School Climate, Cortical Structure, and Socioemotional Functioning: Associations across Family Income Levels

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Abstract

■ School climates are important for children's socioemotional development and may also serve as protective factors in the context of adversity. Nevertheless, little is known about the potential neural mechanisms of such associations, as there has been limited research concerning the relation between school climate and brain structure, particularly for brain regions relevant for mental health and socioemotional functioning. Moreover, it remains unclear whether the role of school climate differs depending on children's socioeconomic status. We addressed these questions in baseline data for 9- to 10-year-olds from the Adolescent Brain and Cognitive Development study (analytic sample for socioemotional outcomes, n = 8,887), conducted at 21 sites across the United States. Cortical thickness, cortical surface area, and subcortical volume were derived from T1-weighted brain magnetic resonance imaging. School climate was measured by youth report, and socioemotional functioning was measured by both youth and parent report. A positive school climate and higher family income were associated with lower internalizing and externalizing symptoms, with no evidence of moderation. There were no associations between school climate and cortical thickness or subcortical volume, although family income was positively associated with hippocampal volume. For cortical surface area, however, there was both a positive association with family income and moderation: There was an interaction between school climate and income for total cortical surface area and locally in the lateral orbitofrontal cortex. In all cases, there was an unexpected negative association between school climate and cortical surface area in the lower-income group. Consequently, although the school climate appears to be related to better socioemotional function for all youth, findings suggest that the association between a positive school environment and brain structure only emerges in the context of socioeconomic stress and adversity. Longitudinal data are needed to understand the role of these neural differences in socioemotional functioning over time. ■

INTRODUCTION

Socioeconomic status (SES) during childhood and adolescence is encompassed by a family's material and financial resources, education levels, power and prestige, and broader neighborhood environment (Braveman et al., 2005; Evans, 2004; Leventhal & Brooks-Gunn, 2000; Krieger, Williams, & Moss, 1997). SES is thus associated with systematic differences in experiences and exposures, including formal and informal learning environments; psychosocial stressors; experiences of threat, including community violence; differences in parenting, as poverty-related stressors can make it more challenging for parents to be as responsive and warm as often as they intend; environmental toxins and pollutants; and in community and service environments, among others (McLaughlin, Sheridan, & Lambert, 2014; Luby et al., 2013; Miller & Chen, 2013; Duncan & Murnane, 2011; Hackman, Farah, & Meaney, 2010; Conger & Donnellan, 2007; Evans, 2004; Bradley & Corwyn, 2002; Leventhal & Brooks-Gunn, 2000; Robert, 1999; McLoyd, 1998). Children and adolescents from lower-SES families or neighborhoods are less likely to succeed in or be ready to enter school than their counterparts from higher SES families, both in terms of performance on standardized achievement tests and educational attainment (Wolf, Magnuson, & Kimbro, 2017; Chetty, Hendren, & Katz, 2016; Dahl & Lochner, 2012; Duncan, Morris, & Rodrigues, 2011; Reardon, 2011; Duncan, Ziol-Guest, & Kalil, 2010; Sirin, 2005). Lower SES is also associated with worse youth mental health and socioemotional functioning (Duncan, Magnuson, & Votruba-Drzal, 2017; Reiss, 2013; Akee, Copeland, Keeler, Angold, & Costello, 2010; Wadsworth & Achenbach, 2005; Costello, Compton, Keeler, & Angold, 2003; Aneshensel & Sucoff, 1996).

In addition, SES has been associated with differences in both whole-brain and regional indices of brain structure (Noble & Giebler, 2020; Johnson, Riis, & Noble, 2016; Brito & Noble, 2014). Although many disparities in outcomes may be because of societal factors that are independent of the brain, in some cases, the brain may also play a

