Received: 3 August 2017 | Accepted: 19 May 2018

DOI: 10.1111/desc.12699

PAPER

WILEY Developmental Science

Accounting for the shared environment in cognitive abilities and academic achievement with measured socioecological contexts

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Funding information
This project was supported by National Institutes of Health grants R21 HD081437, R01 HD083613, R21 AA023322, and R21 AA020588. The Population Research Center at the University of Texas at Austin is supported by National Institutes grant R24 HD042849.

Abstract

Behavioral and molecular genetic research has established that child cognitive ability and academic performance are substantially heritable, but genetic variation does not account for all of the stratification of cognitive and academic outcomes across families. Which specific contexts and experiences contribute to these *shared environmental* influences on cognitive ability and academic achievement? Using an ethnically and socioeconomically diverse sample of N = 1728 twins ages 7–20 from the Texas Twin Project, we identified specific measured family, school, and neighborhood socioecological contexts that statistically accounted for latent shared environmental variance in cognitive abilities and academic skills. Composite measures of parent socioeconomic status (SES), school demographic composition, and neighborhood SES accounted for moderate proportions of variation in IQ and achievement. Total variance explained by the multilevel contexts ranged from 15% to 22%. The influence of family SES on IQ and achievement overlapped substantially with the influence of school and neighborhood predictors. Together with race, the measured socioecological contexts explained 100% of shared environmental influences on IQ and approximately 79% of shared environmental influences on both verbal comprehension and reading ability. In contrast, nontrivial proportions of shared environmental variation in math performance were left unexplained. We highlight the potential utility of constructing "polyenvironmental risk scores" in an effort to better predict developmental outcomes and to quantify children's and adolescents' interrelated networks of experiences. A video abstract of this article can be viewed at: https://youtu.be/77E_DctFsr0

KEYWORDS

academic achievement, behavioral genetics, cognitive ability, neighborhoods, shared environment, socioecological contexts

1 | INTRODUCTION

Children vary widely in their abilities to deploy cognitive resources in support of complex behavior, reasoning, and decision making. Individual differences in children's cognitive development and academic achievement have immediate consequences for their mental health (Deary, Strand, Smith, & Fernandes, 2007; Gottfredson & Deary, 2004) and life course consequences for their psychological, physical, and economic wellbeing (Deary, 2008; Harden et al., 2017; Koenen et al., 2009). Given the importance of cognitive skills to a wide variety of social, economic, and health outcomes, researchers have long been interested in investigating the sources of these individual differences, with the hope of identifying etiological factors that are amenable to intervention. Indeed, a broad variety of health, educational, and parenting factors has been examined in relation to children's cognitive abilities and academic achievement (e.g. Burchinal, Peisner-Feinberg, Pianta, & Howes, 2002; Dupéré, Leventhal, Crosnoe, & Dion, 2010; Leventhal & Brooks-Gunn, 2000; Needham, Crosnoe, & Muller, 2004; Pinquart, 2016).

One approach to understanding the sources of individual differences in cognitive and academic skills has been to partition the variance in the outcome of interest into latent genetic and environmental factors using quantitative genetic methodology (Neale & Maes, 2004). Most commonly, a twins-raised-together design compares identical (monozygotic; MZ) twins' similarity on a phenotype to fraternal (dizygotic; DZ) twins' similarity on that phenotype. This comparison leverages the differences between MZ and DZ pairs' genetic similarity in order to decompose phenotypic variance into three primary factors: additive genetic influences (*A*), which make individuals from the same family more similar on the outcome of interest; shared environmental influences (*C*), or experiences shared by the twins that make them more similar on the outcome, above and beyond genetic similarity; and nonshared environmental influences (*E*), or events that individuals from the same family experience uniquely and make the individuals more distinct in the outcome, regardless of genetic similarity. To the extent that the phenotype is measured with error, *E* also encompasses variance due to measurement error.

The quantitative genetic approach to understanding the sources of individual variation has highlighted the contribution of genetic variants to cognitive ability (Bouchard & McGue, 1981). In middle childhood and adolescence, about 50% of the variation in general cognitive ability is attributable to additive genes (Tucker-Drob, Briley, & Harden, 2013). This estimate increases to about 70% by late adolescence and remains similarly high for much of adulthood (Briley & Tucker-Drob, 2017; Pedersen, Plomin, Nesselroade, & McClearn, 1992). In addition, behavioral genetic studies have also revealed moderate—but consistent—effects of shared family-level factors (*C*) on these traits. Shared or family-level factors are experiences common across children raised in the same household.

Although *C* has often been conceptualized as representing the home environment (e.g. parental socioeconomic status [SES], access to goods and services), it actually comprises all factors that serve to make children raised in the same family more similar on the outcome of interest, regardless of their genetic relatedness. This may include parenting styles, shared classroom experiences, and neighborhood characteristics. Nevertheless, estimates of *C* do not indicate *which* specific experiences or contexts that cluster within families give rise to between-family stratification in cognitive ability and academic achievement. Rather, *C* is a latent variable that serves as a placeholder for potentially myriad environmental factors that have yet to be measured or identified.

Initial efforts to incorporate measured environments into genetic models primarily focused on individual environmental measures and individual genetic variants (reviewed by Nigg, Nikolas, & Burt, 2010; Rutter, Moffitt, & Caspi, 2006). Candidate gene-by-environment studies have used many measured psychosocial contexts, including SES and childhood adversity composites (Retz et al., 2008), yet the contexts are seldom modeled simultaneously, yielding a limited representation of participants' environments. As a separate matter, candidate gene studies have generally evinced poor replication.

RESEARCH HIGHLIGHTS

- Behavioral genetic work indicates that shared environments explain 10–30% of variance in children's cognitive outcomes, but this methodology alone cannot specify which experiences are relevant.
- We examined the extent to which constellations of measured socioecological contexts accounted for shared environmental variance (*C*) in children's and adolescents' cognitive and academic abilities.
- Along with race, the measured home, school, and neighborhood contexts accounted for 100% of shared environmental variance in IQ.
- Socioecological contexts and race explained lower—but substantial—proportions of *C* for verbal reasoning, reading, and math abilities (78%, 80%, and 50% of *C*, respectively).

Twin studies, which provide omnibus estimates of both genetic and environmental influences, have also used the measured environment approach to assess relative contributions of specific contexts on child and adolescent outcomes such as substance use (Dick et al., 2007; D'Onofrio et al., 2008) and cognitive ability (Hart, Petrill, Deater-Deckard, & Thompson, 2007; Petrill, Deater-Deckard, Schatschneider, & Davis, 2005). Measured contexts range from parenting practices and behaviors (Dick et al., 2007; D'Onofrio et al., 2008; Koenen, Moffitt, Caspi, Taylor, & Purcell, 2003) to a composite index of family-level SES (Hanscombe et al., 2012; Hart et al., 2007) to neighborhood disadvantage (Burt, Klump, Gorman-Smith, & Neiderhiser, 2016). Explicitly measured contexts have also been examined with respect to *non*shared environmental influences, comprehensively reviewed in Turkheimer and Waldron (2000). Although many studies have examined multiple environmental indices in conjunction with genetically informed approaches, they have tended to incorporate the indices into separate, single-predictor models, rather than entering them into multi-predictor models that consider their joint and unique effects. Notable exceptions have considered the cumulative effect of multiple indices of the environment, for instance by constructing composites representing parental involvement (Petrill et al., 2005), familial negativity (Pike, McGuire, Hetherington, Reiss, & Plomin, 1996), and the school environment (Walker, Petrill, & Plomin, 2010); or by assessing multiple contexts measured at varying proximities to the child (Asbury, Wachs, & Plomin, 2005). Fortunately, behavioral genetics has been at the forefront of comprehensively characterizing the developing child's experiences, which presents additional opportunities to investigate environmental influences in a multivariate framework (Boivin et al., 2012; Klump & Burt, 2007; Leve et al., 2013; Trouton, Spinath, & Plomin, 2002).

