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RESEARCH ARTICLE

Effects of the physical and social environment on youth cognitive performance

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Abstract

Individual differences in children's cognitive abilities impact life and health outcomes. What factors influence these individual differences during development? Here, we test whether children's environments predict cognitive performance, independent of well-characterized socioeconomic effects. We analyzed data from 9002 9- to 10-year olds from the Adolescent Brain Cognitive Development Study, an ongoing longitudinal study with community samples across the United States. Using youth- and caregiver-report questionnaires and national database registries (e.g., neighborhood crime, walk-ability), we defined principal components summarizing children's home, school, neighborhood, and cultural environments. In two independent samples (*ns* = 3475, 5527), environmental components explained unique variance in children's general cognitive ability, executive functioning, and learning/memory abilities. Furthermore, increased neighborhood enrichment was associated with an attenuated relationship between sociodemographics and general cognitive abilities. Thus, the environment accounts for unique variance in cognitive performance in children and should be considered along-side sociodemographic factors to better understand brain functioning and behavior across development.

KEYWORDS
cognition, development, individual differences, physical environment, social environment, socioeconomic factors

1 | INTRODUCTION

Children's cognitive abilities vary widely, and these individual differences have significant consequences for later life and health outcomes. What factors influence individual differences in cognitive performance during development? Previous research investigating the structural and social determinants of health highlights the importance of context, particularly larger sociopolitical and socioeconomic factors that may create conditions of social inequity (e.g., health-care access, discrimination and stigma, macroeconomic policies; Link & Phelan, 1995, 2001; Phelan et al., 2004). The environment is one important contextual factor that affects cognitive development through multiple pathways (Berman et al., 2019). For example, physical and psychosocial environmental factors, such as noise in the home, violence exposure, and crowding, can impact cognition across development through accumulated chronic stress (Evans & Kim, 2012; Evans & Schamberg, 2009). Conversely, exposure to natural spaces, such as parks and greenspaces, improves cognitive performance in adults (Stenfors et al., 2019) and reduces stress and attentional deficits in youth (Faber Taylor & Kuo, 2009; Wells & Evans, 2003).

Research on cognitive development highlights socioeconomic status as a related aspect of experience impacting cognitive performance. Socioeconomic status is typically characterized by caregiver educational attainment, income, and occupational prestige

(Mueller & Parcel, 1981; Sirin, 2005; White, 1982). On average, children from higher socioeconomic backgrounds show stronger language skills including phonological processing (Noble et al., 2007), have larger vocabularies (Hart & Risley, 1995), and perform better on tests of executive function (Noble et al., 2005) compared to children from lower socioeconomic backgrounds (for reviews see Duncan & Magnuson, 2012; Hackman & Farah, 2009; Pace et al., 2017; Perkins et al., 2013). Higher childhood socioeconomic status also relates to improved physical and mental health outcomes later in life (Cohen et al., 2013; Luo & Waite, 2005; Poulton et al., 2002).

Despite evidence that environmental and socioeconomic factors impact youth cognitive performance, the pathways by which they affect cognition remain unclear. One possibility is that environmental and socioeconomic factors independently impact cognition. For example, greenspace exposure improves youth working memory performance across development, even when accounting for individual and neighborhood-level socioeconomic indicators (Dadvand et al., 2015). Another non-mutually exclusive possibility is that socioeconomic factors affect the environments and resources available to families—such as childcare quality and learning environments—which in turn impact children's cognitive performance over time (Blums et al., 2017). The reverse could also be true, such that caregivers' neighborhood environments during their childhood affect the neighborhood environments and socioeconomic experiences of their children, which in turn impacts the children's cognitive abilities (Sharkey & Elwert, 2011). Finally, socioeconomic and environmental factors may have interactive effects on cognition. This is highlighted by recent research indicating adverse environments result in some positive and adaptive cognitive abilities (Frankenhuis et al., 2019; Gonzalez et al., 2019; Mittal et al., 2015; Young et al., 2018)

Recent work using the Adolescent Brain Cognitive Development[SM] (ABCD) Study (Volkow et al., 2018) sample has shown that characteristics of neighborhood environment deprivation, measured by items from the Area Deprivation Index (Singh, 2003) like percentage of neighborhood residents with a high school diploma and unemployment rate, can uniquely explain differences in behavioral measures of neurocognition, brain morphology, and resting-state functional connectivity (Hackman et al., 2021; Rakesh et al., 2021; R. L. Taylor, Cooper, et al., 2020; Vargas et al., 2020). Furthermore, measures of home and school environments appear to moderate relationships between neighborhood deprivation and resting-state functional connectivity (Rakesh et al., 2021), whereas measures of perceived neighborhood safety partially attenuate relationships between neighborhood deprivation and brain morphology (Hackman et al., 2021).

Building on these results, the current study seeks to characterize youth's home, school, neighborhood, and cultural environments using both database-derived and self-report measures of these environments. We then test the independent and interactive effects of these physical and social environmental factors on youth cognitive performance using data from 9002 U.S. 9- to 10-year olds participating in the ABCD Study. To this end, we first derived summary measures of each child's sociodemographics and home, school, neighborhood, and cultural environments. We next used linear mixed-effects modeling to test whether these summary measures predict three previously published dimensions of neurocognition in development: general cognitive ability, executive function, and learning and memory (Thompson et al., 2019; Figure 1). Our results replicate reported relationships between socioeconomic indicators and cognitive achievement. Importantly, they also demonstrate that children's home, school, neighborhood, and cultural environments explain significant variance in dimensions of cognition even when controlling for sociodemographic factors. Together these findings support predictions that physical and social environments play a key role in individual differences in children's cognitive performance, independently of and interactively with sociodemographic factors.

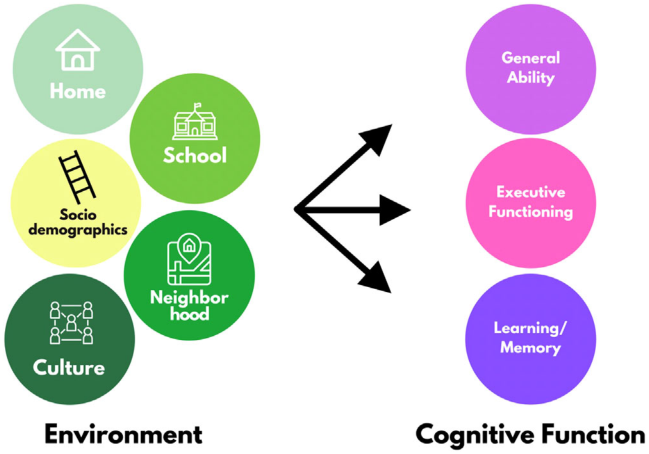

FIGURE 1 Schematic for modeled relationships between sociodemographic, environmental, and cognitive performance factors

2 | METHODS

2.1 | The ABCD Study sample

The ABCD Study® is a 10-year, 22-site longitudinal study of neurocognitive development launched in September 2016 (Luciana et al., 2018). The current participant sample includes 11,875 U.S. children from different geographic, demographic, and socioeconomic backgrounds (Garavan et al., 2018). Data collection, which began when children were 9–10 years old, includes behavioral assessments, interviews, questionnaires, biosample collection, and MRI scans (Casey et al., 2018). Ethics oversight for the ABCD Study is administered by the University of California, San Diego Institutional Review Board. Secondary analysis of these data was approved by the University of Chicago Institutional Review Board.

Here, we analyzed cognitive, sociodemographic, and environmental data collected during the baseline (i.e., Year 1) study visit. Data were downloaded from the curated Study 817: Adolescent Brain Cognitive Development DEAP Study release 2.0.1 update (DOI 10.15154/1506087) hosted by the National Institute of Mental Health Data Archive (nda.nih.gov). We present results from 9002 participants with no missing environmental or sociodemographic variables, which are described in detail below. We elected to include complete-case data to help prevent biased estimates because some measures from the ABCD sample are not missing at random (Rosenberg et al., 2020). Descriptive statistics for our study subsample are summarized in Tables 1 and 2. Variable names from the Study 817 curated dataset are presented in Table S1.

2.1.1 | Discovery and replication samples

To test the replicability and robustness of our results, we performed all analyses in two completely independent groups of participants: a discovery sample of data included in ABCD curated Release 1.1 ($n = 3475$) and a replication sample of unique data included in Release 2.0.1 ($n = 5527$).

2.2 | Demographic data

Participants' age (rounded to chronological month and then converted to years), sex, race, and ethnicity were collected from caregiver self-report questionnaires. Sex, race, and ethnicity were retrieved from two curated ABCD data files: the ABCD Parent Demographics Survey and the American Community Survey Post Stratification Weights data file. On the Parent Demographics Survey, each child's primary (i.e., participating) caregiver indicated the sex their child was assigned at birth on their original birth certificate. Caregivers reported the race and ethnicity they considered their child to be, which was available in the American Community Survey Post Stratification Weights file (ABCD curated data file acspsw03.txt) as five categories that are consistent across multiple data sources and socioeconomic constructs: non-Hispanic white, non-Hispanic Black, Hispanic, non-Hispanic Asian, and other. Participants' race and ethnicity were included in our analyses as an indirect measure of the underlying structural factors that confer advantages and disadvantages for different racial and ethnic groups in the United States.

2.3 | Socioeconomic data

Socioeconomic variables included yearly income and education level. Each child's primary caregiver selected their total yearly household income from the following categories: less than \$5000; \$5000–\$11,999; \$12,000–\$15,999; \$16,000–\$24,999; \$25,000–\$34,999; \$35,000–\$49,999; \$50,000–\$74,999; \$75,000–\$99,999; \$100,000–\$199,999; and \$200,000 or greater. For each income category, we reassigned the values to the median of the range, except for the two categories without an explicit start or endpoint (less than \$5,000 and \$200,000 or greater). These two income categories were recoded as 5000 and 200,000, respectively.