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role in elucidating socioeconomic disparities in mental health and educational success, potentially as a mediator, moderator, or sensitive measure of the function of neurocognitive or affective systems (Hackman & Kraemer, 2020; Farah, 2017). Large-sample studies have indicated that greater disadvantage is associated with lower surface area across the whole brain, as well as in the pFC and regions of the temporal and parietal lobes (Hackman et al., 2021; Noble & Giebler, 2020; Noble et al., 2015). Similarly, socioeconomic disadvantage is correlated with less total and prefrontal cortical gray matter volume (Noble & Giebler, 2020; Gur et al., 2019; McDermott et al., 2019; Holz et al., 2014), and with less total subcortical (Hackman et al., 2021) and hippocampal volume as well (Noble & Giebler, 2020; McDermott et al., 2019; Raffington et al., 2019; Noble, Houston, Kan, & Sowell, 2012; Hanson, Chandra, Wolfe, & Pollak, 2011), with mixed results for the amygdala (McDermott et al., 2019; Merz, Tottenham, & Noble, 2018; Noble et al., 2012; Hanson et al., 2011).

Such socioeconomic differences highlight the need to understand processes of resilience, or adaptive processes in challenging circumstances or environments (Masten, Lucke, Nelson, & Stallworthy, 2021) as well as the factors that promote positive outcomes for all youth. Of particular importance for youth who have experienced adversity are protective, moderating factors that interact with environmental exposures. One source of such protection may be the school environment, which has been hypothesized to have the potential to exacerbate or reduce disparities (Raudenbush & Eschmann, 2015). More specifically, recent work has highlighted the potential importance of the school environment, which is oriented to support child development, as a key component of resilience from a multilevel perspective (Longhi, Brown, & Fromm Reed, 2021; Masten & Motti-Stefanidi, 2020; Ungar, Connelly, Liebenberg, & Theron, 2019). Therefore, understanding the role of the school environment in affective and brain development, and whether it is independent of SES or interacts with it, is of central importance.

School Climate: Definitions and Potential Mechanism

The school climate is an expansive, multidimensional construct that captures academic and institutional environments, as well as the school community and school safety (for reviews, see the works of Astor & Benbenishty, 2019; Berkowitz, Moore, Astor, & Benbenishty, 2017; Wang & Degol, 2016; Thapa, Cohen, Guffey, & Higgins-D'Alessandro, 2013; Sugai & Horner, 2006). It includes the sense of connectedness to school; the quality of relationships, trust, and support between students and staff; norms, culture, and practices of the school, including the clarity and fairness of rules; the experience of physical and emotional safety; fairness, diversity, and equity; use of positive reinforcement and opportunities; and rewards for prosocial involvement.

These aspects of the school climate may influence developmental outcomes via multiple potential mechanisms (Wang & Degol, 2016). Among the many plausible mechanisms are the importance of strong relationships, in a manner that may be analogous to the broader influence of warm, responsive parenting or healthy attachment (Wang & Degol, 2016), as well as the promotion, through norms, rewards, or curriculum, of children's socioemotional development (Durlak, Weissberg, Dymnicki, Taylor, & Schellinger, 2011; Sugai & Horner, 2006). A positive climate may also create a safe and emotionally supportive environment that reduces stress and threats (Durlak et al., 2011; Sugai & Horner, 2006), which may be particularly salient in the context of socioeconomic risk, which is associated with increased stress exposure (Evans, 2004; Turner & Avison, 2003; Leventhal & Brooks-Gunn, 2000; McLoyd, 1998). In this way, positive school climates may reduce stressors but also provide youth with the resources to cope effectively and thus perhaps also modify the appraisal or experience of varied stressors (Compas et al., 2017; Blascovich & Mendes, 2010; Chen, Langer, Raphaelson, & Matthews, 2004; Pearlin & Schooler, 1978). Consequently, a positive school climate may also promote more adaptive functioning and potentially buffer the effect of broader environmental stressors on development and on the limbic system and pFC (McEwen, Nasca, & Gray, 2016; McLaughlin et al., 2014; Durlak et al., 2011; McEwen & Gianaros, 2010; Arnsten, 2009; Lupien, McEwen, Gunnar, & Heim, 2009; Ellis & Boyce, 2008; Sugai & Horner, 2006). These factors highlight the potential importance of school climates for healthy socioemotional development and brain development for young students and also help explain why the supportive functions of a positive school climate may be most influential in the context of stress and adversity, or for students from lower SES families.