In summary, the majority of genetically informed work typically models a small number of measured environmental factors at one time, with attention focused on family-level indicators. Indeed, characteristics of the parent or home environment provide a broad proxy for children's experiences. However, a large body of work within developmental psychology has demonstrated that child outcomes are associated with an interrelated network of socioeconomic contexts spanning multiple settings, including school and neighborhood quality (Ellen & Turner, 1997; Hart, Hodgkinson, Belcher, Hyman, & Cooley-Strickland, 2013; Sampson, Raudenbush, & Earls, 1997). For example, school-aged children's academic performance has been linked to multiple psychosocial contexts across family, school, and neighborhood levels, including classroom quality (Pianta, Belsky, Vandergrift, Houts, & Morrison, 2008; Tarr et al., 2008), parent involvement (El Nokali, Bachman, & Votruba-Drzal, 2010), and neighborhood resources (Theokas & Lerner, 2006).

Prominent theoretical frameworks, such as Bronfenbrenner's ecological systems theory of child development (Bronfenbrenner, 1992), posit that human development is shaped by contexts ranging from very proximal to distal from the individual in question. That is, an individual is influenced not only by more direct home and classroom contexts, but also by broader contexts related to neighborhoods, politics, the media, and cultural attitudes. According to this perspective, the contexts that are meaningful for cognitive abilities and academic achievement are thought to come from a variety of sources, not just those occurring in the home. These experiences are thought to combine and potentially interact with one another in their effects on child outcomes (Bronfenbrenner, 1992; Brooks-Gunn, Klebanov, & Duncan, 1996; Hart et al., 2007; Leventhal & Brooks-Gunn, 2000).

The current project aims to deconstruct latent shared environmental variation in cognitive abilities, reading, and mathematics achievement using a multivariate constellation of measured family, school, and neighborhood factors. The multilevel battery of contextual measures was selected based on an expansive literature from sociology, developmental psychology, educational psychology, and human ecology (e.g. Duncan, Yeung, Brooks-Gunn, & Smith, 1998; Farah et al., 2008; Lee & Burkam, 2002; Luby et al., 2013; Luo & Waite, 2005; Sirin, 2005; Tucker-Drob & Bates, 2016). Drawing on a sample of third through twelfth grade twins from the Texas Twin Project, we (1) employ behavioral genetic models to estimate the degree to which a broad factor representing shared environmental influences contributes to individual differences in cognitive and academic abilities; (2) use measured indices of home, school, and neighborhood factors previously implicated in child cognitive and behavioral development; (3) incorporate the measured socioecological indices into the behavioral genetic model to estimate the extent to which they account for the latent shared environmental variance estimated in step 1. In other words, to the extent that behavioral genetic models indicate that the cognitive and achievement outcomes are influenced by a latent shared environmental variance component, we attempt to explain this influence with multilevel predictors relevant to cognitive ability and academic achievement. Adding a measured predictor to a behavioral genetic model reduces the latent shared environment estimate by a proportion equivalent to the degree of variance that predictor explains (Turkheimer, D'Onofrio, Maes, & Eaves, 2005). If a measured environment is a meaningful correlate of an outcome, residual shared environmental contributions will be reduced when the environmental measure is included in the model.

The goal of the paper can be understood in relation to an analogous effort by geneticists to account for latent genetic effects with measured genetic variants. Recognizing that genes play a critical role in cognitive outcomes, molecular geneticists have begun to identify the specific genetic variants that contribute to latent heritability estimates from twin and family studies. Genome-wide association studies are identifying an increasing number of specific genetic variants that account for non-trivial proportions of variance in cognitive abilities (Davies et al., 2011; Deary et al., 2012; Okbay et al., 2016; Sniekers et al., 2017; Trzaskowski, Yang, Visscher, & Plomin, 2014), with the discrepancy between the latent estimate of heritability from twin and family studies and the proportion of variance accounted for by measured genetic variants commonly referred to as the 'missing heritability gap' (Manolio et al., 2009). As more variants related to cognitive ability are discovered, the missing heritability gap for cognitive ability narrows (Plomin & von Stumm, 2018). Thus, just as genetic association studies aim to identify specific, measurable constituents of latent heritable variance in a phenotype, the current project aims to identify measurable characteristics of children's environments that account for latent shared environmental variance in cognitive abilities and academic achievement.

2 | METHODS

2.1 | Participants

Families of twins and other multiples were recruited from public school rosters as part of the Texas Twin Project (Harden, Tucker-Drob, & Tackett, 2013). The current sample consisted of 1,728 children and adolescents in grades three to twelve, 212 of whom returned for repeat testing no earlier than one year after the previous visit (age range$_{\text{visit1}}$ 7.80–20.11 years, M = 12.85, SD = 2.96; age range$_{\text{all visits}}$ 7.80–20.11 years, M = 13.11, SD = 2.97). Repeat observations were included to cover a wider range of schools and census tracts, as many participants changed schools and residences between lab visits. Statistical adjustments for the inclusion of repeat participants are described in the *Analyses* section. As we did not employ a model that separated levels from longitudinal change, the current analyses should be considered cross-sectional.

Across all 1953 data points (individuals and time), 50% of the sample consisted of females. Of families reporting race and ethnicity, 58.9% were Caucasian, 22.2% were Hispanic, 8.0% were African American, 4.4% were Asian, 0.4% were another race/ethnicity, and

6.1% were multiple races/ethnicities. Race and ethnicity were entered as effect-coded, mutually exclusive categories in the analyses, with effect codes for each category weighted by group size as a proportion of the sample. Thirty percent of the families reported receiving needs-based public assistance (e.g. food stamps; women, infants, and children benefits) at some point during the twins' lives. Three families had two sets of twins, putting the total number of unique families at 847. The current sample consisted of 1026 pairs: 927 twin pairs and 99 pairwise combinations from 33 triplet sets.

Opposite-sex pairs were classified as dizygotic (DZ). To determine the zygosity of same-sex pairs, we conducted a latent class analysis that included experimenters', parents', and (for high school students) self ratings of each pair's physical similarity. Using latent class analysis to assess zygosity from physical similarity ratings has been reported to be over 99% accurate, as compared to genotyping-based classifications (Heath et al., 2003). The current sample included 364 (35.5%) monozygotic (MZ) pairs, 352 (34.3%) same-sex dizygotic pairs, and 310 (30.2%) opposite-sex dizygotic pairs.

We collected a broader set of academic achievement measures from a subsample of 1064 third through eighth graders, 45 of whom returned for repeat testing (age range$_{visit1}$ 7.80–15.25 years, M = 10.79, SD = 1.76; age range$_{all\ visits}$ 7.80–15.25 years, M = 10.83, SD = 1.76; 50% female across data points). The subsample was highly similar to the full sample on race (59.0% Caucasian, 23.7% Hispanic, 6.4% African American, 4.0% Asian, 0.6% other race, 6.3% multiple races), receipt of public assistance (29%), and zygosity (35.9% MZ, 34.2% same-sex DZ, 29.9% opposite-sex DZ). For analyses conducted on the younger subsample alone, weighted effect codes for race/ethnicity were based on group size within the subsample.

2.2 | Measures

2.2.1 | Adversity and socioecological deprivation

We compiled multiple indices of adversity and socioecological deprivation at each of three measurement levels: home, school, and neighborhood. Table S1 in the Supporting Information provides details about and sources for the selected measures of adversity and deprivation. Home variables came from parent reports of income, education, financial difficulty, major changes during the twins' lives, and parental conflict. Parent SES constituted one measure of the home environment; this composite was computed as the average of standardized parent educational attainment and standardized, log-transformed income. Another home variable was cumulative adversity, which was created by averaging eight variables that measured the presence or absence of financial difficulty during the twins' lifetime, as well as major life changes in the six years preceding the twins' study participation (for an overview of cumulative risk measurement in childhood, see Evans, Li, & Whipple, 2013). The final home variable was parent conflict, which assessed children's exposure to conflict related to finances, discipline, etc. (Porter & O'Leary, 1980).