Primary caregivers also reported the highest level of education received, ranging from *none/kindergarten* to *professional school degree* (e.g., JD, PhD, MD). When applicable, the participating caregiver also reported their partner's highest level of education. (In questions presented to caregivers, the ABCD Study® describes a partner as "any significant figure in your life that helps you in raising your child or has helped you for more than 2 years" and "should be involved in 40% or more of the daily activities your child does.") We used a continuous measure of caregiver education, the maximum number of years of education completed by either the primary caregiver or the caregiver's partner, which reflects the economic and cultural capital of the caregivers (Bourdieu, 1986; Reay, 2004).

2.4 | Environmental data

To characterize children's physical and social environments, we divided environmental measures (caregiver-and youth-report questionnaires and national database information) into four hypothesis-driven categories: (1) neighborhood environment, (2) home environment, (3) school environment, and (4) cultural environment. Measures for these four categories are described below, along with reliability estimates where available. For all environmental measures, we only used data reported for children's primary addresses (i.e., address 1). All available environmental measures, including questionnaires completed by both caregivers and children, were included in the analyses[1]. We grouped measures into these four categories based on work suggesting their importance in cognitive development and their potential role as protective factors for experiences of adversity, threat, and deprivation (Henry et al., 2019; Zolkoski & Bullock, 2012; Zucker et al., 2018).

2.4.1 | Home environment

The home environment category includes four subscale scores from caregiver and youth reports of familial dynamics. These include the following:

- One youth and one caregiver report on the Conflict subscale of the **Family Environment Scales** (modified from PhenX; Moos & Moos, 1994) on openly expressed family conflict in the home. In a subset of the ABCD Study cohort, reliability for this measure was moderate for both youth (Cronbach's $\alpha = 0.68$) and their caregivers (Cronbach's $\alpha = 0.63$; Zucker et al., 2018).
- One youth report for the Parent Monitoring subscale of the **Parental Monitoring Survey** (Karoly et al., 2016; Stattin & Kerr, 2000), which assesses the degree to which caregivers keep track of their

[1] Caregiver- and youth-reported data were included to maximize the measures used to characterize different aspects of the environment and allow for multiple informants for a given environmental feature, potentially mitigating lower reliability in youth-reported measures (Barch et al., 2018; Karcher & Barch, 2021; Zucker et al., 2018). Excluding either caregiver- or youth-reported measures in instances where both were available would create discrepancies in the informant for each category. For example, if caregiver-report measures were excluded, the cultural environment component would be derived from caregiver questionnaires and home, school, and neighborhood environment components would be derived from youth questionnaires.

children's whereabouts inside and outside the home. Reliability for the Parental Monitoring survey in a subset of the ABCD cohort was low (Cronbach's $\alpha = 0.44$; Zucker et al., 2018).
- One youth report for the Parent Acceptance subscale from the **Child Report of Parenting Behavior Inventory—Short** (CRPBI; Schaefer, 1965), which assesses youth perceptions of caregivers' warmth, acceptance, and responsiveness. Reliability for the Parent Acceptance subscale of the CRPBI in a subset of the ABCD cohort was acceptable (Cronbach's $\alpha = 0.71$; Zucker et al., 2018).

2.4.2 | School environment

The school environment category includes the School Environment, School Involvement, and School Disengagement subscales of the **School Risk and Protective Factors Survey** derived from the Communities That Care (CTC) Youth Survey (Arthur et al., 2007). This youth-report questionnaire assesses children's attitudes toward school, relationships with educators, and class engagement. Reliability was moderate for the School Environment (Cronbach's $\alpha = 0.60$) and School Involvement (Cronbach's $\alpha = 0.64$) subscales and poor for the School Disengagement subscale (Cronbach's $\alpha = 0.21$; Zucker et al., 2018).

2.4.3 | Neighborhood environment

The neighborhood environment category includes 30 variables assessing physical, social, and structural neighborhood characteristics, including air pollution, walkability, crime, neighborhood-level resource availability, median socioeconomic status of the neighborhood, and youth and caregiver perceptions of neighborhood safety. Variables were taken from the youth- and caregiver-report surveys as well as national database registries to provide both subjective and objective measures of children's experiences in their neighborhood environments.

Youth- and caregiver-reports

For all self-report questionnaires, neighborhoods were defined as the area within a 20-min walk from the child's place of residence. Caregiver and youth report measures include the following:

- The **Neighborhood Safety/Crime Caregiver Survey**, which provides subjective assessments of neighborhood safety and crime. A summary score is obtained from responses on three questions related to: (1) how safe their neighborhood is to walk in, (2) how safe their neighborhood is from crime, and (3) whether violence is a problem in their neighborhood.
- The **Neighborhood Safety/Crime Youth Survey** is a shortened version of the Caregiver Survey, where youth only report whether their neighborhood is safe from crime.

Ratings were reliable for both the caregiver and youth Neighborhood Safety/Crime survey (Cronbach's $\alpha = 0.87$; Zucker et al., 2018).

National database statistics

For variables from national database registries, neighborhoods were defined based on census tracts. The ABCD Consortium obtained residential data by linking caregivers' reported addresses to federal digital archives at the census-tract level (Fan et al., 2021). Residential data were aggregated at the level of census tracts, as they are originally designed to be homogeneous with respect to population characteristics, economic status, and living conditions (U.S. Bureau of the Census, 1992).

- **Residential density** and national **walkability** indices were sourced from the Environmental Protection Agency (EPA).
- **Proximity to roads** was derived from the US Geological Survey North America Atlas for Roads up to 2013 (U.S. Geological Survey, 2014) and reflects the proximity of a participant's residential address to major roads and highways in meters.
- Uniform **crime reports** including county-level data, 2010–2012 averages for adult violent crimes, drug abuse violations, drug sales, marijuana sales, drug possession charges, and driving under the influence charges were compiled by the Inter-University Consortium for Political and Social Research from FBI data.
- **Area deprivation indices** from the American Community Survey include 2011–2015 averages for education, employment, income, and housing statistics at census tract resolution (Kind et al., 2014; Singh, 2003).
- Estimates of 2009–2011 **nitrogen dioxide (NO_2) pollution** at 100 km^2 resolution (Geddes et al., 2016, 2017; https://doi.org/10.7927/H4JW8BTT) and 2012 **atmospheric particulate matter with a diameter less than 2.5 micrometers (i.e., PM 2.5)** at 100 km^2 resolution (van Donkelaar et al., 2016, 2018; https://doi.org/10.7927/H4ZK5DQS) were taken from NASA's Socioeconomic Data and Applications Center.

2.4.4 | Cultural environment

The cultural environment category includes seven measures of family values and connection to one's ethnic identity. At the ABCD baseline data collection session, the cultural measures used here were only collected from caregivers. Some youth measures will be administered in subsequent data collection sessions.

- Five subscales of the **ABCD Mexican American Cultural Values Scale Modified** (caregiver-report; adapted from Knight et al., 2010) measuring aspects of familism such as feelings of obligation toward one's family (*family obligation*), using family as a reference to define one's self (*family as referent*), *family support*, *degree of independence and self-reliance* (reverse-coded), and *religion*. While the Mexican American Cultural Values Scale was developed to assess Mexican–American cultural values, previous work suggests that these subscales are useful to describe family values from multiple cultural, racial, and ethnic identities (Zucker et al., 2018). Reliability in a subset of the ABCD cohort was high for family obligation (Cronbach's

$\alpha = 0.70$), family as referent (Cronbach's $\alpha = 0.78$), family support (Cronbach's $\alpha = 0.80$), and religion (Cronbach's $\alpha = 0.97$) subscales, and was moderate for the degree of independence and self-reliance subscale (Cronbach's $\alpha = 0.61$; Zucker et al., 2018).

- Two subscales of the **Multi-Ethnic Identity Measure–Revised** (caregiver-report; Phinney & Ong, 2007; Zucker et al., 2018) characterizing *caregiver's personal exploration* and *commitment* to the self-reported ethnic identity. Reliability for the combined subscales was high (Cronbach's $\alpha = 0.90$; Zucker et al., 2018).

Additional scales assessing cultural values and beliefs, the PhenX Acculturation Survey and Vancouver Index of Acculturation—Short Survey, were not included in this analysis due to the frequency of missing data (>30%).

2.5 | Sociodemographic and environmental principal components

To reduce the dimensionality of the sociodemographic and environmental data, we applied principal components analysis (PCA) to sociodemographic measures and to each environmental category separately. This allowed us to combine a data-driven dimensionality reduction approach with our hypothesis-driven category definitions. To this end, we submitted sociodemographic, home, school, neighborhood, and cultural environmental data to five separate PCAs using the FactoMineR package in R (Lê et al., 2008). Data were *z*-scored and PCAs were performed separately for the discovery and replication samples. We retained the first principal component (which accounts for the most variance across all variables) from each PCA, and regressed age and sex variables from participant loadings for each. The resulting residuals were used in all subsequent analyses.

Participant component scores for neighborhood and cultural environment factors were reverse-sored (i.e., multiplied by −1) for subsequent analyses so that higher loadings reflected more enriched environments for all environmental principal components (PCs). For the neighborhood environmental factors, this corresponds to higher community-level resource availability and lower disparity for the neighborhood environment factor. Higher loadings for the cultural environment factor correspond to greater cultural familism (a multifaceted value emphasizing close family relationships and prioritizing family needs over the self) and social embeddedness.

2.6 | Cognitive dimensions

The ABCD Study measures children's cognitive performance with 15 tasks completed inside and outside the MRI scanner (detailed in Casey et al., 2018; Luciana et al., 2018; Rosenberg et al., 2020). These tasks assess distinct but related aspects of cognitive performance including attention, memory, fluid intelligence, language skills, processing speed, and visuospatial reasoning (Rosenberg et al., 2020).

