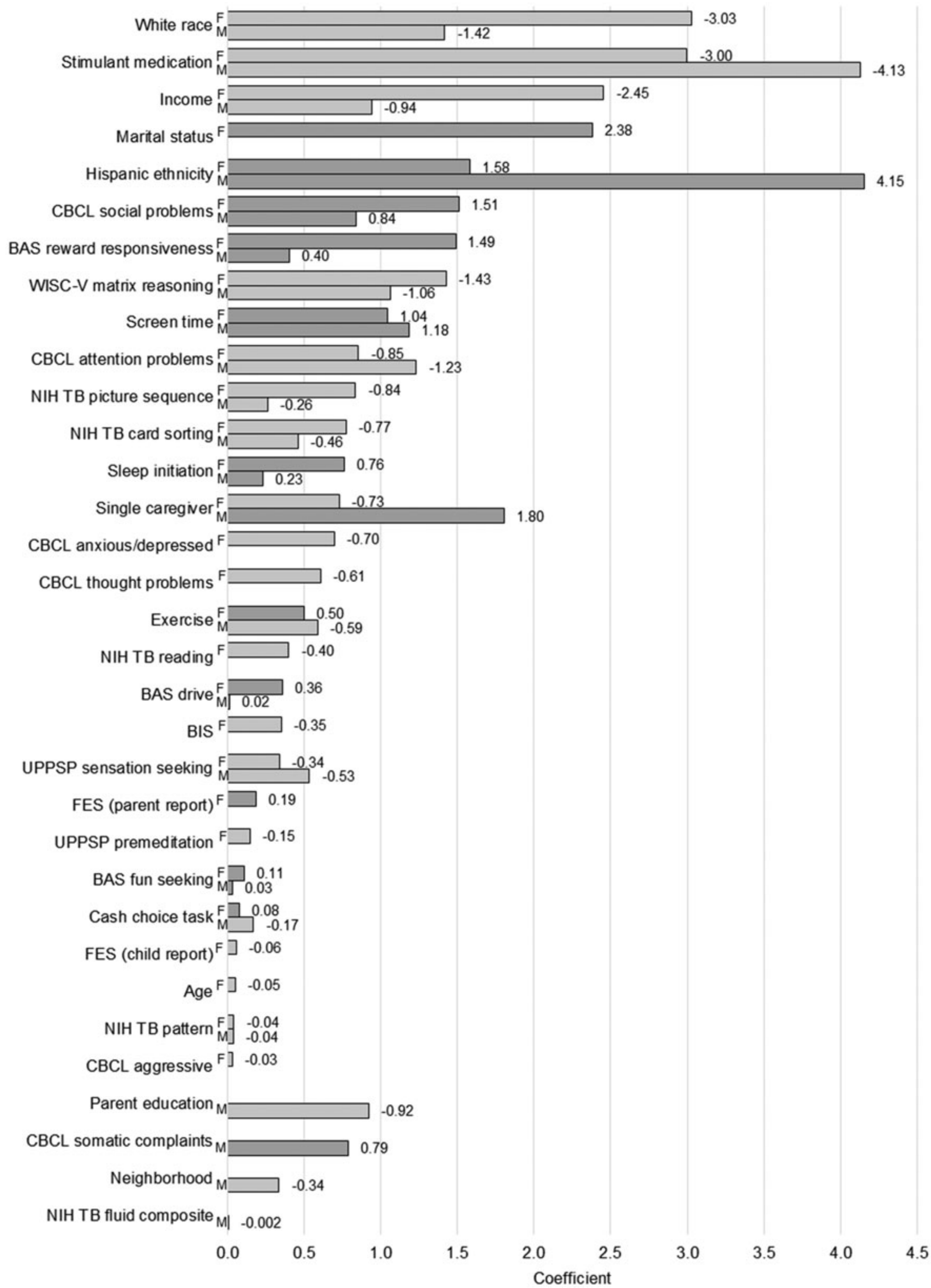

Fig. 2. Variable importance for LASSO in the female training set ($n = 1271$) and elastic net in the male training set ($n = 1453$). F, female; M, male; BIS/BAS, Behavioral Avoidance/Inhibition Scales; CBCL, Child Behavior Checklist; FES, Family Environment Scale; LASSO, least absolute shrinkage and selection operator; NIHTB, NIH Toolbox; UPPSP, Urgency, Premeditation, Perseverance, Sensation Seeking, Positive Urgency, Impulsive Behavior Scale for Children-Short Form; WISC-V, Wechsler Intelligence Scale for Children-V.