To characterize school and neighborhood quality, we drew upon publicly available reports of structural (i.e. resource-based) and compositional (i.e. people-based) characteristics for all schools and census tracts represented in our sample. Variables of interest were chosen to represent each of several dimensions on an a priori basis, drawing on previous theoretical and empirical work (Ellen, Mijanovich, & Dillman, 2001; Franzini, Caughy, Spears, & Fernandez Esquer, 2005). Variables were formed into composite scores by extracting the first principal component from each set, using separate principal components analyses (PCAs). School variables were derived from yearly state-mandated reports of student demographics, student achievement, and teacher characteristics (Texas Education Agency). We pulled the same outcomes of interest for each school year from 2011 to 2015 for each of the 230 schools that participants in the current sample had attended. The final school composites were school performance (attendance, as well as proficiency on a statewide test of math and reading); student demographics (students' racial/ethnic minority status, English language learner status, low SES by virtue of eligibility for free/reduced lunch, and mobility); and teacher characteristics (years of teaching experience, salary, and student-to-teacher ratio).

Neighborhood variables came from the American Community Survey, an annual survey administered by the US Census Bureau to gather information on resident demographics, employment, and housing characteristics (United States Census Bureau). We pulled the same variables of interest from 2011 to 2015 for each of the 239 census tracts in which the current sample's participants resided. The final neighborhood variables were SES (educational attainment, single motherhood, management positions, impoverishment, and unemployment); residential instability (housing owned, relocation in the past year, maintain the same residence for a decade, and number of children and adolescents); and diversity (a weighted composite of racial/ethnic minority status and immigration).

To derive school composites, estimates for each variable of interest (e.g. ratio of students to teachers in each school) were averaged across available years, producing 11 cross-year indicators of school quality for every school. The same approach was taken for the neighborhood data: Tract-specific estimates for each of the 12 variables of interest were averaged across available years to generate cross-year indicators of neighborhood quality for every tract. The cross-year averages for each measure and each school/tract were submitted to a series of PCAs using the *nsprcomp* package (Sigg & Buhmann, 2008) implemented in *R* version 3.2.3 (R Core Team, 2015). In total, six PCAs were conducted on distinct sets of indicators representative of the following contexts: school performance, student demographics, teacher characteristics, neighborhood SES, residential instability, and neighborhood diversity (see Table 1). To ensure that PCA results were not biased by the number of families in a particular school or tract, each school and tract was included once in each PCA.

We extracted the first principal component from each PCA. By definition, the first principal component explains the maximum amount of variance possible for a one-dimensional representation, while simultaneously maximizing parsimony (Jolliffe, 2002). We next weighted the raw, year-specific school and neighborhood data by the corresponding unstandardized loadings derived from

TABLE 1 Loadings on and variance explained by first principal components (PCs)

Component Indicator	Unstandardized PC loading	Standardized PC loading	Proportion of variance
School performance			0.82
Met standard on statewide reading test	0.28	0.53	
Met standard on statewide math test	0.96	0.99	
Attendance	0.08	0.57	
Student demographics			0.87
African American race	0.08	0.46	
Hispanic ethnicity	0.57	0.96	
Low SES	0.73	0.99	
English language learner	0.33	0.81	
Student mobility	0.15	0.64	
Teacher characteristics			0.62
Average years' experience	0.77	0.93	
Average salary	0.64	0.87	
Ratio of students to teachers	0.02	0.02	
Neighborhood SES			0.96
Educational attainment above grade 12	0.75	0.99	
Single mother	−0.01	−0.60	
Management position	0.66	0.98	
Impoverished	−0.02	−0.72	
Unemployed	−0.06	−0.53	
Residential instability			0.82
Housing owned	−0.90	−0.99	
Moved in last year	0.32	0.89	
Same residence for 10+ years	−0.29	−0.61	
Children and adolescents	−0.08	−0.46	
Diversity			0.72
African American race	0.49	0.67	
Hispanic ethnicity	0.04	0.62	
Immigrant	0.87	0.94	

Note. Each PC and its indicators correspond to a separate analysis from which the first PC was extracted. Standardized loadings were computed by multiplying the unstandardized loading by the ratio of the standard deviation of the PC to the standard deviation of the indicator. The final column refers to the proportion of variance associated with the first PC.

the PCA. Finally, we computed weighted composite scores for each family by averaging the weighted indicator scores comprising each component. For example, the neighborhood diversity composite was formed by averaging the weighted estimates of proportion of Hispanic residents, proportion of non-Hispanic African American residents, and proportion of immigrants. In total, three school composites and three neighborhood composites, specific to the year of testing, were created for each family. This approach ensured that PCA scores specific to year of testing were derived for each family, but that the PCA weights were not biased by dependencies that would have resulted from entering each individual year for the same variable into the PCA.

2.2.2 | Cognitive abilities

To assess intelligence, we administered the Wechsler Abbreviated Scale of Intelligence (WASI-II; Wechsler, 2011), which consists of two tests measuring verbal comprehension (Vocabulary and Similarities) and two tests measuring perceptual reasoning (Block Design and Matrix Reasoning). Scores on each test are standardized relative to a nationally representative reference sample, and standardized scores are combined to form a full-scale intelligence quotient (FSIQ). Average FSIQ across all observations was 103.83 with a standard deviation of 13.75, which is comparable to national norms, which carry a mean FSIQ of 100 and standard deviation of

15. We also used the WASI-II to examine specific components of intelligence using the verbal comprehension index (a composite of age-standardized Vocabulary and Similarities scores) and the perceptual reasoning index (a composite of age-standardized Block Design and Matrix Reasoning scores).

2.2.3 | Academic achievement

To assess more specific reading comprehension and mathematics skills, participants in grades three through eight completed the Passage Comprehension and Calculation subtests, respectively, of the Woodcock-Johnson III Tests of Academic Achievement (Woodcock, McGrew, & Mather, 2001). The dependent variable for the reading and math subtests is total number of items correct. Descriptive statistics for cognitive and academic outcomes are provided in Table S2 of the Supporting Information.

2.3 | Analyses

2.3.1 | Multiple regressions

We fit a series of structural equation models in M*plus* Version 7.11 (Muthén & Muthén, 2012) to estimate associations between the socio-ecological deprivation components, race, and each of the outcomes. We implemented the Complex Survey option in M*plus* to correct for the nonindependence of data from repeat participants and from individuals nested within families. Cognitive and academic scores were residualized for age and sex prior to being entered into models. Race variables (Caucasian, Hispanic, African American, Asian, other, and multiple) were effect coded, with other race serving as the reference group.

2.3.2 | Commonality analyses

Multiple regression is well suited for identifying predictors that account for variance incremental of all other predictors included in the model. Because the predictors we included correlated with one another, we were also interested in the extent to which overlapping variance among the socioecological contexts and race contributed to prediction of the cognitive and achievement outcomes. To achieve this, we extended the multiple regression framework to commonality analysis, which estimates the amount of variance in a dependent variable that is uniquely predicted by individual predictors, as well as variance in the dependent variable that is shared across sets of predictors (Ray-Mukherjee et al., 2014). Commonality analyses were carried out with R package *yhat* (Nimon, Oswald, & Roberts, 2013), producing R^2 explained by each of 16,383 combinations of the predictors.