Here, we operationalized cognitive performance with three PCs relating to independent dimensions of neurocognition reported in a previous analysis of baseline ABCD data (Thompson et al., 2019). Specifically, Thompson et al. applied Bayesian Probabilistic Principal Component Analysis (BPPCA; Bishop, 1999; Tipping & Bishop, 1999) to nine of the 11 behavioral (i.e., out-of-scanner) cognitive measures with low missingness. These included the seven tasks from the NIH Toolbox cognition battery (List Sorting Working Memory Test, Picture Vocabulary Test, Flanker Task, Dimensional Change Card Sort Task, Pattern Comparison Processing Speed Test, Picture Sequence Memory Test, and Oral Reading Recognition Task; Weintraub et al., 2013), the Rey Auditory Verbal Learning Test (RAVLT; Luciana et al., 2018), and the Little Man Task (Acker & Acker, 1982). The three BPPCA components include (a) general cognitive ability, which explained 21% of the variance in performance across all tasks and had the strongest loadings for the Picture Vocabulary and Oral Reading Recognition tasks, (b) executive functioning, which explained 20% of the variance and had the strongest loadings for the Flanker, Dimensional Change Card Sort, and Pattern Comparison Processing Speed tasks, and (c) learning/memory, which explained 18% of the variance and had the strongest loadings for the Picture Sequence Memory test and total number correct for the RAVLT. BPPCA component weights for each participant were made available with the ABCD curated data release 2.0.1.

2.7 | Mixed-effects models

Mixed-effects modeling was implemented to characterize how sociodemographic and environmental PCs were related to cognitive performance at age 9–10. Specifically, we included the sociodemographic PC and the four environmental PCs—home, school, neighborhood, and cultural—as predictors in a linear mixed-effects model for each of the three cognitive components. Fixed main effects for sociodemographic characteristics and environmental factors measured the direct relationships to cognitive component scores, and two-way fixed effect interactions measured the interactive effect of sociodemographic characteristics with each environmental factor on cognitive component scores. For each model, intercepts for study site and family were included as random effects to account for differences in cognitive performance attributed to site-level differences in study populations and biases associated with including data from multiple children from the same family and environment. The three mixed-effects models were expressed as

$$
\begin{aligned}
\text{Cog PC} = {} & \beta_0 + \beta_1(\text{Sociodemo PC}) + \beta_2(\text{Home PC}) + \beta_3(\text{School PC}) \\
& + \beta_4(\text{Neighborhood PC}) + \beta_5(\text{Culture PC}) \\
& + \beta_6(\text{Sociodemo PC} \times \text{Home PC}) \\
& + \beta_7(\text{Sociodemo PC} \times \text{School PC}) \\
& + \beta_8(\text{Sociodemo PC} \times \text{Neighborhood PC}) \\
& + \beta_9(\text{Sociodemo PC} \times \text{Culture PC}) + (1|\text{site}) + (1|\text{family}) + \varepsilon
\end{aligned}
$$

where $\beta_{1\text{-}9}$ terms correspond to estimates of fixed main effects and two-way interaction effects for sociodemographic and environmental components, and (1|site) and (1|family) correspond to the random effects of study site and family.

Analyses were conducted using the lme4 and lmerTest packages in R (Bates et al., 2015; Kuznetsova et al., 2017). Models were optimized using the limited-memory Broyden–Fletcher–Goldfarb–Shanno algorithm (Byrd et al., 1995) with the Optimx package (Nash & Varadhan, 2011).

3 | RESULTS

3.1 | Descriptive statistics

Mean and standard deviations for each environmental, sociodemographic, and cognitive variable are reported in Table 1 for discovery and replication samples. Descriptive statistics for the Full ABCD sample (Release 1.1, Release 2.0.1, and excluded participants) as well as the complete case sample (Release 1.1. and Release 2.0.1) are reported in Table S2. Variable counts and percentages for categorical variables are reported in Table 2. Missingness for each variable is reported in Tables S3 and S4. Distributions of environmental, sociodemographic, and cognitive variables across discovery and replication samples are visualized as histograms in Figures S1–S6.

3.2 | Correlations between sociodemographic, environmental, and cognitive variables

As a first step to characterize relationships between sociodemographic factors, environmental variables, and cognitive dimensions (general ability, executive function, and learning/memory), we performed Spearman rank correlations between all pairs of variables. Correlations were performed in the discovery and replication samples separately to assess the consistency of relationships (Figure 2). We do not report corresponding *p*-values for this analysis because our goal was to visualize the overall pattern of relationships between measures rather than to evaluate the statistical significance of any particular pairwise relationship, and effect sizes as small as approximately $r^2 = 0.00043$ would be statistically significant given our large sample size of 9002.

Results reveal that, in general, within-environmental-category correlations are numerically stronger than between-environmental-category correlations, providing support for the hypothesis-driven groupings. Furthermore, the three cognitive performance dimensions were positively correlated with one another (*r*-values: 0.16–0.34), replicating previous relationships reported by Thompson et al. (2019). General cognitive ability, executive functioning, and learning/memory component scores were also related to environmental variables across all four categories (*r*-values: −0.31 to 0.32).

Replicating previous findings in this sample (Alnæs et al., 2020), socioeconomic indicators, including caregiver income and education, were positively associated with cognitive performance. Racial and ethnic identity was also related to cognitive performance, such that markers of structural advantage associated with non-Hispanic white identities positively correlated with general cognitive ability, executive functioning, and learning/memory component scores.

3.3 | Principal component analysis of sociodemographic and environmental variables

We applied principal components analysis to sociodemographic and environmental data from the discovery and replication samples separately to define latent variables and assess their robustness (Figure 3).

In both the discovery and replication samples, the first principal component of the seven sociodemographic variables reflected aspects of relative structural advantage in the United States, such as non-Hispanic white racial identities, and levels of income and education strongly load positively alongside negative contributions from non-Hispanic Black and Hispanic/Latinx racial and ethnic identities (Figure 3). This component explained 33.19% of the variance for sociodemographic variables in the discovery sample and 33.20% of the variance in the replication sample.

The first principal component of the home environment variables reflected aspects of familial cohesion and parental involvement, with positive loadings for Parental Acceptance and Parental Monitoring subscale scores and negative loadings for Family Conflict Youth Report measure. The first principal component of the school environment variables reflects student immersion and enrichment, with positive loadings for school involvement and school environment measures and a negative loading for school disengagement. The first principal component of the neighborhood environment variables was related to area resource scarcity, with positive loadings for census tract-level poverty rates and income disparity and negative loadings for median family income, rates of home ownership, and education levels at or above a high school diploma. The first principal component for the cultural environment variables is largely dominated by contributions from the Family as Referent, Family Obligation, and Family Support subscales, which are coded such that lower scores were related to putting members of one's family first and trying to support other members and higher scores were related to self-oriented, individualistic ideals. These familial cultural values align with ideas of social embeddedness. Interpretations for environmental components and their variable loadings are detailed in the Supporting Information.

For subsequent analyses, participants' neighborhood component scores were multiplied by negative one, such that more positive scores correspond to more enriched environments. Participants' cultural environment component scores were also multiplied by negative one, such that more positive scores reflect more socially embedded cultural environments rather than individualistic cultural environments.

The first principal component of each environmental category is highly consistent in the discovery and replication samples. Pearson correlations of variable loadings for corresponding discovery and replication sample PCs were highly robust, *r*-values = 0.99 (all $p < .002$, two tailed). The home environment first principal component explained

TABLE 1 Descriptive statistics for sociodemographic, environmental, and cognitive variables in discovery (Release 1.1) and replication (Release 2.0.1) samples, as well as the full Adolescent Brain Cognitive Development (ABCD) sample. Variables that were log transformed prior to data analysis include a parenthetical “log” label. Mean and standard deviation are reported for each continuous variable

Variable	Discovery (Release 1.1) *M* (SD)	Replication (Release 2.0.1) *M* (SD)	Full ABCD Sample (Release 1.1, Release 2.0.1, and excluded participants) *M* (SD)
Sociodemographics			
Age	10.01 (0.61)	9.86 (0.63)	9.91 (0.62)
Household Income	$104,320.43 ($60,389.19)	$95,890.36 ($62,452.19)	$97,435.71 ($62,177.15)
Caregiver Education (years)	17.09 (2.42)	16.69 (2.68)	16.60 (2.77)
Home Environment			
FES – Family Conflict – Parent	2.45 (1.87)	2.56 (2.02)	2.54 (1.96)
Parent Monitoring – Parent Monitoring	4.42 (0.48)	4.38 (0.52)	4.38 (0.52)
FES – Family Conflict – Youth	1.94 (1.90)	2.08 (1.99)	2.05 (1.95)
CRPBI – Parent Acceptance	2.80 (0.29)	2.78 (0.30)	2.78 (0.30)
School Environment			
SRPF – School Environment	19.96 (2.74)	19.94 (2.79)	19.93 (2.83)
SRPF – School Involvement	13.15 (2.28)	13.04 (2.36)	13.06 (2.37)
SRPF – School Disengagement	3.67 (1.40)	3.76 (1.47)	3.74 (1.46)
Cultural Environment			
MEIM – Ethnic Identity Exploration	2.81 (1.01)	2.88 (1.04)	2.83 (1.03)
MEIM – Ethnic Identity Commitment	2.48 (0.89)	2.53 (0.92)	2.50 (0.91)
MACV – Family Obligation	3.59 (0.65)	3.62 (0.66)	3.63 (0.66)
MACV – Family as Referent	3.33 (0.77)	3.37 (0.77)	3.38 (0.78)
MACV – Family Support	4.12 (0.61)	4.17 (0.60)	4.16 (0.61)
MACV – Independence/Self Reliance	3.55 (0.60)	3.53 (0.61)	3.56 (0.62)
MACV – Religion	3.22 (1.43)	3.35 (1.42)	3.35 (1.41)
Cognitive Measures			
NIH Toolbox Pic Vocab	86.01 (7.97)	84.28 (8.01)	84.45 (8.12)
NIH Toolbox Flanker	95.01 (8.70)	93.86 (9.03)	94.00 (9.14)
NIH Toolbox List Sorting	98.60 (11.12)	96.42 (12.30)	96.64 (12.09)
NIH Toolbox Card Sort	93.80 (8.98)	92.32 (9.51)	92.52 (9.51)
NIH Toolbox Pattern Recognition	89.10 (14.25)	87.68 (14.56)	88.06 (14.59)
NIH Toolbox Picture	103.95 (11.93)	102.80 (12.05)	102.81 (12.07)
NIH Toolbox Reading	91.72 (6.52)	90.87 (6.91)	90.85 (6.91)
RAVLT	45.47 (9.76)	43.95 (10.04)	44.14 (10.00)
Little Man	0.60 (0.17)	0.59 (0.17)	0.59 (0.17)
Neighborhood Environment			
Participant Questionnaire			
Neighborhood Safety – Parent	4.01 (0.91)	3.87 (0.97)	3.89 (0.98)
Neighborhood Safety – Youth	4.12 (1.04)	4.02 (1.09)	4.02 (1.10)
Geocoded Data			
Walkability	10.40 (4.02)	10.73 (4.06)	10.65 (4.06)
NO_2 Exposure (2009–2011)	2.37 (1.59)	2.42 (1.62)	2.45 (1.67)
PM2.5 Exposure (2012)	7.42 (2.54)	7.51 (2.59)	7.53 (2.57)