School Climate and Socioemotional Health

There is considerable evidence that positive school climates are associated with lower levels of mental health problems or better socioemotional functioning (Astor & Benbenishty, 2019; Aldridge & McChesney, 2018; Wang & Degol, 2016; Thapa et al., 2013; Durlak et al., 2011). For example, numerous studies have found inverse associations between a school climate and depressive symptoms (Wang & Peck, 2013; Li & Lerner, 2011; Wang, 2009; Costello, Swendsen, Rose, & Dierker, 2008; Bond et al., 2007; Loukas & Murphy, 2007; Way, Reddy, & Rhodes, 2007; Loukas, Suzuki, & Horton, 2006; Roeser & Eccles, 1998), as well as beneficial associations with externalizing problems, self-esteem, and measures of general emotion and psychological well-being (Oberle, Guhn, Gadermann, Thomson, & Schonert-Reichl, 2018; Murray & Zvoch, 2011; Freeman et al., 2009; Witvliet, van Lier, Cuijpers, & Koot, 2009; Way et al., 2007). Although the evidence may be strongest for adolescents (Wang & Degol, 2016), there is also evidence that socioemotional learning interventions for younger children that include school-wide components that modify school climate also result in reduced emotional and behavioral problems (Durlak et al., 2011).

Nevertheless, fewer studies have considered the role of socioeconomic adversity, and the potential independent or moderating roles of schools and SES in socioemotional development (Aldridge & McChesney, 2018; Wang & Degol, 2016). Positive school climates have been found to reduce the association between achievement and both SES and neighborhood crime (Laurito, Lacoe, Schwartz, Sharkey, & Ellen, 2019; Berkowitz et al., 2017), suggesting school climates may be a protective factor. In addition, there is evidence that low levels of school connectedness may only be associated with more depressive symptoms in the presence of perceived economic hardship (Arora & Wheeler, 2018). Similarly, in middle and high school, a stronger association between a positive school climate and lower levels of problem behaviors was found for lower- compared to higher-SES youth (Hopson & Lee, 2011). Although the opposite pattern has also been found (Sampasa-Kanyinga & Hamilton, 2016), the bulk of research suggests that school climate may serve as a protective factor that buffers against adversity, and that it is most strongly associated with socioemotional outcomes for lower-SES youth. Nevertheless, no studies have tested this hypothesis in a large population-level sample.

School Climate and Neurocognitive Development: Early Data and Evidence of Moderation

Although support of socioemotional functioning is a factor that might explain why positive school climates may serve as a protective buffer against developmental adversity, no large-scale study to date has tested this hypothesis on either a cognitive or a neural level. Predictions for neural systems that would be implicated in this putative association can be drawn from the vast literature on the neural basis of socioemotional functioning in youth, adolescents, and adults. This research highlights the role of subcortical-prefrontal connections—including amygdala, nucleus accumbens, and orbitofrontal cortex—underlying emotional responsivity (Kim, Gee, Loucks, Davis, & Whalen, 2011; Pessoa & Adolphs, 2010; Williams & Gordon, 2007; Whalen, 1998), as well as a network of lateral prefrontal-parietal regions that subserve emotion regulation (Braunstein, Gross, & Ochsner, 2017; Buhle et al., 2014; Lee, Heller, van Reekum, Nelson, & Davidson, 2012; McRae et al., 2012; Ochsner, Silvers, & Buhle, 2012; Perlman et al., 2012; Goldin, McRae, Ramel, & Gross, 2008). For instance, several studies have associated the activity and connectivity of these regions with developmental markers of emotion regulation and emotional responsivity (Lee et al., 2012; McRae et al., 2012; Casey, Jones, & Somerville, 2011; Casey, Somerville, et al., 2011; Somerville & Casey, 2010). It would therefore be expected that long-term neural changes associated with environmental influences on socioemotional development might be observed in these regions as well.

Although few studies have examined the direct associations between school environment and neural markers of socioemotional development, school environments have been included as part of a multidimensional pattern of environmental risk exposures associated with brain structure (Hong et al., 2021; Modabbernia, Janiri, Doucet, Reichenberg, & Frangou, 2021; Alnæs, Kaufmann, Marquand, Smith, & Westlye, 2020). Moreover, one functional study found that hostile school environments are associated with greater activity during social exclusion in the right subgenual anterior cingulate cortex (Schriber et al., 2018), suggesting that social and emotional components of school environments may be related to affective neural systems. However, there is less work on either the independent association of school environment with brain structure or its role in buffering the potential role of socioeconomic risk.