2.3.3 | Univariate behavioral genetic analyses

We fit behavioral genetic models in M*plus* to decompose the variance in each outcome y (σ^2_y) into additive genetic (a^2), shared environmental (c^2), and nonshared environmental (e^2) variance, which includes measurement error, or:

$$\sigma^2_y = a^2 + c^2 + e^2 \text{ (Neale \& Maes, 2004).}$$

To provide estimates of these variance components, behavioral genetic models leverage differences in the patterns of MZ twins (who share 100% of the genes that vary across humans) and those of DZ twins (who share 50% of their genes). For twins raised in the same household, within-pair covariances (*cov*) for an outcome can be expressed as:

$$cov_{MZ} = 1a^2 + 1c^2 \text{ and}$$
$$cov_{DZ} = 0.5a^2 + 1c^2$$

where twin similarity is attributable to shared genetic factors (100% overlapping for MZ twins, 50% overlapping for DZ twins) and shared environmental experiences (100% overlapping for both pair types). Rearranging and substituting terms from the above equations allows us to derive the following equations for estimating heritability, shared environmental variance, and non-shared environmental variance, respectively:

$$a^2 = 2(cov_{MZ} - cov_{DZ})$$

$$c^2 = cov_{MZ} - a^2$$

$$e^2 = \sigma^2_y - cov_{MZ}$$

Data from triplet pairs were down-weighted by 50%, as each triplet was included in two pairwise combinations in the behavioral genetics dataset. We implemented the Complex Survey option in M*plus* to correct for the nonindependence of data from repeat participants and multiple pairs nested within families.

2.3.4 | Inclusion of measured contexts into behavioral genetic models

Recall that the c^2 estimate from the univariate analyses serves as a theoretical upper limit of variance that can be accounted for by the measured environments shared by family members. We incorporated the socioecological composites and race—which are necessarily constant across members of a twin pair and therefore categorized as a shared environment—into the models as predictors, which allowed us to estimate the extent to which the *measured* shared environmental variables accounted for *latent* shared environmental variance in the cognitive and academic outcomes. In a series of individual models, we assessed how much of the total C variance in each outcome was attributable to the following sets of predictors: home contexts, home contexts and race, school contexts, school contexts and race, neighborhood contexts, neighborhood contexts and race, all contexts, all contexts and race. For example, the following equation would be used to estimate contributions to IQ from additive genetic sources (a), three home contexts, residual or unexplained shared environmental sources (c_{resid}), and nonshared environmental sources (e):

$$IQ = a + \underbrace{\beta_{SES} \cdot SES + \beta_{adversity} \cdot adversity + \beta_{conflict} \cdot conflict + c_{resid}}_{c} + e$$

We applied false discovery rate (FDR) corrections to the significance estimates of each set of nested models that incorporated the measured environments into the *ACE* estimations for a given outcome. FDR corrections were conducted with the Benjamini-Hochberg procedure at an FDR of 0.10 (Benjamini & Hochberg, 1995). Continuing with the example above, we evaluated the significance estimates of the three home composites across four separate models in which IQ scores were regressed on (1) the home contexts alone, (2) the home contexts and race, (3) all of the contexts, and (4) all of the contexts and race. Original significance estimates that were greater than the critical value assigned using the Benjamini-Hochberg procedure (i.e. significance estimates that did not pass FDR correction) are noted in the tables.

For all analyses, the latent *ACE* parameters were standardized with respect to total variance of the outcome, not with respect to residual variance after accounting for the composites. This allowed us to track the residual shared environmental variance estimate across stepwise models in which additional sets of measured family-level predictors were added. As these measured predictors accounted for an increasing amount of variance in the phenotype, we expected to observe a corresponding reduction in the proportion of residual shared environmental variance. Standardizing the *ACE* parameters with respect to total variance also kept the a^2 and e^2 estimates constant across models for a given outcome, even as the residual c^2 estimate changed with the addition of family-level predictors. In the IQ example, a^2 and e^2 estimates would be the same as in the univariate model ($\sigma^2_{IQ} = a^2 + c^2 + e^2$), and contributions from the home contexts would lead to reduced residual c^2, as those contexts would account for a portion of the total or univariate c^2 estimate.

2.3.5 | Polyenvironmental risk score construction

Estimating the extent to which measured environments account for the latent shared environment parallels the polygenic risk score approach in molecular genetics, in which scores represent the combined effect of many genetic variants on behavioral outcomes. To test the viability of this approach with respect to environmental measures, we constructed "polyenvironmental risk scores" and assessed the degree to which they predicted cognitive and academic outcomes by conducting *k*-fold cross-validation in *R*. The *k*-fold procedure entails (1) shuffling observations within the dataset; (2) partitioning the shuffled data into *k* (ten, in this analysis) equally sized samples or folds; (3) assigning nine of the folds to a training set and the remaining fold to a test set; (4) within the training set, regressing an outcome on the nine socioecological composites and five race variables; (5) extracting the regression coefficient for each predictor from the training model output; (6) weighting the predictor values from the test set by the corresponding regression weights from the training model; (7) summing the weighted values to produce predicted values for the test set; (8) computing R^2 from the predicted values of the test set; (9) repeating steps 3 through 8, but using a new fold for the test set until each fold has been used exactly once as a test set. The predicted values from the test sets represent polyenvironmental risk scores whose weights have been informed by an independent sample (the training set). For each outcome, we computed mean R^2 for test sets across ten iterations of the *k*-fold procedure. We then compared the mean R^2 to the shared environmental variance estimates from the initial behavioral genetic model.

3 | RESULTS

3.1 | Descriptive statistics and correlations

Principal component loadings for the socioecological adversity composites are reported in Table 1. Correlations between the nine composites, age, sex, race, and the cognitive and academic outcomes are reported in Table 2. The signs of these and subsequent relationships are driven, in part, by the valence of the composites and their constituent variables. The absolute magnitude of intercorrelations among composites from the same domain (home, school, or neighborhood) was high, with the exception of correlations between parent conflict and the remaining home composites. Correlations between the composites and the outcomes measured across the full sample (full-scale IQ, verbal comprehension, perceptual reasoning) were all significant at $p < 0.05$, aside from correlations with parent conflict.

Correlations were highly similar when only the younger participants were considered (see upper diagonal of Table 2). In this younger subsample, cognitive and academic outcomes (full-scale IQ, verbal comprehension, perceptual reasoning, reading, math) significantly correlated with all socioecological composites except for parent conflict and teacher characteristics.

3.2 | Multiple regression results

We conducted a series of multiple regressions to estimate the extent to which each socioecological composite and race independently predicted the cognitive and academic outcomes. Here and in Table 3, we report standardized regression coefficients from these models for the composites and standardized mean effect sizes (Cohen's *d*) relative to the mean of the outcome across the sample.

The total proportion of variance in the outcomes accounted for by race and the socioecological measures ranged from 0.15 for perceptual reasoning to 0.22 for reading performance (see final row of Table 3). Incremental of one another and of the other predictors, full-scale IQ was significantly predicted by parent SES, schoolwide student demographics, neighborhood SES, and Caucasian, Hispanic, African American, and Asian race designations. With the exception of student demographics and Asian race, the same predictors significantly contributed to variance in verbal comprehension. Perceptual reasoning was incrementally predicted by parent SES, student demographics, Caucasian, African American, and Asian race. Within the subsample

TABLE 2 Correlations between socioecological adversity composites, race, age, sex, and cognitive and academic scores