(Continues)

TABLE 1 (Continued)

Variable	Discovery (Release 1.1) *M* (SD)	Replication (Release 2.0.1) *M* (SD)	Full ABCD Sample (Release 1.1, Release 2.0.1, and excluded participants) *M* (SD)
Proximity to Roads (log)	6.61 (1.15)	6.58 (1.11)	6.59 (1.12)
Residential Density (log)	1.25 (0.76)	1.26 (0.74)	1.28 (0.76)
FBI Crime Statistics			
Violent Crime Rate (log)	6.13 (2.54)	6.25 (2.59)	6.27 (2.60)
Drug Abuse Rate (log)	7.11 (2.67)	7.25 (2.76)	7.24 (2.75)
Drug Sales Rate (log)	5.50 (2.27)	5.56 (2.36)	5.59 (2.36)
Drug Possession Rate (log)	6.90 (2.63)	7.06 (2.72)	7.05 (2.71)
DUI Rate (log)	6.98 (2.56)	7.04 (2.65)	7.06 (2.64)
Marijuana Sales Rate (log)	4.60 (2.06)	4.62 (2.10)	4.66 (2.10)
Census Tract Data			
Education < HS (%)	4.27 (6.03)	4.81 (6.61)	4.95 (6.90)
Education – HS Diploma (%)	89.72 (10.18)	88.32 (11.34)	88.17 (11.62)
Occupation– White Collar (%)	93.79 (4.00)	93.76 (4.47)	93.70 (4.46)
Median Family Income	$81,129.16 ($35,587.90)	$76,093.47 ($36,149.43)	$76,523.30 ($36,183.45)
Income Disparity Index	1.96 (1.19)	2.15 (1.38)	2.14 (1.35)
Median Home Value	$273,989.80 ($188,320.39)	$254,057.60 ($176,911.05)	$260,068.51 ($183,934.74)
Median Gross Rent	$1,112.16 ($381.05)	$1,090.83 ($398.40)	$1,092.68 ($391.14)
Median Monthly Mortgage	$1,486.78 ($594.27)	$1,427.08 ($598.62)	$1,438.79 ($604.92)
Home Ownership (%)	67.41 (21.59)	65.69 (22.57)	65.20 (22.75)
Unemployed (%)	8.11 (4.81)	9.20 (6.32)	9.07 (6.06)
Families in Poverty (%)	9.55 (9.60)	11.77 (12.57)	11.60 (12.26)
Families Below 138% Pov. Line (%)	18.84 (13.85)	21.47 (16.63)	21.33 (16.30)
Single/Not Married (%)	15.93 (10.37)	18.35 (13.41)	18.09 (12.93)
No Car Owned (%, log)	7.49 (9.60)	9.09 (11.70)	9.03 (11.64)
No Telephone in Home (%, log)	2.01 (2.06)	2.20 (2.39)	2.17 (2.30)
No Plumbing in Home (%, log)	0.29 (0.65)	0.31 (0.71)	0.31 (0.70)
Overcrowding (%)	3.24 (5.73)	3.54 (6.03)	3.69 (6.37)

41.14% of the variance in the discovery sample and 41.10% of the variance in the replication sample. The school environment first principal component explained 64.55% of the variance in the discovery sample and 64.34% of the variance in the replication sample. The neighborhood first principal component explained 28.02% of the variance in the discovery sample and 30.98% of the variance in the replication sample[2]. The cultural environment first principal component explained 43.40% of the variance in the discovery sample and 42.80% of the variance in the replication sample.

We further assessed the robustness of these principal component decompositions by projecting participant data from the discovery and the replication samples onto the other group's feature space and correlating the resulting PC scores across participants. Participant scores were highly correlated across original and projected PC weights (r-values > 0.99; Figure 4).

Reliability for caregiver- and youth-reports comprising the environmental components varied across measures (Cronbach's αs = 0.21–0.90). To confirm that environmental components were robust to the inclusion of relatively less reliable variables, we recomputed components after excluding measures with $\alpha < 0.70$, or in cases where all reliability scores were below $\alpha = 0.70$, the subscale with the lowest α. For the home environment, we excluded the Parent Monitoring subscale from the Parental Monitoring Survey (Cronbach's $\alpha = 0.44$). For the school environment, we excluded the School Disengagement subscale (Cronbach's $\alpha = 0.21$) from the School Risk and Protective Factors Survey. For the cultural environment, we excluded the independence and self-reliance subscale (Cronbach's $\alpha = 0.61$) of the ABCD

[2] The first neighborhood principal component may explain less variance in the neighborhood measures than the first home, school, and cultural environment principal components explain in their respective measures because the neighborhood environment category includes database statistics and questionnaire responses, whereas the other categories only include questionnaire responses. Thus, the neighborhood environment variables may reflect multiple, heterogeneous aspects of experience.

TABLE 2 Descriptive statistics for categorical variables in the discovery (Release 1.1) and replication (Release 2.0.1) samples, as well as the full Adolescent Brain Cognitive Development (ABCD) sample. Counts and percentage of sample for each value are reported

Variable	Discovery (Release 1.1) *n* (%)	Replication (Release 2.0.1) *n* (%)	Full ABCD Sample (Release 1.1, Release 2.0.1, and excluded participants) *n* (%)
ABCD site			
Site 01	87 (2.5)	162 (2.9)	405 (3.4)
Site 02	189 (5.4)	272 (4.9)	559 (4.7)
Site 03	207 (6.0)	264 (4.8)	631 (5.3)
Site 04	232 (6.7)	328 (5.9)	743 (6.3)
Site 05	89 (2.6)	205 (3.7)	378 (3.2)
Site 06	185 (5.3)	290 (5.2)	584 (4.9)
Site 07	0 (0.0)	263 (4.8)	339 (2.9)
Site 08	112 (3.2)	175 (3.2)	351 (3.0)
Site 09	110 (3.2)	215 (3.9)	433 (3.6)
Site 10	199 (5.7)	333 (6.0)	740 (6.2)
Site 11	99 (2.8)	267 (4.8)	450 (3.8)
Site 12	85 (2.4)	337 (6.1)	604 (5.1)
Site 13	245 (7.1)	342 (6.2)	728 (6.1)
Site 14	259 (7.5)	264 (4.8)	606 (5.1)
Site 15	113 (3.3)	195 (3.5)	458 (3.9)
Site 16	342 (9.8)	515 (9.3)	1011 (8.5)
Site 17	208 (6.0)	235 (4.3)	579 (4.9)
Site 18	113 (3.3)	229 (4.1)	384 (3.2)
Site 19	177 (5.1)	116 (2.1)	550 (4.6)
Site 20	214 (6.2)	342 (6.2)	707 (6.0)
Site 21	185 (5.3)	178 (3.2)	599 (5.0)
Site 22	25 (0.7)	0 (0.0)	36 (0.3)
Sex			
Female	1648 (47.4)	2652 (48.0)	6687 (47.9)
Male	1827 (52.6)	2875(52.0)	6188 (52.1)
Race/ethnicity			
Non-Hispanic white	2120 (61.0)	2847 (51.5)	6174 (52.1)
Non-Hispanic Black	322 (9.3)	883 (16.0)	1779 (15.0)
Hispanic	646 (18.6)	1085 (19.6)	2407 (20.3)
Non-Hispanic Asian	71 (2.0)	119 (2.2)	252 (2.1)
Other	316 (9.1)	593 (10.7)	1245 (10.5)

Mexican American Cultural Values Scale. Variable loadings for the reliability-selective home, school, and cultural environment components are shown in Figure S7. See Table S6 for more detail and Pearson correlations between variable loadings for these reliability-selective components and the original components. All reliability-selective components were significantly correlated with their corresponding original components (Pearson's *r*s = 0.88–0.99) in both the discovery and replication samples. Thus, components are robust to the inclusion of relatively less reliable environmental measures.