children with ADHD). Stimulants have been shown to decrease appetite, and have been used in adults to manage weight (Pilitsi *et al.*, 2019). Indeed, a recent meta-analysis found that while ADHD and obesity are typically positively related, this association becomes non-significant when controlling for pharmacological treatment (Cortese *et al.*, 2016). Furthermore, a recent

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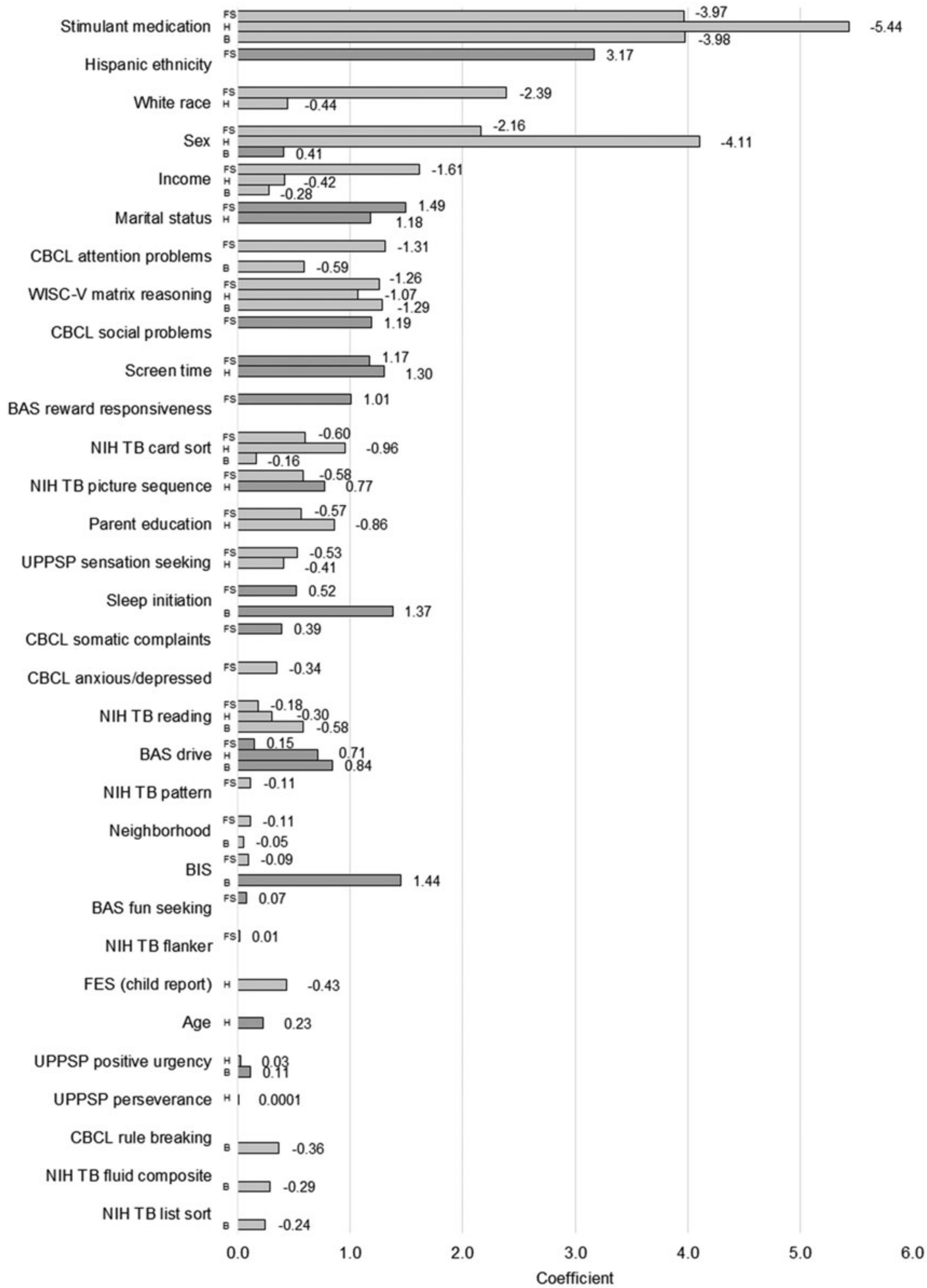