Nevertheless, there is another early evidence that suggests that positive school climates may function as moderators, reducing the association between disadvantage and neural outcomes. One study of 9- to 18-year-olds found that higher levels of academic support at school was associated with both higher levels of executive function and greater cortical thickness, although they found no associations with cortical surface area nor with a more comprehensive measure of school climate (Piccolo, Merz, & Noble, 2019). This same study found a reduced association between family SES and executive function performance with high levels of academic support. In a separate study, the school environment moderated the associations between neighborhood disadvantage and both within- and between-networks resting-state functional connectivity in a small subset of networks in a large community sample (Rakesh, Seguin, Zalesky, Cropley, & Whittle, 2021).

Combined, these findings highlight the possibility that school environments may be associated with brain structure and affective functioning and that their role may also depend on SES, thus underscoring the importance of examining these questions at the population level. Specifically, more research is needed to address the role of positive school climate in supporting socioemotional functioning and associated neural development, as well as interactions with SES.

Current Study

Consequently, this study aimed to determine if SES and school climates exhibit independent or interactive associations with (a) socioemotional functioning and (b) cortical and subcortical brain structure, both at the whole-brain level and in regions relevant for socioemotional functioning, in a large, diverse community sample. To address these questions, we utilized baseline data from the

Adolescent Brain and Cognitive Development (ABCD) study, the largest study of youth health and neurodevelopment in the United States (Garavan et al., 2018; Volkow et al., 2018). We hypothesized that SES and school climate would both be associated with socioemotional functioning, that a supportive school climate would correlate with brain structure in regions relevant for socioemotional development and mental health, and that the effects would be strongest at the lowest income levels.

METHODS

Participants and Procedures

Participants for this analysis come from the baseline wave of data collection in the ABCD study (ABCD release 2.0.1), a diverse cohort of 11,875 youth enrolled at age 9–10 years who will be followed longitudinally for 10 years (Garavan et al., 2018; Volkow et al., 2018). ABCD is conducted at 21 sites across urban and rural settings in the West, South, Midwest, and Northeast United States chosen in a competitive grant application process (Garavan et al., 2018), and baseline visits for youth and caregivers include interviews, surveys, neurocognitive tests, and neuroimaging assessments. As detailed previously, youth were recruited through a stratified probability sampling for each site at the school level, based on public, public charter, and private schools identified within approximately a 50-mile radius of the data collection site (Garavan et al., 2018), whereas a subgroup of twins was recruited through direct contact using birth registries (Garavan et al., 2018; Iacono et al., 2018). Consequently, the sample is not technically a representative subsample of the U.S. population but is diverse and was designed to resemble the regional and demographic diversity of the U.S. population (Compton, Dowling, & Garavan, 2019; Garavan et al., 2018). Centralized institutional review board (IRB) approval was obtained from the University of California, San Diego, for the ABCD study, and each study site obtained local IRB approval. Written informed consent was provided by each parent or caregiver, and children provided written assent. Secondary data analysis was approved by the IRB of the University of Southern California.

To determine the final analytic sample, we accounted for family relatedness, as 9,987 families are included at baseline, with 8,146 families having one participant and 1,841 families having two or more youth enrolled. To reduce nonindependence, we randomly picked one youth for inclusion from each family with more than one participant (n = 9,987), because of the small proportion of families with more than one participant. We further excluded 25 participants with missing responses on the school environment questionnaire and 1,075 participants' missing data on family income, parental education, household size, or other covariates.[1] This resulted in an analytic sample of n = 8,887 overall for socioemotional outcomes, ranging from n = 8,884 to n = 8,886 for each model based on additional missing data for outcome measures. The analytic sample for neuroimaging analyses was n = 7,932, after excluding an additional 597 participants whose imaging data did not meet quality control, 354 participants whose scan had abnormal image artifacts or warranted clinical referral, and 4 participants' missing data on neuroimaging-specific covariates or magnetic resonance imaging (MRI) data. Participant characteristics are illustrated in Table 1.