The discovery and replication samples could include data from different participants from the same ABCD data collection site. To ensure that results replicated across independent data collection sites (which differed in their target sociodemographics; Garavan et al., 2018), we compared the consistency of the sociodemographic and environmental PCs across different subsamples of the full ABCD baseline sample. To this end, we randomly split the 22 study sites into two groups 100 times and compared the consistency of the sociodemographic and environment PCs across the split halves (Table S7, Figure S8). Across all splits, the first principal component explained approximately 41.06% of the variance for home environment variables, 64.43% of the variance for school environment variables, 31.01% of the variance for neighborhood environment variables, and 43.00% of the variance for cultural

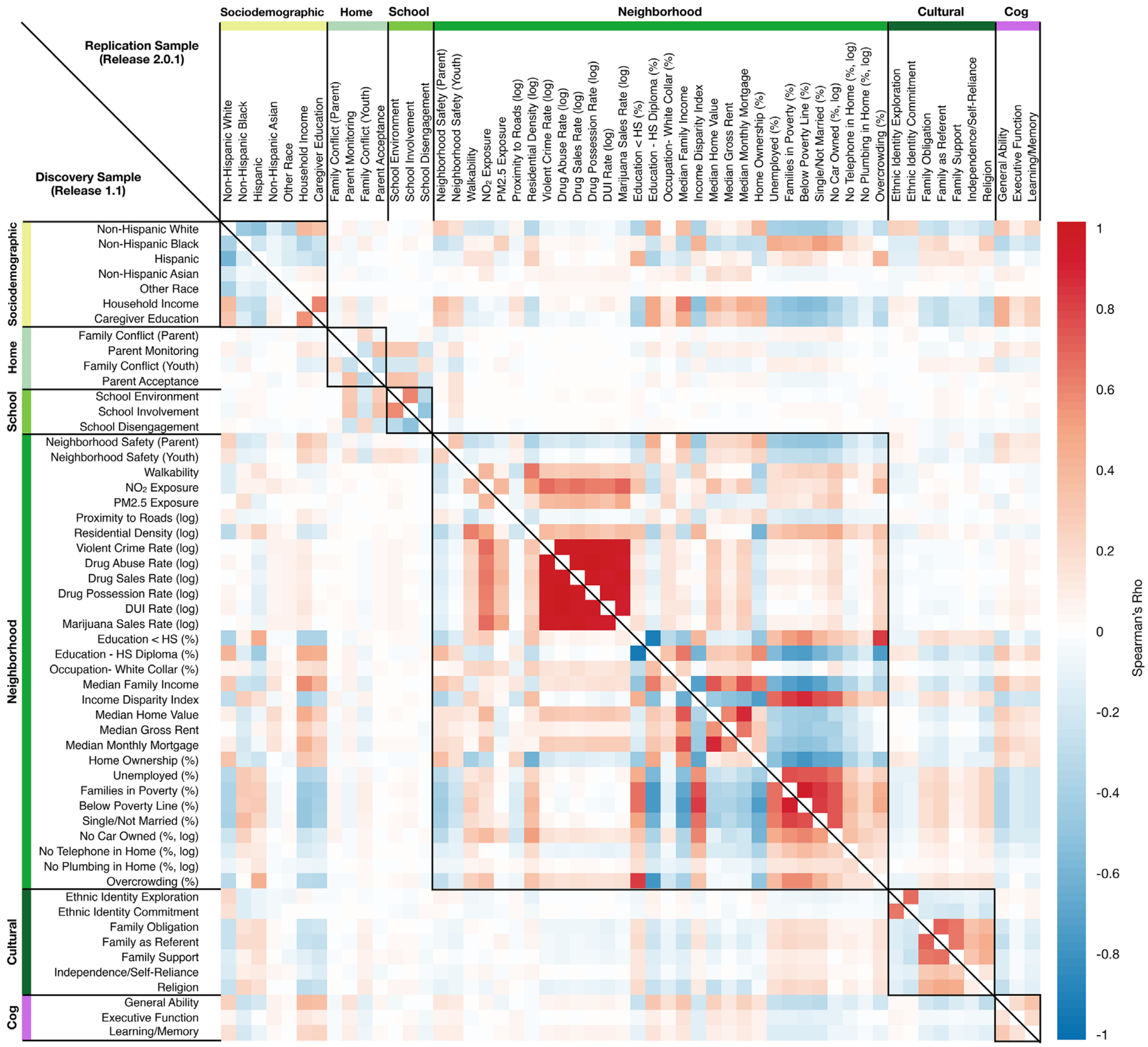

FIGURE 2 Correlation matrix relating sociodemographic variables, environmental variables, and cognitive Bayesian Probabilistic Principal Component Analyses (BPPCAs) across Release 1.1 and Release 2.0.1. Variables that were log transformed prior to data analysis include a parenthetical "log" label. Spearman correlations for Release 1.1 data are plotted in the lower triangle, and Spearman correlations for Release 2.0.1 are plotted in the upper triangle. Variables are clustered by category

environment variables. The first principal component across site splits for the sociodemographic variables explained 33.31% of the variance.

As a final robustness check, we compared the consistency of the sociodemographic and environmental PCs in two independent subsamples of the full ABCD baseline sample that were matched for study site, age, sex ethnicity, grade, highest level of parental education, handedness, combined family income, exposure to anesthesia, and family-relatedness. The matched groups used for these sensitivity analyses are part of the Study 3165: DCAN Labs ABCD-BIDS MRI Pipeline Inputs and Derivatives, available from the National Institute of Mental Health Data Archive (https://nda.nih.gov/edit_collection.html?id = 3165). Variable contributions to the first components for each sociodemographic and environment PC across matched groups are visualized in Figure S9. Demonstrating that components are consistent in independent matched groups of ABCD participants, variable loadings for each sociodemographic and environment component across matched groups were significantly correlated (r-values > 0.97; Table S10).

3.4 | Cognitive components

We operationalized cognitive performance using Bayesian PCA weights, published by Thompson et al. (2019), for three dimensions of

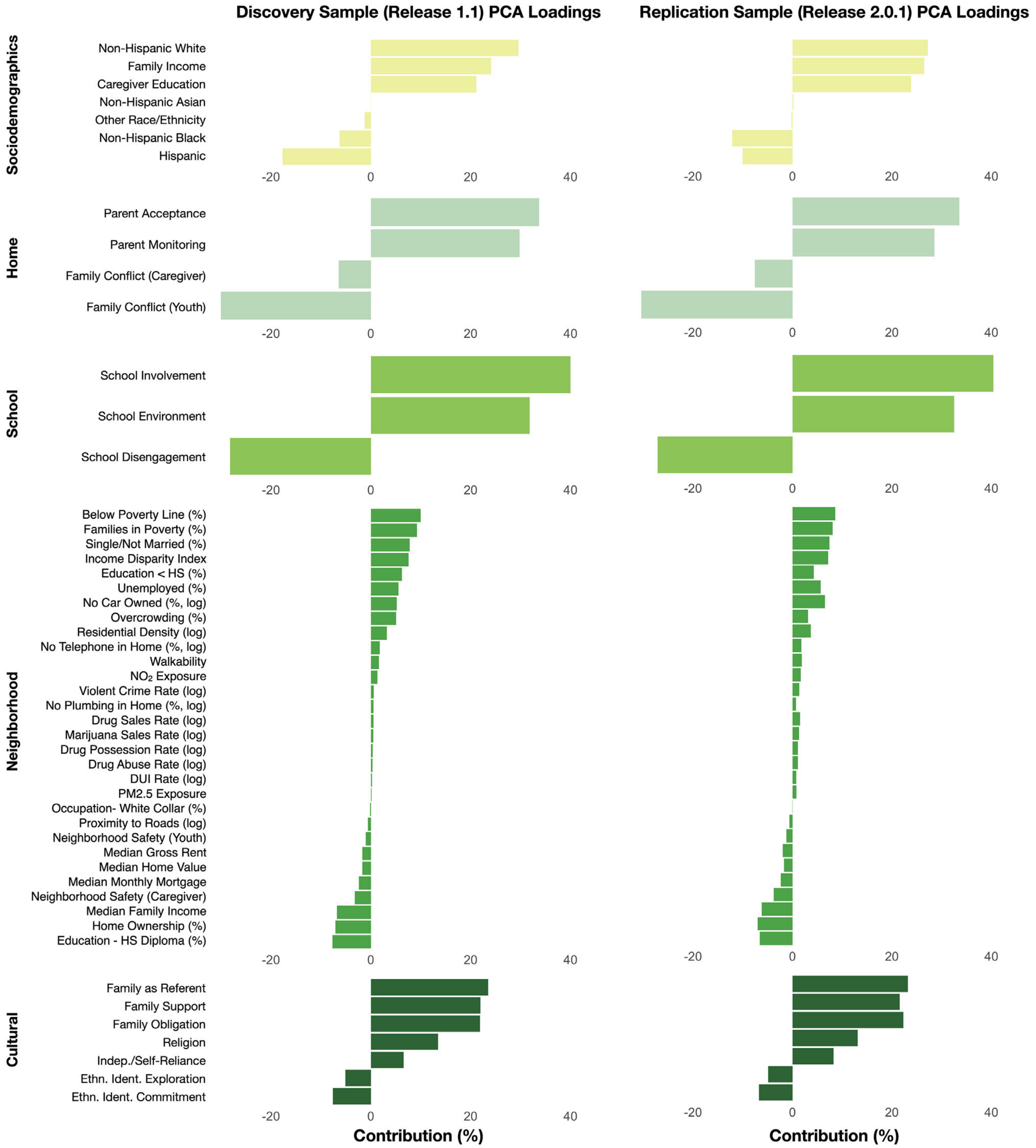

FIGURE 3 Variable contributions for the home, school, neighborhood, and cultural environment principal components (PCs) and sociodemographic PC. PCA was conducted on the discovery (Release 1.1; left) and replication (Release 2.0.1; right) samples separately. Variable contributions are plotted for both discovery and replication samples in the order of the percent contribution for the discovery sample PCs for comparison. Variables that were log transformed prior to data analysis include a parenthetical "log" label. Positive and negative contribution values reflect the sign of the variable weighting for the principal component. Variable loading scores are reported in Table S5

cognitive ability: general cognitive ability, executive functioning, and learning/memory. To confirm that these components are consistent in our complete-case subsample of the full ABCD baseline cohort, we compared participant weights from the first three dimensions of a PCA using the same nine cognitive variables previously used in the BPPCA analysis. Participant weights for all three cognitive components, general cognitive ability, executive functioning, and learning/memory, were positively correlated with participant weights from components identified in our replication PCA ($r_s = 0.67–0.76$; Table S11).