Predictor	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. Parent SES		−0.44	−0.06	0.11	−0.62	0.20	0.60	−0.30	−0.32	0.01	−0.05	−0.04	0.03	−0.01	−0.05	−0.06	0.40	0.37	0.30	0.31	0.20
2. Cumulative adversity	−0.45		0.06	−0.03	0.33	−0.09	−0.41	0.25	0.25	0.00	0.02	0.06	−0.02	0.01	−0.01	−0.03	−0.27	−0.22	−0.24	−0.21	−0.16
3. Parent conflict	−0.06	0.06		0.03	0.00	0.03	0.01	0.02	0.04	−0.13	−0.11	−0.11	−0.11	−0.12	0.04	−0.01	−0.02	−0.01	−0.03	0.01	0.01
4. School performance	0.19	−0.09	0.03		−0.12	−0.07	0.12	0.06	−0.09	0.05	0.04	0.03	0.04	0.03	0.27	0.00	0.11	0.08	0.10	0.23	0.22
5. Student demographics	−0.60	0.33	−0.01	−0.21		−0.37	−0.73	0.36	0.51	−0.07	−0.02	−0.02	−0.08	−0.06	0.04	0.08	−0.32	−0.27	−0.28	−0.26	−0.17
6. Teacher characteristics	0.26	−0.14	0.00	0.07	−0.41		0.26	−0.15	−0.23	0.06	0.05	0.03	0.07	0.06	−0.14	0.03	0.05	0.07	0.01	0.02	0.01
7. Neighborhood SES	0.60	−0.39	−0.02	0.21	−0.70	0.27		−0.36	−0.54	0.07	0.02	0.01	0.08	0.06	−0.02	−0.07	0.35	0.28	0.31	0.28	0.19
8. Residential instability	−0.27	0.22	0.05	−0.02	0.31	−0.13	−0.33		0.40	0.02	0.04	0.05	0.02	0.02	0.06	−0.01	−0.14	−0.14	−0.09	−0.13	−0.06
9. Diversity	−0.37	0.27	0.05	−0.15	0.50	−0.27	−0.56	0.40		−0.06	−0.03	−0.02	−0.04	−0.05	0.01	0.04	−0.20	−0.17	−0.16	−0.19	−0.09
10. Race: Caucasian	0.01	−0.01	−0.10	0.03	−0.06	0.05	0.05	0.02	−0.05		–	–	–	–	−0.06	0.00	−0.03	−0.04	−0.01	−0.10	−0.07
11. Race: Hispanic	−0.06	0.02	−0.09	0.01	0.00	0.03	−0.01	0.05	−0.01	–		–	–	–	−0.05	0.00	−0.06	−0.07	−0.04	−0.13	−0.08
12. Race: African American	−0.06	0.07	−0.09	0.00	0.01	0.01	−0.03	0.06	0.01	–	–		–	–	−0.05	−0.01	−0.08	−0.07	−0.06	−0.14	−0.08
13. Race: Asian	0.02	−0.03	−0.09	0.03	−0.07	0.06	0.06	0.03	−0.03	–	–	–		–	−0.07	0.00	−0.02	−0.03	0.01	−0.11	−0.04
14. Race: Multiple	−0.02	0.02	−0.09	0.02	−0.04	0.04	0.03	0.04	−0.02	–	–	–	–		−0.06	0.00	−0.03	−0.05	−0.01	−0.11	−0.07
15. Age	0.02	−0.01	0.01	0.05	−0.01	0.06	0.00	0.02	−0.02	0.01	0.01	0.02	0.01	0.01		0.03	0.01	0.03	−0.02	0.54	0.71
16. Sex	0.00	−0.01	0.00	−0.03	0.05	0.01	−0.03	0.00	0.02	0.02	0.02	0.01	0.01	0.02	0.02		0.05	−0.02	0.09	−0.03	0.01
17. Full-scale IQ	0.40	−0.25	−0.05	0.12	−0.35	0.14	0.35	−0.14	−0.21	−0.03	−0.07	−0.09	−0.01	−0.04	−0.01	0.03		0.86	0.84	0.53	0.38
18. Verbal comprehension	0.39	−0.22	−0.05	0.11	−0.31	0.16	0.32	−0.15	−0.20	−0.02	−0.06	−0.07	−0.02	−0.04	−0.03	−0.02	0.86		0.46	0.52	0.35
19. Perceptual reasoning	0.30	−0.20	−0.03	0.08	−0.28	0.08	0.27	−0.10	−0.17	−0.02	−0.05	−0.08	0.00	−0.03	0.01	0.07	0.85	0.46		0.37	0.29
20. Reading	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–		0.69
21. Math	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–

Note. Zero-order Pearson correlation coefficients. Correlations for the full sample (N = 1,953) are below the diagonal. Coefficients specific to the younger subsample (N = 1,064), which completed a broader battery of achievement tests, are above the diagonal. Correlations between racial/ethnic categories are omitted, as categories were mutually exclusive. Bold signifies $p < 0.05$.

TABLE 3 Multiple regression results for cognitive and academic outcomes

Predictor	Cognitive or academic outcome: Full-scale IQ	Verbal comprehension	Perceptual reasoning	Reading	Math
Parent SES	0.22***	0.25***	0.13***	0.25***	0.18***
	[0.03]	[0.03]	[0.03]	[0.04]	[0.05]
Cumulative adversity	−0.04	−0.02	−0.03	−0.02	−0.05
	[0.03]	[0.03]	0.03]	[0.04]	[0.04]
Parent conflict	−0.03	−0.03	−0.02	0.00	−0.03
	[0.02]	[0.03]	[0.02]	[0.03]	[0.03]
School performance	0.02	0.03	0.00	0.06*	0.02
	[0.02]	[0.02]	[0.02]	[0.03]	[0.03]
Student demographics	−0.09**	−0.03	−0.13***	−0.02	−0.04
	[0.03]	[0.03]	[0.04]	[0.05]	[0.05]
Teacher characteristics	−0.01	0.05	−0.05	0.01	0.07
	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
Neighborhood SES	0.07*	0.07*	0.05	0.06	0.10
	[0.03]	[0.03]	0.04]	[0.05]	[0.05]
Residential instability	0.00	−0.02	0.02	−0.04	−0.02
	[0.02]	[0.02]	[0.03]	[0.03]	[0.03]
Diversity	0.02	0.03	0.01	−0.02	0.03
	[0.03]	[0.03]	0.03]	[0.04]	[0.04]
Race: Caucasian	0.09***	0.08***	0.07**	0.09**	−0.05
	[0.02]	[0.02]	[0.02]	[0.03]	[0.03]
Race: Hispanic	−0.16**	−0.17***	−0.09	−0.15**	−0.05
	0[.05]	[0.05]	[0.05]	[0.06]	[0.06]
Race: African American	−0.47***	−0.25**	−0.56***	−0.49***	−0.09
	[0.08]	[0.08]	[0.07]	[0.13]	[0.12]
Race: Asian	0.26*	0.09	0.35**	0.02	0.89***
	[0.11]	[0.11]	[0.11]	[0.12]	[0.15]
Race: Multiple	0.06	0.04	0.07	0.12	0.07
	[0.08]	[0.09]	[0.08]	[0.10]	[0.11]
Multiple R^2	.21	.18	.15	.22	.17

Note. Estimates for the socioecological contexts correspond to standardized regression coefficients; estimates for the race variables correspond to Cohen's *d* effect sizes relative to the sample mean. Standard errors are reported in brackets. Full-scale IQ, verbal comprehension, and perceptual reasoning came from the full sample; reading and math came from the younger subsample. Socioecological composites and age- and sex-residualized outcomes were standardized prior to model fitting.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

of third through eighth graders, parent SES, Caucasian race, Hispanic race, and African American race independently accounted for variance in full-scale IQ, verbal comprehension, and perceptual reasoning. Incremental to these and the other predictors, neighborhood SES predicted IQ; and teacher characteristics, neighborhood SES, and Asian race significantly predicted perceptual reasoning. Table S3 in the Supporting Information details the complete set of estimates.

Within the subsample of third through eighth graders, for which a broader set of academic achievement measures were available, reading scores were incrementally predicted by parent SES, schoolwide performance, Caucasian, Hispanic, and African American race. Math was independently predicted by parent SES and Asian race.