Fig.3. Variable importance for LASSO in the full sample training set ($n = 2724$) and elastic net in the full Hispanic ($n = 727$) and Black non-Hispanic ($n = 366$) subsamples. FS, full sample training set, H, Hispanic subsample, B, Black non-Hispanic subsample. BIS/BAS, Behavioral Avoidance/Inhibition Scales; CBCL, Child Behavior Checklist; FES, Family Environment Scale; LASSO, least absolute shrinkage and selection operator; NIHTB, NIH Toolbox; UPPSP, Urgency, Premeditation, Perseverance, Sensation Seeking, Positive Urgency, Impulsive Behavior Scale for Children-Short Form; WISC-V, Wechsler Intelligence Scale for Children-V.

longitudinal research study found that methylphenidate, a stimulant medication commonly used to treat attention problems, led to a reduction in BMI in children with ADHD, particularly in children who had overweight/obese status (Mellström et al., 2018). Of note, the strong inverse association between attention problems and %BMI_{p95} observed in the present study may be better accounted for by the use of stimulant medications, such that individuals with greater attention problems are also those likely to be taking more and higher dose stimulant medications; however, this was not tested in the current analyses given that we controlled for presence or absence (and not dose) of stimulants.

The robust link between social problems and %BMI_{p95}, even after accounting for relevant demographic variables, corroborates existing literature demonstrating that peer victimization, social rejection, and social deficits are associated with weight status in youth (Puhl and King, 2013). This relationship is likely bidirectional insofar as youth with high BMI are most likely to be bullied and the victims of bullying and peer rejection frequently report using food to cope with negative affect and avoiding physical activity (Puhl and Luedicke, 2012), both of which may promote excess weight gain. Findings support the further need to address peer victimization, social exclusion, and social deficits in both schools and clinical interventions (Frankel *et al*., 2007).

With regard to screen time, given it is increasing in adolescents (Bucksch *et al*., 2016) and is linked to obesity in this study and others (van Ekris *et al*., 2016), it may be beneficial for health care providers to encourage youth and primary caregivers to limit (Wu *et al*., 2016) or alter screen time to emphasize video games that incorporate physical activity (Gao *et al*., 2015).

While abstract reasoning has been studied less, a recent well-powered investigation identified an association with childhood obesity (Nghiem *et al*., 2018). Although assessments of executive functioning (e.g. Dimensional Change Card Sort) were associated with %BMI_{p95} as expected (Pearce *et al*., 2018), others which measure response inhibition, were not, and abstract reasoning was the most robust cognitive variable in all samples. Despite a growing interest in cognitive enhancement interventions, there is currently limited evidence that performance in tasks of abstract reasoning is modifiable (Melby-Lervåg *et al*., 2016). However, this possibility warrants further exploration.

The full and sex-separated samples were broadly similar in total variance accounted for and variables selected, underscoring shared risk and protective effects across sexes for the demographic, psychological, behavioral, and cognitive variables tested. For ethnicity, the best performing model captured notably less variance in Hispanic individuals than in matched White non-Hispanic individuals (4% and 8%, respectively). Although similar variables exhibited the strongest associations with %BMI_{p95} in Hispanic youth, the limited variance accounted for suggests that many of the target variables may not generalize as well to minority groups. Indeed, research indicates that early childhood dietary factors (e.g. fast food exposure, sugar-sweetened beverage intake, age of solid food exposure) may drive much of the elevated risk for obesity in minority populations (Taveras *et al*., 2013). In addition, sociocultural factors, such as minority stress (Meyer *et al*., 2008) that were not assessed in ABCD, may play a role in the development and maintenance of pediatric obesity. Likewise, with regard to the analysis in the Black non-Hispanic sample, the model captured limited variance compared to a sample of matched White non-Hispanic individuals (3% and 8%, respectively), again suggesting the worse performance of target variables in the minority sample. Nonetheless, the four variables exhibiting the strongest associations with %BMI_{p95} in Black non-Hispanic participants were stimulant medications, self-reported behavioral inhibition, sleep initiation, and abstract reasoning, suggesting some overlap with the other subsamples. The worse model performance in Hispanic and Black non-Hispanic youth are consistent with research finding that there is a multitude of unique social conditions (e.g. parental body weight, feeding practices, socioeconomic status, stress) that contribute differentially to elevated risk for obesity in minority populations (Taveras *et al*., 2013). Indeed, studies have found a reduction in the observed difference in BMI scores between racial/ethnic groups after controlling for many of the unique social conditions not measured in this study (Wang and Chen, 2011; Powell *et al*., 2012). In sum, these findings highlight the importance of prioritizing the study of relevant social conditions among minority populations, particularly those at elevated risk for unhealthy weight. Strengths of the study include the use of a large, representative healthy volunteer sample of US youth across weight strata, which enabled the simultaneous exploration of 43 variables, sub-group analyses, and generalizability of results to the larger population of US youth. Of note, analyses used the ABCD sample and thus an important future direction will be to replicate these findings in a completely independent dataset (e.g. Yarkoni and Westfall, 2017). Consistent with the open science framework (Gilmore *et al*., 2018), another strength is our inclusion of the syntax used to assemble and clean the data and analyze the results (see https://github.com/jgray7700/ABCD_BMI). As such, we have enabled other investigators to build from our findings as additional waves of data are released.