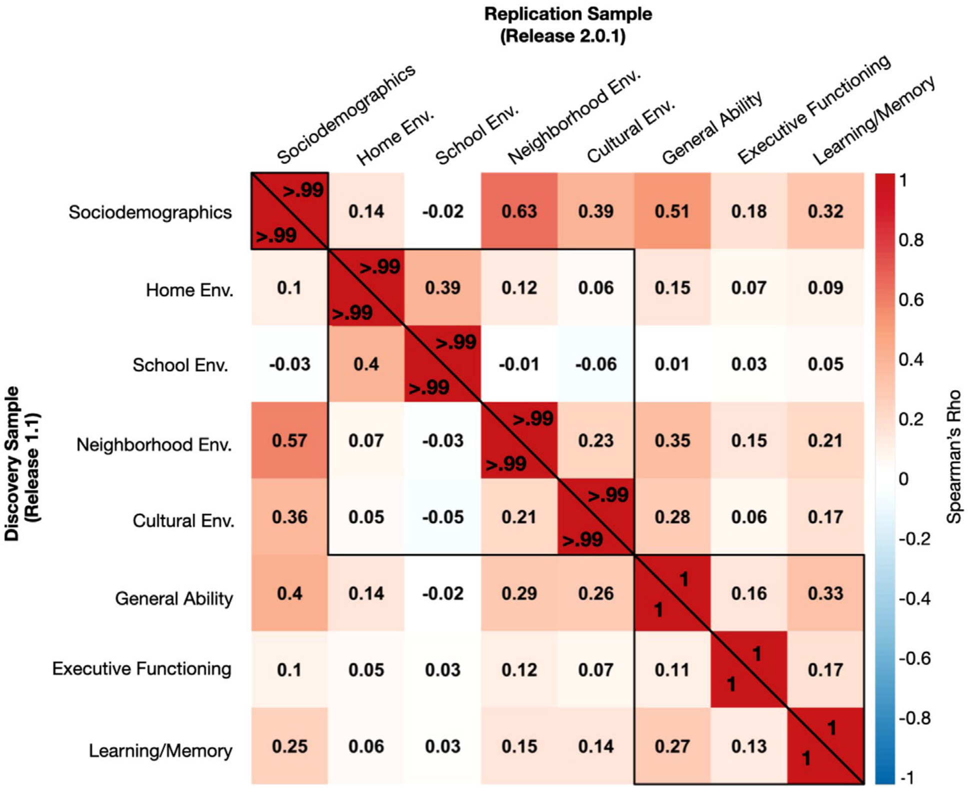

FIGURE 4 Spearman rank correlations between sociodemographic and environmental principal components (PCs) and cognitive performance Bayesian Probabilistic Principal Components (BPPCs) across discovery (Release 1.1) and replication (Release 2.0.1) samples. Relationships in Release 1.1 data are plotted in the lower triangle, and correlations for Release 2.0.1 are plotted in the upper triangle. Participant weights for cultural and neighborhood environmental components are reverse coded such that higher scores reflect more enriched environments. Correlation coefficients along the diagonal reflect consistency of participants' principal component scores generated from PCs calculated in different data releases. For example, the lower triangle in a cell along the diagonal represents the correlation between Release 1.1 participants' component scores generated from the Release 1.1 and Release 2.0.1. Cognitive PCs (general ability, executive functioning, and learning/memory) were defined in previous work, so each participant only has one component score per cognitive PC

3.5 | Correlations between sociodemographic, environmental, and cognitive principal components

We Spearman rank-correlated the loadings of the sociodemographic PC, the four environmental PCs, and three cognitive performance PCs (i.e., rather than correlating their constituent variables) for the discovery and replication samples separately (Figure 4) to assess the degree to which they are similar. Across discovery and replication samples, the strongest correlation between any two environmental components was $r = 0.40$, again suggesting that our hypothesis-driven categories capture distinct but related facets of the environment. The two most strongly correlated components are the home and school environment PCs, indicating that aspects of the home environment are highly related to perceptions of school engagement and support. The neighborhood and cultural environment components were also positively correlated (r-values $\sim$0.22), demonstrating relationships between community-level education, income, and resource availability and cultural familism and social embeddedness.

Briefly, the sociodemographic component is most strongly related to the neighborhood and cultural environment components and the general cognitive ability and learning/memory performance components. This provides preliminary evidence that sociodemographic measures are related to different aspects of the physical and social environment as well as to cognitive performance. In addition, neighborhood and cultural environment PCs are, numerically, most strongly related to the general cognitive ability component, suggesting that community-level neighborhood characteristics and cultural familial values are related to broad cognitive functioning.

3.6 | Mixed-effects linear models

Do sociodemographic and environmental components explain unique variance in different aspects of cognition? To address this question, we conducted individual mixed-effects models for each cognitive dimension, including the sociodemographic and environmental components and their interactions as predictors, with study site and family modeled as random effects.

We ran three mixed-effects models to ask whether home, school, neighborhood, and cultural environments and sociodemographic characteristics explain unique variance in general cognitive ability, executive functioning, and learning/memory for the discovery and replication

TABLE 3 Overview of mixed-effects model results for separate general ability, executive functioning, and learning/memory models. Significant effects from each two-tailed test (Type III comparisons) that replicated across Release 1.1 and Release 2.0.1 samples are indicated with a dot

	General ability	Executive function	Learning/memory
Sociodemographics	●		●
Home	●		
School			●
Neighborhood	●	●	
Cultural	●		●
Sociodemo × Home			
Sociodemo × School			
Sociodemo × Neighborhood	●		
Sociodemo × Cultural			

samples separately (Tables 3 and 4). (Note that all mixed-effects model results replicate when using natural log transformed income data for the sociodemographic component, as demonstrated in Table S8.)

The sociodemographic factor was significantly related to general cognitive ability and learning/memory in both the discovery and replication samples. However, sociodemographics did not replicate as a predictor of executive functioning across samples. These results highlight the way in which socioeconomic and racial factors that relate to relative privilege (i.e., higher socioeconomic status [SES]) are associated with better performance on cognitive measures reflecting general cognitive ability and learning/memory.

The home environment PC was related to increased general cognitive ability across discovery and replication samples, such that an increase in parental acceptance and involvement is related to higher cognitive measure scores related to general cognitive ability. School environment factors, such as school involvement and positive youth perception of the school environment, were related to higher learning/memory scores. Neighborhood environmental factors, such as increases in neighborhood-level resource availability and decreases in disparity, were related to higher general cognitive ability and executive functioning scores. The cultural environment factor was related to general cognitive ability and learning/memory components, such that an increase in cultural familism and social embeddedness was associated with higher cognitive performance scores for these components. Importantly, all of these effects reflect independent contributions of each factor and significance for each effect is not determined sequentially (i.e., all variance is partitioned simultaneously).

There was a significant interaction effect for sociodemographic and neighborhood factors that replicated across samples for the model predicting general cognitive ability. For youth living in more enriched neighborhoods, indicated by higher neighborhood environment component scores, there was a weaker relationship between sociodemographics and general cognitive ability scores. Conversely, for youth living in less enriched neighborhoods, there was a stronger relationship between increased sociodemographics and general cognitive ability scores. The interaction effect for neighborhood and sociodemographic factors on the general cognitive ability component are plotted for discovery and replication samples in Figure 5, and observed values for neighborhood environment, sociodemographic, and general cognitive ability components are plotted in Figure S10.

We fit the same three mixed-effects models using the Study 3165 matched groups (https://nda.nih.gov/edit_collection.html?id = 3165) as a robustness check for the observed results. All significant effects in both the discovery (Release 1.1) and replication (Release 2.0.1) samples replicated in matched groups 1 and 2. In addition, the sociodemographic component predicted higher executive functioning scores in the matched group mixed-effects models. Results from the matched group mixed-effects models are shown in Table S9.

4 | DISCUSSION

Are children's physical and social environments related to their cognitive performance, even when controlling for socioeconomic indicators? We asked this question using data from a heterogeneous sample of 9002 9- to 10-year olds from the ABCD study. Specifically, we characterized relationships between sociodemographic factors, aspects of children's physical and social environments, and three dimensions of cognitive performance. We first used principal components analysis to generate summary scores of children's sociodemographics and their home, school, neighborhood, and cultural environments. We next built mixed-effects linear models to predict each cognitive component from the sociodemographic and environmental components and their interactions. Results revealed that—in two independent subsets of the ABCD Study sample—children's neighborhood environments were related to general cognitive ability and executive functioning, whereas cultural environments were related to general cognitive ability and learning and memory abilities, even when controlling for socioeconomic indicators. Additionally, children's home environments related to their general cognitive ability, and their school environments are related to their learning and memory abilities. Overall, these results suggest that distinct aspects of the environment are related to distinct aspects of children's cognition.