Measures

School Climate

The ABCD study employed a modified 12-item School Risk and Protective Factors (SRPF) scale, completed by youth, to capture the quality of the school environment as well as involvement in and connection to school (Zucker et al., 2018; Arthur et al., 2007). Each item includes a statement, and youth indicate if the statement is 1 = definitely not true for you; 2 = mostly not true for you; 3 = mostly true for you; and 4 = definitely true for you.

We utilized a cross-validation approach, using Mplus Version 8 (Muthén & Muthén, 1998), to characterize the factor structure of this scale, and to identify a subscale that captures the overall quality of the school climate. The factor analysis was conducted utilizing SRPF responses from all individuals with complete SRPF data, after randomly selecting one youth per family with multiple participants, before other exclusionary criteria for analyses (total of 9,962 individuals). The study sample was randomly split into two groups, and exploratory factor analysis was conducted to examine a range of one to three latent factors among the 12 manifest variables with one of the randomly split subgroups. Eigenvalues and scree plot suggested a two-factor model that explained 40.7% of the total variance. The first factor included four items that uniquely loaded on this factor, with loadings above 0.4, including items such as "In my school, students have lots of chances to help decide things like class activities and rules" and "My teacher(s) notices when I am doing a good job and lets me know about it" (see Table 1 for item distributions). These items capture the school's opportunities for engagement, communication with parents/students, and use of positive reinforcement. An additional factor, with three items that uniquely loaded, included items such as "I like school because I do well in class" and "Usually, school bores me," which captures less about perceptions of the school environment and more about how children feel about their performance and how they enjoy school. The remaining five items had low factor loadings (< 0.4) or loaded on both factors. Given the first factor more closely represented the school climate/environment of focus in this study, we conducted a confirmatory factor analysis with these four items with the other randomly split subgroup, which exhibited a very good fit to the data (CFI = 0.96, RMSEA = 0.09, SRMR = 0.025), suggesting a reliable measurement of school climate

Table 1. Sample Characteristics for Final Analytic Sample (n = 8,887)

	Mean (SD) or N (%)
Age	9.9 (0.6)
Gender	
Female	4250 (47.8%)
Male	4637 (52.2%)
Race/ethnicity	
Hispanic/Latino	1756 (19.8%)
White, Not Hispanic/Latino	4750 (53.5%)
Black or African American	1185 (13.3%)
Native American, American Indian, or Alaskan Native	27 (0.3%)
Asian	176 (2.0%)
Other	993 (11.2%)
Parental education	
Less than high school	331 (3.7%)
High school/GED	743 (8.4%)
Some college	2270 (25.5%)
Bachelor's degree	2309 (26.0%)
Post graduate degree	3234 (36.4%)
Family income-to-needs ratio (InR)	3.97 (2.90)
≤ 2	2764 (31.1%)
> 2	6123 (68.9%)
School climate	
In my school, students have lots of chances to help decide things like class activities and rules	2.8 (0.9)
My teacher(s) notices when I am doing a good job and lets me know about it	3.4 (0.7)
The school lets my parents know when I have done something well	3.2 (0.9)
There are lots of chances to be part of class discussions or activities	3.4 (0.7)
Factor score	0 (0.3)
Child Behavior Checklist	
Internalizing behavior	48.7 (10.5)
Externalizing behavior	45.8 (10.2)
BIS/BAS Scale	
Behavioral inhibition	9.5 (3.7)
Reward responsiveness	11.0 (2.9)
Drive	4.1 (3.0)
Fun seeking	5.7 (2.6)

in this study sample. Thus, a factor score based on these four items was created and used in all analyses.

Socioemotional Functioning

Psychopathology symptoms. Parents report on symptoms using the Child Behavior Checklist of the Achenbach System of Empirically Based Assessment (Barch et al., 2018; Achenbach & Rescorla, 2001), a widely validated measure across cultures that shows good reliability and internal consistency in the ABCD data set (Clark et al., 2021; Barch et al., 2018). For all items, parents report whether they are not true, somewhat or sometimes true, or very or often true within the last 6 months. Analyses focused on parent reports of internalizing (33 items; $\alpha = .87$) and externalizing problems (35 items; $\alpha = .90$), which exhibit very good reliability in our analytic sample.