3.2.1 | Commonality analysis results

In addition to estimating the effects of each predictor individually, we sought to understand commonalities across the predictors in their impact on the outcomes of interest, in particular because of substantial correlations between the socioecological contexts. We used commonality analyses to partition the total variance explained for each outcome (i.e. R^2) into variance uniquely

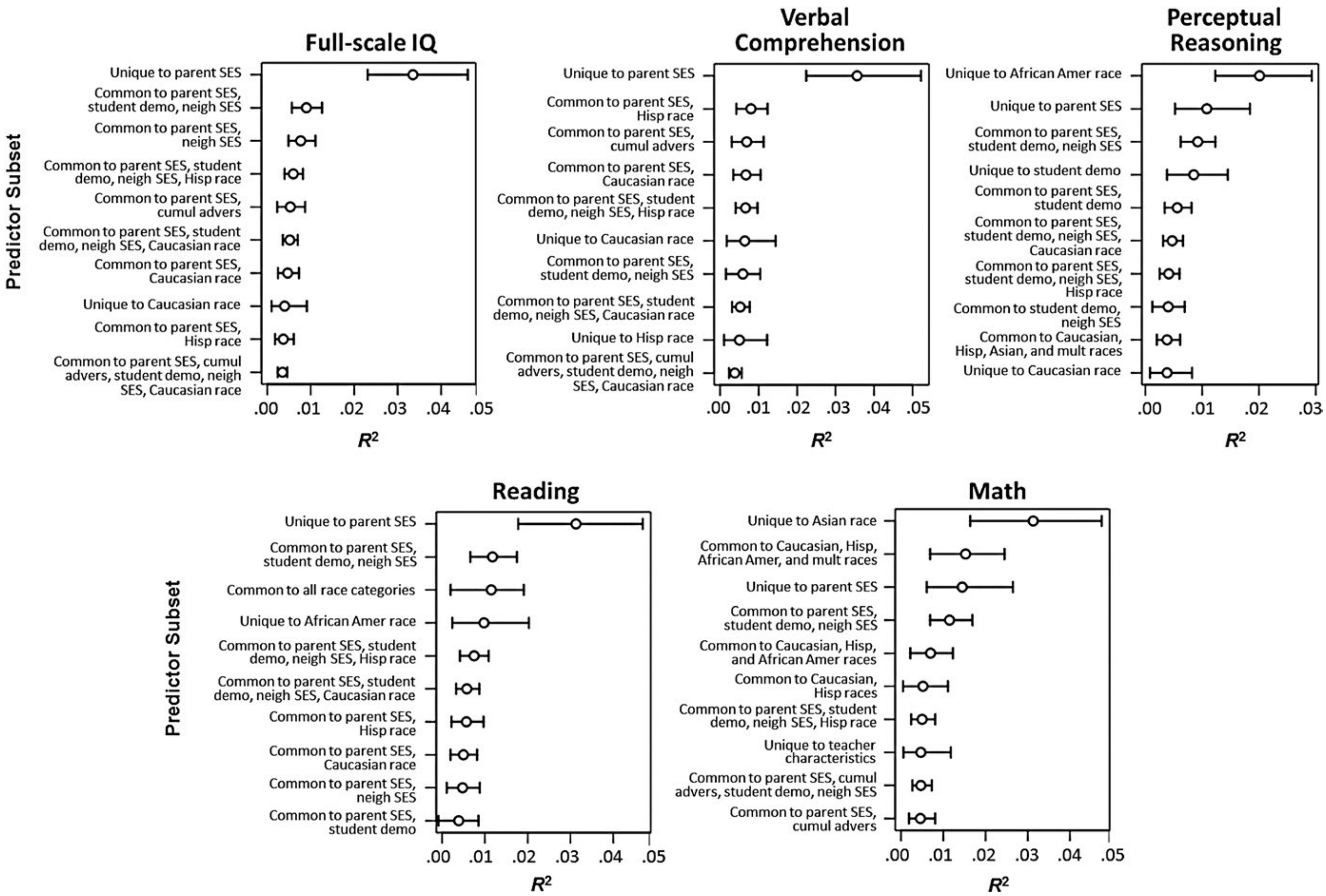

FIGURE 1 Commonality R^2 estimates for predictor subsets explaining the most variance in cognitive or academic outcomes.
Note: R^2 and 95% confidence intervals from commonality analyses. Each plot displays the 10 predictor subsets that explained the greatest proportion of total variance in the respective outcome. All depicted subsets explained at least 2% of total variance in the respective outcome. Effects of a subset are independent of all other subsets. Confidence intervals were computed by bootstrapping 70% of the data (randomly selected with each iteration) 1,000 times. Full-scale IQ, verbal comprehension, and perceptual reasoning came from the full sample; reading and math came from the younger subsample for which data on these outcomes were available. SES = socioeconomic status, cumul advers = cumulative adversity, demo = demographics, neigh = neighborhood, Hisp = Hispanic, Amer = American, mult = multiple

attributable to each predictor and that shared by sets of predictors. Table S4 in the Supporting Information reports the unique and common contributions of each predictor to the cognitive and academic outcomes.

Parent SES emerged as the primary contributor to variance in all five outcomes, both in terms of its unique effects (accounting for an average of 13.39% of total variance explained) and in its effects shared with other predictors, namely cumulative adversity, schoolwide student demographics, and neighborhood SES. Unique and common effects of predictor subsets accounting for the greatest amount of total explained variance in each outcome are depicted in Figure 1.

3.3 | Behavioral genetic results

3.3.1 | Univariate *ACE* models

We decomposed variance in the cognitive and academic outcomes into their respective genetic and environmental factors. As age-residualized outcomes were standardized prior to modeling, all estimates reported here and in the tables may be interpreted as standardized values. Twin correlations and *ACE* estimates are reported in Table 4. For all outcomes, within-pair correlations were higher for MZ pairs (r = 0.65 to 0.77) than for DZ pairs (r = 0.33 to 0.49). Additive genetic and nonshared environmental influences significantly contributed to variance in each of the five outcomes. Shared environmental contributions were significant for all outcomes aside from perceptual reasoning (c^2 = 0.02, p = 0.67). The estimates presented in Table 4 were highly consistent when only the younger subsample was considered: full-scale IQ r_{MZ} = 0.77, r_{DZ} = 0.42; verbal comprehension r_{MZ} = 0.66, r_{DZ} = 0.42; perceptual reasoning r_{MZ} = 0.72, r_{DZ} = 0.32.

3.3.2 | Incorporating measured contexts into *ACE* models

After characterizing the genetic and environmental structures of our outcomes, we incorporated the measured socioecological

TABLE 4 Univariate twin correlations and *ACE* estimates

Outcome	Twin correlations MZ	DZ	Variance components a^2	c^2	e^2
Full-scale IQ	0.77	0.45	0.55***	0.19***	0.25***
Verbal comprehension	0.65	0.41	0.40***	0.22***	0.37***
Perceptual reasoning	0.71	0.33	0.65***	0.02	0.32***
Reading performance	0.68	0.49	0.34***	0.32***	0.33***
Math performance	0.72	0.49	0.39***	0.30***	0.30***

Note. Full-scale IQ, verbal comprehension, and perceptual reasoning came from the full sample; reading and math came from the younger subsample. Age- and sex-residualized outcomes were standardized prior to model fitting. MZ = monozygotic, DZ = dizygotic, a^2 = additive genetic variance, c^2 = shared environmental variance, e^2 = nonshared environmental variance.
***p < 0.001.