Enriched home environments, greater neighborhood resource availability with lower disparity, and greater cultural familial values and social embeddedness were associated with stronger general

TABLE 4 Summary table for general cognitive ability, executive functioning, and learning/memory mixed-effects models. Statistics for each model are reported for both Release 1.1 and Release 2.0.1 samples. Random effect variance and standard deviations are reported underneath. Significant effects for each discovery and replication model were determined by two-tailed tests (Type III comparisons) and are bolded. Significant effects that replicated across discovery and replication samples are underlined. Marginal and conditional R-square values for each mixed-effect model were calculated using the MuMIn package in R (Bartón, 2020) and are reported underneath the random effects statistics. Marginal R-square values reflect the variance explained by the fixed effects (R^2_{fixed}), and conditional R-square values reflect the variance explained by both fixed and random effects ($R^2_{fixed} + R^2_{random}$). Replication across discovery and replication samples demonstrates the reliability of effects. Cohen's F-square statistics were calculated using the multilevelTools package (Wiley, 2020) for fixed effects and overall models as an estimate of effect size (Selya et al., 2012). For these effect size estimates, F-square reflects the relative change in R-square between a full model and a model with the fixed effect removed (c.f. Conley et al., 2020). Marginal (F^2_{fixed}) effect sizes for each fixed effect are shown alongside the model estimates. For the overall model, marginal (F^2_{fixed}) and conditional ($F^2_{fixed} + F^2_{random}$) effect sizes are shown at the bottom of the table

	General ability								Executive function								Learning/memory							
	Release 1.1				Release 2.0.1				Release 1.1				Release 2.0.1				Release 1.1				Release 2.0.1			
Model estimates	Estimated	SE	*p*	Cohen's F^2	Estimated	SE	*p*	Cohen's F^2	Estimated	SE	*p*	Cohen's F^2	Estimated	SE	*p*	Cohen's F^2	Estimated	SE	*p*	Cohen's F^2	Estimated	SE	*p*	Cohen's F^2
Intercept	0.057	0.037	.15	–	0.042	0.029	.15	–	−0.009	0.034	.81	–	0.011	0.045	.81	–	0.007	0.022	.74	–	−0.012	0.025	.63	–
Sociodemo	**0.131**	**0.010**	**<.001**	**0.074**	**0.203**	**0.008**	**<.001**	**0.133**	0.017	0.011	.13	0.001	**0.061**	**0.010**	**<.001**	0.009	**0.093**	**0.010**	**<.001**	**0.033**	**0.121**	**0.009**	**<.001**	**0.046**
Home	**0.054**	**0.009**	**<.001**	**0.010**	**0.035**	**0.007**	**<.001**	**0.005**	0.015	0.010	.16	0.001	0.006	0.008	.45	<0.001	0.007	0.009	0.48	<0.001	0.011	0.007	.16	<0.001
School	−0.015	0.008	.07	0.001	0.003	0.006	.62	<−0.001	0.010	0.009	.29	<0.001	**0.018**	**0.008**	**.02**	0.001	**0.018**	**0.008**	**.03**	**0.001**	**0.023**	**0.007**	**<.001**	**0.002**
Neighborhood	**0.016**	**0.006**	**.003**	**0.005**	**0.011**	**0.005**	**.02**	**0.003**	**0.021**	**0.006**	**<0.001**	**0.005**	**0.021**	**0.005**	**<.001**	**0.005**	−0.003	0.006	.54	<−0.001	0.007	0.005	.13	0.001
Cultural	**0.048**	**0.007**	**<.001**	**0.020**	**0.044**	**0.006**	**<.001**	**0.014**	0.014	0.008	0.09	0.001	<0.001	0.006	.89	<0.001	**0.025**	**0.007**	**<.001**	**0.005**	**0.027**	**0.006**	**<.001**	**0.005**
Sociodemo × Home	−0.001	0.006	.81	<−0.001	−0.002	0.005	.60	<0.001	−0.008	0.007	0.23	<0.001	<0.001	0.005	.89	<0.001	0.005	0.006	.46	<0.001	0.005	0.005	.28	<0.001
Sociodemo × School	0.008	0.005	.14	<0.001	0.006	0.004	.14	0.001	0.008	0.006	0.17	<0.001	0.002	0.005	.64	<0.001	−0.004	0.005	.51	<0.001	<−0.001	0.004	.83	<−0.001
Sociodemo × Neighborhood	**−0.009**	**0.003**	**<.001**	**0.002**	**−0.009**	**0.002**	**<.001**	**0.003**	0.006	0.003	0.06	0.001	−0.003	0.002	.28	<0.001	**−0.005**	**0.003**	**.049**	<0.001	<−0.001	0.002	.98	<−0.001
Sociodemo × Cultural	<0.001	0.004	.88	<0.001	0.002	0.003	.47	<0.001	−0.009	0.005	0.07	0.001	−0.001	0.004	.70	<0.001	0.001	0.004	.79	<−0.001	<0.001	0.004	.97	<−0.001
Random effects	Variance		SD		Variance		SD		Variance		SD		Variance		SD		Variance		SD		Variance		SD	
Family	0.262		0.512		0.277		0.527		0.291		0.540		0.304		0.552		0.283		0.532		0.293		0.542	
Study site	0.025		0.158		0.014		0.120		0.019		0.139		0.038		0.196		0.006		0.077		0.010		0.098	
Residual	0.134		0.366		0.122		0.349		0.206		0.454		0.217		0.466		0.138		0.371		0.135		0.367	
Model variance explained	R^2_{fixed}		$R^2_{fixed} + R^2_{random}$		R^2_{fixed}		$R^2_{fixed} + R^2_{random}$		R^2_{fixed}		$R^2_{fixed} + R^2_{random}$		R^2_{fixed}		$R^2_{fixed} + R^2_{random}$		R^2_{fixed}		$R^2_{fixed} + R^2_{random}$		R^2_{fixed}		$R^2_{fixed} + R^2_{random}$	
R^2	0.185		0.741		0.274		0.787		0.016		0.607		0.040		0.627		0.064		0.698		0.104		0.724	
Model effect size	F^2_{fixed}		$F^2_{fixed} + F^2_{random}$		F^2_{fixed}		$F^2_{fixed} + F^2_{random}$		F^2_{fixed}		$F^2_{fixed} + F^2_{random}$		F^2_{fixed}		$F^2_{fixed} + F^2_{random}$		F^2_{fixed}		$F^2_{fixed} + F^2_{random}$		F^2_{fixed}		$F^2_{fixed} + F^2_{random}$	
Cohen's F^2	0.229		2.850		0.379		3.681		0.017		1.538		0.042		1.674		0.068		2.302		0.116		2.617	

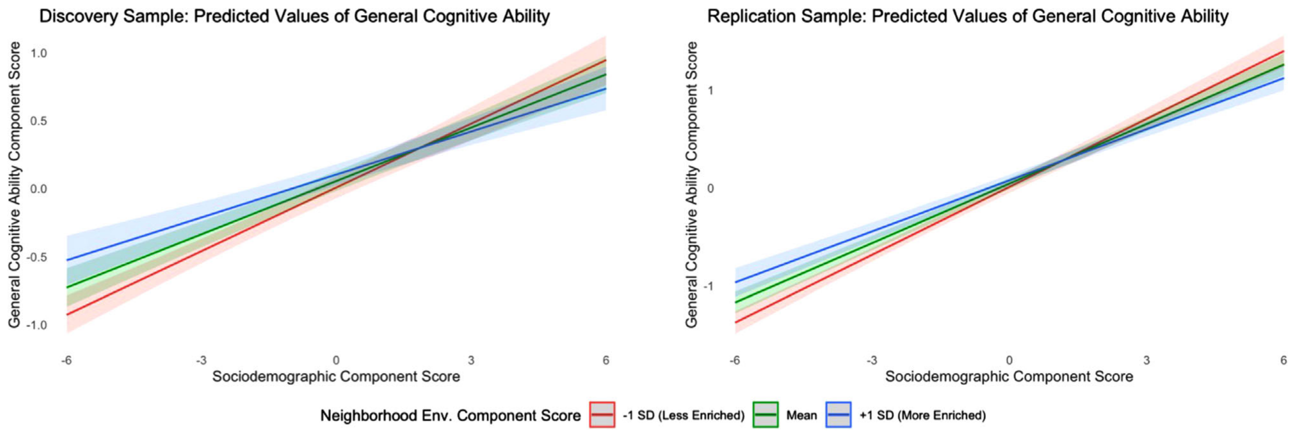

FIGURE 5 Neighborhood environment × sociodemographics interaction effects for general cognitive ability in the discovery and replication sample. Specifically, for youth in more enriched neighborhood environments (blue line), there is a decreasing relationship between sociodemographic scores and general cognitive ability component scores. General cognitive ability, neighborhood environment, and sociodemographic components are residualized for age and sex

cognitive performance. Neighborhood factors were also related to executive functioning, and school and cultural factors were related to learning/memory ability. The interaction between neighborhood and sociodemographic factors was also significantly related to general cognitive ability, where increased neighborhood environment enrichment diminished the relationship between sociodemographic characteristics and general cognitive ability. This result highlights the potential for additional interactive or indirect relationships between environments, sociodemographics, and youth cognitive performance.

The current results align with work highlighting connections between environments and socioeconomic status and their effects on cognition (Blums et al., 2017). Specifically in the ABCD sample, greater neighborhood disadvantage is related to lower cognitive performance on six of the seven NIH Toolbox cognitive measures (Flanker, List Sorting Working Memory, Dimensional Change Card Sort, Oral Reading Recognition, Pattern Comparison Processing Speed, and Picture Vocabulary) and neurally, lower gross cortical and subcortical surface area and volume (Hackman et al., 2021). Furthermore, Hackman et al. (2021) found that associations between neighborhood disadvantage and brain morphometry were partially attenuated by caregiver and child perceptions of neighborhood safety, demonstrating pathways by which subjective experience may buffer against structural disadvantage factors. The neighborhood environment component used in our analyses incorporated both database-derived (e.g., census tract measures) and self-report neighborhood measures, providing opportunity for longitudinal examination of the relative contributions of subjective experience and database-derived quantifications to the component across future data release waves. Complementary analyses of the ABCD sample revealed that home and school environment factors moderated relationships between neighborhood disadvantage and resting-state functional connectivity (Rakesh et al., 2021), suggesting that positive personal and interpersonal experiences (e.g., parental acceptance) may also buffer against community-level structural markers of disadvantage (e.g., community violence, neighborhood unemployment level). The unique contributions of home, school, neighborhood, and cultural environment factors to cognitive performance in our mixed-effects models also demonstrate the unique influence of multiple environmental contexts. Future work can explore how enrichment across multiple environment types affect and interact with socioeconomic factors to promote healthy cognitive development.