Limitations include the reliance on cross-sectional data which precludes any determination of causality. In addition, the study is limited by the lack of energy intake and objective expenditure data. Furthermore, some of the limited associations with self-report measures may be because many had questionable reliability ($\alpha < 0.7$) and assessments of delayed reward discounting and physical exercise only comprised one item and thus lacked the granularity to best assess these constructs (Prince *et al*., 2008; Koffarnus and Bickel, 2014). Analyses among the Black non-Hispanic subsample may have been underpowered due to sample size; exploring the unique model performance in Black non-Hispanic individuals and other minority groups will be an important future direction as more ABCD data are released.

Given the growing concerns regarding the replication crisis in psychology (Open Science Collaboration, 2015), it is increasingly important to enhance methodological rigor by applying robust statistical methods, making analytical syntax available, and attempting to replicate prior findings using well-powered samples as we have in this study (Tackett *et al*., 2019). The primary analyses found only 25 of the original 43 variables to be associated with %BMI_{p95}, and many of those had negligible effects. By rank-ordering by variable importance, this study helps to prioritize variables that appear to be most associated with BMI after controlling for the effects of all others. Beyond demographics and stimulant use, this study highlighted both modifiable variables that are implicated in BMI (e.g. screen time, social problems) irrespective of sex and also variables that are not particularly relevant to BMI in this sample (e.g. response inhibition, working memory), despite the findings of previous research (Pearce *et al*., 2018). Although abstract reasoning is considered refractory to intervention (Melby-Lervåg *et al*., 2016), this study also highlights its importance for future study in youth prior to adolescence. Additional prospective data are needed to understand both the distinct and collective predictive power of these behaviors for BMI gain across racial and ethnic groups.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S0033291719001545.

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Acknowledgements. Data used in the preparation of this article were obtained from the Adolescent Brain Cognitive Development (ABCD) Study (https://abcdstudy.org), held in the NIMH Data Archive (NDA). This is a multisite, longitudinal study designed to recruit more than 10 000 children age 9–10 and follow them over 10 years into early adulthood. The ABCD Study is supported by the National Institutes of Health and additional federal partners under award numbers U01DA041022, U01DA041028, U01DA041048, U01DA041089, U01DA041106, U01DA041117, U01DA041120, U01DA041134, U01DA041148, U01DA041156, U01DA041174, U24DA041123, and U24DA041147. A full list of supporters is available at https://abcdstudy.org/nih-collaborators. A listing of participating sites and a complete listing of the study investigators can be found at https://abcdstudy.org/principal-investigators.html. ABCD consortium investigators designed and implemented the study and/or provided data but did not necessarily participate in analysis or writing of this report. This manuscript reflects the views of the authors and may not reflect the opinions or views of the NIH or ABCD consortium investigators. The ABCD data repository grows and changes over time. The ABCD data used in this report came from https://dx.doi.org/10.15154/1503881. This research received no specific grant from any funding agency, commercial or not-for-profit sectors.

Conflict of interest. None.

Disclaimer. The opinions and assertions expressed herein are those of the authors and do not necessarily reflect the official policy or position of the Uniformed Services University or the Department of Defense.

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