Affective function. In addition, children completed the BIS/BAS, which assesses the behavioral inhibition and activation motivational systems, capturing both passive avoidance behavioral inhibition scale and also positive emotion and reinforcement (Barch et al., 2018; Carver & White, 1994). Analyses focused on the Behavioral Inhibition subscale ($\alpha = .63$), as well as the Drive ($\alpha = .77$), Fun ($\alpha = .66$), and Reward Responsivity ($\alpha = .73$) scales, which displayed good reliability.

Family Income

Family income, reported by the primary caregiver, covered all sources of income for all members of the family, including wages, benefits, social security, unemployment benefits, child support payments, help from relatives, and other sources. It was collected in ordinal ranges (< \$5,000; \$5,000 – \$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; ≥ \$200,000. We created an income-to-needs ratio for each participant, utilizing the midpoint of each ordinal range (with ≥ \$200,000 estimated as \$250,000) divided by the federal poverty line for 2017 (https://aspe.hhs.gov/topics/poverty-economic-mobility/poverty-guidelines/prior-hhs-poverty-guidelines-federal-register-references/2017-poverty-guidelines) based on household size reported by caregivers. Household sizes lower than 2 ($n = 46$) were treated as missing data, as the minimum plausible household size included the participant and caregiver, and values greater than 20 ($n = 2$) were also treated as missing. The mean income-to-needs ratio was 3.97 ($SD = 2.90$); it ranged from 0.03 to 15.39, and 1,331 (14.98%) and 2,764 (31.1) participants were below 100% or 200% of the federal poverty line, respectively. The income-to-needs ratio measure was then dichotomized as ratio ≤ 2 (31.1%) versus ratio > 2 (68.9%), to specifically capture the role of economic need (Neckerman, Garfinkel, Teitler, Waldfogel, & Wimer, 2016; Fass, 2009; Lynch, Kaplan, & Shema, 1997).

Neuroimaging Acquisition and Preprocessing

Participants complete a T1-weighted neuroanatomical MRI scan as part of a comprehensive, multimodal neuroimaging assessment (Hagler et al., 2019). The MRI methodology, equipment, acquisition parameters, and preprocessing steps have been optimized and harmonized across ABCD sites for 3 T scanners (General Electric 750, Philips, Siemens Prisma), and details regarding all steps have been described previously (Hagler et al., 2019; Casey et al., 2018). Images were only included if they passed the ABCD Data Analysis, Informatics and Resource Center quality control protocols, to gauge the severity of motion, pial overestimation, white matter underestimation, intensity inhomogeneity, and magnetic susceptibility artifact (Hagler et al., 2019). In addition, images were not included in analyses if scans displayed findings that warranted clinical referral or incidental findings with abnormal image artifacts. Cortical surface reconstruction and subcortical segmentation were processed via FreeSurfer (Version 5.3.0) for subcortical volume (mm^3), cortical thickness (mm), and cortical surface area (mm^2; Hagler et al., 2019; Casey et al., 2018; Dale, Fischl, & Sereno, 1999). Cortical thickness and surface area for ROIs were segmented using the Desikan-Killiany Atlas (Desikan et al., 2006).

Given the prior literature, we focused on both whole-brain measures as well as additional analyses in six subcortical regions (amygdala, caudate, hippocampus, nucleus accumbens, pallidum, and putamen) and 11 cortical regions (caudal anterior cingulate, rostral anterior cingulate, entorhinal, insula, middle temporal, lateral orbitofrontal, medial orbitofrontal, pars opercularis, rostral middle frontal, superior frontal, and superior temporal). Regions were included that have been implicated in socioemotional functioning, depression or mental health problems, across multiple measures of brain structure, including cortical thickness, surface area, and gray matter volume (Hare & Duman, 2020; Whittle, Vijayakumar, Simmons, & Allen, 2020; Barch et al., 2019; Suh et al., 2019; Schmaal et al., 2017; Snyder, Hankin, Sandman, Head, & Davis, 2017; Brumback et al., 2016; Luby et al., 2016; Casey, 2015; Whittle et al., 2014; Urošević, Collins, Muetzel, Lim, & Luciana, 2012; Casey & Jones, 2010; Paus, Keshavan, & Giedd, 2008; Ressler & Mayberg, 2007).