TABLE 5 Residual shared environmental variance estimates (c^2) from behavioral genetic models of cognitive and academic outcomes, incorporating measured environments into c^2 component

Environmental context	Residual c^2 estimates by outcome: Full-scale IQ	Verbal comprehension	Reading	Math
None	0.19***	0.22***	0.32***	0.30***
Race	0.07*†	0.13***	0.19***	0.23***
Home	0.05	0.10**	0.15**	0.22***
Race & home	0.01	0.07*	0.09	0.18***
School	0.07*	0.12***	0.17***	0.23***
Race & school	0.03	0.09*	0.12*	0.19***
Neighborhood	0.06	0.10**	0.17***	0.21***
Race & neighborhood	0.02	0.08*	0.11*	0.17***
All contexts	0.01	0.07	0.11*	0.18***
Race & all contexts	0.00	0.05	0.07	0.15***

Note. Residual c^2 estimates correspond to squared standardized coefficients. Models were conducted separately for each outcome and each set of contexts. Socioecological composites and age- and sex-residualized outcomes were standardized prior to model fitting.
*p < 0.05; **p < 0.01; ***p < 0.001; †not significant after FDR correction.

composites and race into the models to estimate the predictors' contributions to shared environmental influences (*C*) acting on scores. Separate models were run with each set of home, school, and neighborhoods alone; with race added to each set of contexts; with all nine socioecological contexts; and with all nine socioecological contexts and race.

Table 5 reports the residual *C* variance for the outcomes that exhibited significant shared environmental variance at the univariate level. Parameter estimates for the standardized regression coefficients or effect sizes corresponding to the predictors can be found in Tables S5–S8. Incorporating race into the model for full-scale IQ reduced the remaining shared environmental variance to from 0.19 to 0.07. In other words, race differences accounted for 63% of the total shared environmental variance for IQ (total *C* variance from the univariate model, minus *C* variance remaining after race was included, divided by total *C* variance). Incorporating only the home composites into the model accounted for 75% of shared environmental influences on IQ; school composites alone accounted for 63%; and neighborhood composites alone accounted for 71%. Adding race to models for home, school, and neighborhood influences explained, respectively, 97%, 86%, and 91% of shared environmental variance in IQ. Modeled together, the nine socioecological contexts explained 94% of the shared environmental variance in full-scale IQ, and 100% of the original shared environmental contributions to IQ were statistically accounted for by the measured environments and race. Figure 2 displays the proportion of variance in cognitive and academic outcomes that was attributable to the measured and residual shared environmental components.

With respect to verbal comprehension, a significant portion of unexplained *C* remained when the home, school, or neighborhood contexts were incorporated by themselves or with race. When all composites were added as predictors, 71% of total shared environmental variance was explained, and residual *C* variance reached nonsignificant levels. Adding race to the full set of contexts increased the percentage of total *C* accounted for to 78%. The estimates for full-scale IQ and verbal comprehension as measured in the younger

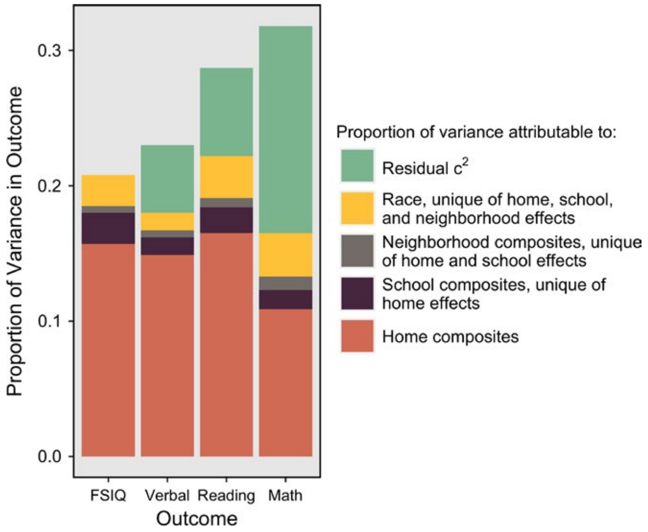

FIGURE 2 Proportion of variance in cognitive and academic outcomes attributable to shared environmental factors.
Note: Home composites were entered into the behavioral genetic model first to determine their specific effect on cognitive and academic outcomes. School composites, neighborhood composites, and race were added sequentially to estimate effects incremental to previously added predictors. Residual shared environmental variance (c^2) came from the final model that included all socioecological composites and race. The absolute height of each bar represents total c^2. Estimates may be interpreted as standardized values, as outcomes were standardized prior to modeling. FSIQ = full-scale IQ

subsample are reported in Tables S9 and S10 of the Supporting Information. The socioecological composites and race together accounted for 100% of shared environmental variance in IQ and 69% of shared environmental variance in verbal comprehension.

In the younger subsample, unexplained shared environmental variance in reading scores reached non-significant levels when home contexts and race were incorporated into the *ACE* model; together, they accounted for 72% of total *C*. The percentage of shared environmental variance in IQ explained by all socioecological contexts and race was 80%. Measured environments accounted for relatively lower proportions of total shared environment variance on math performance, from 25% when race was considered by itself, to 50% when all nine contexts and race were included. Residual shared environmental estimates remained significant across the inclusion of different predictor sets.

To better understand the explanatory utility of incrementally adding predictors into the model for each outcome, we employed a model comparison approach in which the regression coefficients corresponding to predictors of interest were freely estimated and those for the remaining predictors were fixed at zero. This method has the benefit of maintaining a common baseline model for each outcome, against which the models that include measured contexts can be compared. Although this approach is uninformative in terms of absolute fit of the data to the model, it facilitates comparison across models for the same outcome. Comparative fit statistics for all models are reported in Table S11. Across outcomes, model fit comparisons based on the χ^2 statistic (for which larger *p*-values indicate better fit) and the Akaike Information Criterion (for which lower values indicate better fit) favored the inclusion of all contexts and race in the estimation of *C*. The only exception was the behavioral genetic model for verbal comprehension in the younger subsample; fit indices favored the model in which only home composites and race were included in the *C* estimate.

3.3.3 | Polyenvironmental risk scores

We conducted *k*-fold cross-validation analyses to establish the predictive power of polyenvironmental risk scores. The single-value scores were computed by summing the predictor values from a test set that had been weighted by the multiple regression coefficients from an independent training set. Across ten iterations of this procedure, the mean R^2 for full-scale IQ was 0.20 for the training set and 0.19 for the test set. The R^2 for the test set is consistent with the estimate of total shared environmental variance from the unconditional behavioral genetic models (0.19; depicted in the first data column in Table 5 and in the non-green portion of the first bar in Figure 2). For verbal comprehension, mean R^2 was 0.17 for the training set and 0.14 for the test set, with the latter estimate constituting 65% of total c^2 for this outcome. For perceptual reasoning, mean R^2 was 0.14 for the training set and 0.12 for the test set. Mean R^2 for reading ability among the younger subsample was 0.19 for the training set and 0.16 for the test set, the latter estimate comprising 50% of total c^2 for reading. For math ability, mean R^2 was 0.16 for the training set and 0.11 for the test set, or 38% of total c^2 for this outcome.

4 | DISCUSSION

Academic and cognitive skills predict economic, social, and physical wellbeing across the life course. Behavioral genetic research indicates that family-level environments stratify cognitive ability and academic achievement in childhood. Previous work in sociology, human ecology, and developmental psychology has identified a wide assortment of socioecological contexts that are related to child development (Huston & Bentley, 2010). The current study integrated these two approaches: Using detailed measurement of family, school, and neighborhood contexts, we attempted to account statistically for latent shared environmental variation in cognitive and academic outcomes, as estimated with a twin approach.

Parent SES significantly predicted all cognitive and academic outcomes, independent of the other predictors. Relative to the sample mean, Caucasian, Hispanic, and African American group membership also emerged as consistent predictors across a majority of outcomes. Of the socioecological contexts beyond family-level characteristics, student demographics and neighborhood SES accounted for incremental variance in a smaller number of outcomes. Furthermore, commonality analyses revealed that the relations between SES and cognitive and academic outcomes was composed of a mixture of effects unique to SES, as well as to variance shared with other measured socioecological contexts, notably school demographics and neighborhood SES. The identified sociocontextual correlates of cognitive and achievement outcomes were situated at varying proximities to the developing child. In addition, the contexts that were meaningful for key cognitive traits were inter-correlated, suggesting that researchers interested in characterizing children's and adolescents' experiences should consider a wider, interrelated network of environmental exposures.