Our results also complement research on the importance of physical environments for cognitive performance. For example, youth experience reduced stress and attention deficits after exposure to natural greenspace settings (Amoly et al., 2014; Corraliza et al., 2012; Faber Taylor & Kuo, 2009; Wells & Evans, 2003). Natural interventions, such as creating green space and increasing greenspace access, may additionally foster greater positive impact in neighborhoods with higher resource deprivation (Mitchell et al., 2015). This is especially compelling since natural spaces are more commonly found in neighborhoods with higher median socioeconomic characteristics (Dai, 2011; Wolch et al., 2014). Enriched neighborhood greenspaces can also benefit cardiometabolic indicators of allostatic load and cognition across the lifespan (Amoly et al., 2014; Corraliza et al., 2012; Kardan et al., 2015). Furthermore, adolescent cognitive performance improves with neighborhood access to public parks and trees, partially due to reduced air pollution (Dadvand et al., 2015). Although greenspace data are not currently available in the ABCD Study, we demonstrate the importance of neighborhood environments on general cognitive ability and learning and memory during development. The interaction between the neighborhood environment and sociodemographic components in the general cognitive ability model complements this work, where the decreased impact of sociodemographics on cognitive performance in more enriched neighborhoods emphasizes the potential protective role of neighborhood environments against experiences of adversity, threat, and/or deprivation.

Importantly, our findings provide correlational—not causal—evidence of associations between children's environments and their cognitive performance. They do, however, complement existing research on the efficacy of social environment interventions focused on healthy cognitive development. We report a positive relationship between the cultural environment component and children's general cognitive ability and learning/memory scores. This echoes prior work demonstrating community social embeddedness protects against adverse effects of neighborhood disadvantage (May et al., 2018; Witherspoon & Ennett, 2011), buffers stress in youth across racial and ethnic identities (Corona et al., 2017), and improves prosocial behaviors and academic achievement (Smith et al., 2019). In addition, the observed positive relationships between immersed and enriched school environments and learning/memory scores align with social intervention efforts, such as youth after school programs targeting socioemotional learning, which improve social connectedness, school engagement, and academic performance (Durlak et al., 2010).

The current findings replicate across large, independent samples of children and complement existing work in developmental, cognitive, and social psychology. As with many big-data studies, however, they are limited by the reliability of available data. The ABCD data used to generate the four environment components were largely derived from youth and caregiver measures (DOI 10.15154/1506087). These instruments vary in reliability, affecting the reliability of the reported environmental components. Youth-reported measures such as the School Disengagement subscale of the School Risk and Protective Factors Survey (Cronbach's $\alpha = 0.21$) and the Parent Monitoring subscale of the Parental Monitoring Survey (Cronbach's $\alpha = 0.44$) were the least reliable but still successfully predicted youth characteristics in initial analyses performed by the Culture and Environment Working Group, who developed the battery for the ABCD protocol (Zucker et al., 2018). Lower reliability for youth-reported cultural and environmental variables is to be expected within this age range (Boyd et al., 1997; Zucker et al., 2018). Importantly, however, our analyses demonstrated that the home, school, and cultural environment components replicated across multiple independent subsamples of the ABCD cohort and were robust to the removal and the inclusion of the least reliable measures comprising each component. In other words, the least reliable measures were not adding noise to our predictions and actually contained predictive and replicable signal despite their lower reliability. In addition, many neighborhood environment variables were derived from geocoded measures at the census tract-level. Spatial smoothing that occurs at the coarse scale of the census tract may conflate neighborhood-aggregated characteristics with the actual lived experiences of caregivers and youth, which assumes relative homogeneity across the census tract. These conflations may in part account for the lower variance in cognitive scores explained by the first neighborhood environment component compared to the other environmental components. Despite these limitations of the neighborhood environment measures, the relationship between the neighborhood environment component and general cognitive ability and executive functioning scores—and the interaction between the neighborhood environment and sociodemographic components—are robust, replicating across completely independent subsamples of the ABCD Study data. Thus, observed relationships (and lack thereof) and modeling results may be driven not only ground truth relationships between environments and cognition, but also by the reliability and variance for these measures.

Prior work suggests that socioeconomic factors can impact resource availability, which in turn affects executive functioning and language skills (Blums et al., 2017). However, here, we find that sociodemographics as well as home and cultural environmental factors predict general cognitive ability rather than executive functioning. Although one potential explanation for this pattern of results is that executive functioning measures have uniformly low reliability, we do not observe evidence for that here. Rather, previous work demonstrates that test-retest reliability for the NIH Toolbox tasks with the strongest component weights for the executive functioning BPPC—the Dimensional Change Card Sort Task (intraclass correlation coefficients [ICC] = 0.42–0.92), the Pattern Comparison Processing Speed Test (ICC = 0.51–0.84), and the Flanker Task (ICC = 0.32–0.52)—ranges from poor to great in youth and adolescents (Carlozzi et al., 2015; B. K. Taylor, Frenzel, et al., 2020; Zelazo & Bauer, 2013). Furthermore, we observed a significant relationship between neighborhood factors and executive functioning that replicated across independent discovery and replication samples, suggesting our mixed-effects models are sensitive to robust relationships between environments and executive functioning.

Following recommendations for characterizing associations within the ABCD sample (Dick et al., 2021; Simmons et al., 2021), we replicated analyses in independent discovery and replication samples and only report consistent mixed-effects relationships across samples to protect against false positive results and assess robustness and generalizability. Effects also replicated across two independent groups of these same participants matched for study site, age, sex ethnicity, grade, highest level of parental education, handedness, combined family income, exposure to anesthesia, and family-relatedness. These replications demonstrate that the reported associations are not idiosyncratic to one subset of the ABCD cohort but are generalizable across independent samples of 9- to 10-year olds in the United States. Notably, however, the ABCD cohort—a community-based sample recruited from geographically diverse regions of the United States—is not nationally or internationally representative. Thus, reported relationships may differ in other cohorts. Future work incorporating weighting techniques (c.f. LeWinn et al., 2017) and data from complementary big-data samples, such as the Human Connectome Project Development Study (Somerville et al., 2018), the Healthy Brain Network Project (Alexander et al., 2017), and the Consortium on Vulnerability to Externalizing Disorders and Addictions (c-VEDA; Zhang et al., 2020), can inform the population level generalizability of our results.

Future research using the ABCD cohort can leverage the study's longitudinal design to investigate whether relationships between sociodemographic, environmental, and cognitive performance factors change over time. For example, longitudinal data can highlight shifts in the relative contributions of caregiver- and youth-reported subjective measures, as well as subjective and objective measures of the environment to each component across development. Longitudinal analyses can also incorporate additional, multimodal measures of the environment, cognitive functioning, physical health markers, and brain structure and function to better describe relationships between sociodemographics, environmental factors, and cognition, as well as investigate causal relationships between sociodemographic and environmental factors and how these relationships affect youth cognitive performance.

5 | CONCLUSIONS

Together, these results demonstrate that aspects of home, school, neighborhood, and cultural environments explain unique variance in three aspects of cognition above and beyond existing associations between sociodemographics and cognition. Furthermore, the interaction effect between the neighborhood environment and sociodemographic factors on general cognitive ability reveals a varied and complex mechanism through which features of experience relate to cognition. These patterns of direct and interactive effects contrast popular, essentialist mindsets that often inform policy decisions impacting communities, families, and individuals, wherein those who are smarter work harder, achieve more, and earn their increased access to resources. Looking ahead, interventions aimed at improving cognitive outcomes in youth may benefit from considering the ways sociodemographic and environmental factors can independently and interactively affect cognitive development.

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The ABCD data repository grows and changes over time. The ABCD data used in this report came from NIMH Data Archive Digital Object Identifier 10.15154/1504041. DOIs can be found at nda.nih.gov/study.html?id = 721.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Wesley J. Meredith, Carlos Cardenas-Iniguez, Marc G. Berman, and Monica D. Rosenberg developed the plan of analysis. Wesley J. Meredith and Carlos Cardenas-Iniguez wrote the analysis code. Wesley J. Meredith downloaded and analyzed the data with considerable input from Carlos Cardenas-Iniguez. Wesley J. Meredith, Carlos Cardenas-Iniguez, Marc G. Berman, and Monica D. Rosenberg interpreted the results. Wesley J. Meredith drafted the manuscript with considerable input from Carlos Cardenas-Iniguez, Marc G. Berman, and Monica D. Rosenberg. All authors have read and approved the final version of this manuscript.

DATA AND CODE AVAILABILITY STATEMENT

The data used for all analyses from the curated Study 817: Adolescent Brain Cognitive Development DEAP Study release 2.0.1 update (DOI 10.15154/1506087) are available for download from the National Institute of Mental Health Data Archive (nda.nih.gov). All code used for these data and their analyses are available on GitHub (https://github.com/wesmered/EnviroCog_DevPsychobio_MEM). The current study is also registered with the NDA as Study #1277 "Effects of the physical and social environment on youth cognitive performance #1277" (DOI 10.15154/1522895).

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