Together, the socioecological composites and race accounted for 100% of the shared environmental variance in full-scale IQ. That is, there remained no unexplained *C* variance in intelligence after the predictors were included in the behavioral genetic model, meaning that the measured variables we constructed are markers for the statistical dimensions that make up the latent shared environment. Similar patterns were observed for the more specific skill domains of verbal comprehension and reading ability; residual *C* variance was negligible after including the measured contexts into the behavioral genetic models.

The results for math achievement diverged from the general pattern, such that 53% of latent shared environmental variance remained after accounting for the socioecological composites and race. In addition, identifying as Asian was the only racial variable that significantly related to math performance incremental of the other contexts and race categories. These results suggest that the environmental experiences that are meaningful for IQ, verbal comprehension, and reading ability may not be entirely the same as those that are meaningful for math ability. Future research is needed to identify measures beyond those examined here that can fully account for shared environmental contributions to math outcomes. For instance, it is possible that the quality of math lessons specifically, as opposed to overall school quality, accounts for additional shared environmental contributions to performance. More generally, the total latent *C* estimate was slightly higher for specific abilities than for the broader IQ dimension, which may explain, in part, why residual *C* was higher for specific abilities even after including the full set of predictors. In other words, relative to general cognitive abilities, mathematics performance may be affected more greatly by a wider assortment of family, school, and neighborhood environmental factors.

The dimensions we analyzed likely index a host of experiences that were not themselves directly measured. For example, the teacher characteristics composite may serve as an indirect proxy for teaching skill and preparedness in a given school. The results do not imply that increasing one teacher characteristic, salary for example, would necessarily raise student achievement. Instead, we may expect that the broad range of skills indexed by the teacher characteristics measured here indirectly constitute the true causal elements in cognitive development and academic achievement. A related concept that we wish to emphasize is that no single measure represents the broad construct of socioecological inequality. Rather, many dimensions added together form the larger amalgam of environmental risk. The composites that we implemented themselves indexed a range of experiences, suggesting that the network of specific experiences relevant for cognitive ability and academic achievement is vast and highly interconnected. Overall, the environments selected for the current study accounted for approximately one-fifth of phenotypic variance in the outcomes under study. Although moderate at first glance, the R^2 values in the current study are within range of those from previous investigations of the impact of family resources and demographics on achievement (Hart et al., 2007; Sirin, 2005). In addition, results of the twin models highlighted significant genetic influences on all of the outcomes, suggesting that a substantial increase in R^2 by shared environmental measures alone would be implausible.

In the current sample, latent *C* was estimated at zero for perceptual reasoning in both the full sample and the younger subsample. However, perceptual reasoning was still associated with several of the socioecological measures. It is possible that the estimate of *C* is imprecise or biased due to simplifying assumptions of the twin approach. Alternatively, measures of environmental contexts are known to be correlated with children's genotypes. Therefore, correlations between measured environments and child outcomes are potentially confounded by genetic differences (Dickens & Flynn, 2001; Domingue, Belsky, Conley, Harris, & Boardman, 2015; Kendler & Baker, 2007; Meyers et al., 2013; Plomin & Daniels, 1987). In the case of family-level environments, the most common source of genetic confounding is passive genotype–environment correlation (*r*GE), in which the same genetic factors that affect parents' social attainment are inherited and affect their offspring's cognitive development. It is likely that the measured environments included in the current paper are partly associated with children's cognitive abilities via *r*GE, rather than purely environmental mechanisms. (For a review of this issue with regard to twin studies that employ measured environmental variables, see Turkheimer et al., 2005.) For the purposes of this paper, we did not attempt to control for genetic influences on the presumed environmental influences, as our goal was not to investigate the contexts as causal mechanisms per se. Future work using complementary approaches (e.g. a children-of-twins or parental genotype design) would be needed to determine the extent of *r*GE relative to strictly environmental contributions to the outcomes (Koellinger & Harden, 2018; Kong et al., 2018).

It is also important to emphasize that the heritable component of variation may encompass environmental processes that occur via active and evocative *r*GE (Hambrick & Tucker-Drob, 2015; Tucker-Drob et al., 2013; Turkheimer et al., 2005), whereby children select and evoke different environmental experiences on the basis of their genetically influenced traits. These processes are thought to accumulate over development, such that genetic predispositions toward traits are increasingly reinforced by environmental exposures (Briley & Tucker-Drob, 2013, 2017; Scarr & McCartney, 1983; Tucker-Drob & Briley, 2014). The result of this process is to make DZ twins increasingly dissimilar on a trait, which increases *A* estimates at the expense of *C* estimates in the classic twin model. Although the goal of the current study was not to disentangle these effects, it is always important to consider the potential roles of active and evocative *r*GE when interpreting genetic effects on complex phenotypes (Kendler & Baker, 2007).

4.1 | Limitations and future directions

In addition to recognizing the challenge that gene–environment correlation poses to drawing causal conclusions about these associations, we acknowledge a number of limitations in the current study. We employed cross-sectional analyses, further limiting our ability to interpret relationships between environmental contexts and cognitive outcomes as causal. Longitudinal observations are necessary for confirming the direction and size of the effects reported here. We also recognize that the chosen socioecological contexts and models constitute only a subset of many possible ways to measure environments relevant to children's and adolescents' development. For example, many of the indices we modeled were resource-based characteristics of the child's environment; it would be beneficial to consider more nuanced, interpersonal experiences (e.g. parental warmth) in future work. The comparison of various predictors and model parameterizations is a necessary future step in the study of environmental impacts on cognitive and academic ability. For example, while we constrained the current analyses to linear additive effects, future work may incorporate interaction terms between predictors to better represent their synergistic effects on cognition. Another question motivated by our results is whether measured environments differentially account for *C* across age. Finally, environments that do not vary across schools or neighborhoods in the current sample, such as exposure to schooling itself (Gurven et al., 2017; Ritchie & Tucker-Drob, 2017), will not factor into *C* variation, regardless of their importance for cognitive and academic development.

4.2 | Conclusion

The results of this study hold promise for the successful integration of common, but impactful, socioecological contexts into phenotypic and genetic models of many complex traits. Even when associations between these outcomes and individual contexts are small in magnitude, their cumulative effects on downstream risks may be important. These findings parallel advances in molecular genetics, specifically the use of polygenic risk scores to predict behavioral outcomes on the basis of many small genetic effects. By way of analogy, we were able to treat our multivariate battery of socio-contextual measures as a means of constructing polyenvironmental risk scores that index critical environmental contexts associated with cognitive and academic performance. In addition to pushing the study of environmental exposures beyond home experiences, future exploration of polyenvironmental risk scores may present an innovative method by which we can begin to account for shared environmental risk factors on a host of outcomes important for children's and adolescents' physical and psychological wellbeing.

ACKNOWLEDGEMENTS

This project was supported by National Institutes of Health grants R21 HD081437 (ETD and JAC), R01 HD083613 (ETD), R21 AA023322 (KPH), and R21 AA020588 (KPH). The Population Research Center at the University of Texas at Austin is supported by National Institutes grant R24 HD042849. We wish to thank the research team that facilitated data collection. We thank the other members of the Texas Twin Project, especially Andrew Grotzinger and Margherita Malanchini, for their feedback on this manuscript. Finally, we thank our participating families for their time and effort.

CONFLICT OF INTEREST STATEMENT

The authors declare no competing financial interests.

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How to cite this article: Engelhardt LE, Church JA, Paige Harden K, Tucker-Drob EM. Accounting for the shared environment in cognitive abilities and academic achievement with measured socioecological contexts. *Dev Sci*. 2018;e12699. https://doi.org/10.1111/desc.12699