Data Analysis

Multilevel linear mixed-effects models (Fitzmaurice, Laird, & Ware, 2011; Singer & Willett, 2003; Diggle, Heagerty, Liang, & Zeger, 2002) were utilized as the primary analytic strategy to model the association between school climate, family income-to-needs ratio, and all outcomes, with individuals nested within ABCD study sites to account for the correlations among individuals within study site. For socioemotional functioning outcomes, two-level linear mixed-effects models were used with a random intercept for study site. All models adjusted for age, sex, parent-reported race/ethnicity, and the highest level of education completed by either caregiver (see Table 1 for categories and descriptive statistics), with the income-to-needs ratio $\leq$ 2 group utilized as the reference group such that the higher income group is compared to economic need. Additional supplemental analyses were conducted using a continuous measure of income to needs to examine robustness to alternative specifications of family income. The base model for socioemotional outcomes is thus:

$$Y_{ij} = \beta_0 + \beta_1 \ \textit{School Climate}_{ij} + \beta_2 \ \textit{IncomeGroup}_{ij} + \beta_X \textit{CovariateSet}_{ij} + u_j + r_{ij}$$

Here, Y_{ij} is the ith person in the jth study site, β_X corresponds to a set of fixed-effects parameters for each covariate, u_j is the site-level variation in the intercept, following the normal distribution $N(0, \tau_{00})$, and r_{ij} is the random error associated with the ith person in the jth study site, normally distributed, $N(0, \sigma^2)$. Subsequently, moderation analyses for each outcome were conducted by adding the additional term, β_3 *School Climate*$_{ij}$ $\times$ *IncomeGroup*$_{ij}$ to capture the interactions between school climate and income level. To aid in interpretation, stratified analyses by income level were performed for those outcomes with significant interaction terms.

The same overall modeling strategy was employed for the whole-brain structure as for socioemotional outcomes, including for moderation analyses. For ROI analyses, a three-level linear mixed-effects model was applied to account for repeated measures across hemispheres that are nested within individuals that are nested within study sites (Hackman et al., 2021; Cserbik et al., 2020; Diggle et al., 2002). This leads to the following equation:

$$Y_{kij} = \beta_0 + \beta_1 \textit{School Climate}_{ij} + \beta_2 \textit{IncomeGroup}_{ij} + \beta_3 \textit{Hemisphere}_{kij} + \beta_X \textit{CovariateSet}_{ij} + u_j + r_{ij} + v_{kij}$$

Y_{kij} is the outcome for the kth hemisphere, for the ith person in the jth study site. In this model, v_{kij} is the random effect associated with hemispheres within individual, and β_3 captures the fixed effect of hemisphere. In all models for brain structure, covariates were also added for handedness (Veale, 2014) and MRI manufacturer, and for subcortical volume, models were further adjusted for intracranial volume.

All models report results in terms of both unstandardized (B) and standardized (β) betas, to illustrate results in original, meaningful units and in terms of standard deviations (Funder & Ozer, 2019). Main effects and interactions were corrected for multiple comparisons using the false discovery rate (Benjamini & Hochberg, 1995) within six socioemotional functioning outcomes and for ROI analyses, within measurement domain for each of six subcortical regions and 11 cortical regions. All analyses were done in SAS Version 9.4 (SAS Institute Inc., 2015).

RESULTS

Preliminary Analyses

School climate was negatively associated with income-to-needs ratio ($r = -.04$, $p < .001$). Consistently, there were also significant differences in school climate across the two levels of income-to-needs ratio, $F(1, 8885) = 29.06$, $p < .001$. Post hoc tests demonstrate that income-to-needs ratio $\leq$ 2 youth reported a more positive school climate than youth from ratio > 2 ($p < .001$, $d = 0.12$) families.

Socioemotional Functioning

With respect to symptoms of psychopathology, As illustrated in Table 2 and Figure 1, a positive school climate was related to lower levels of internalizing symptoms ($B = -2.40$, $p < .0001$, *p-fdr* < .0001). In addition, higher income ($B = -1.35$, $p < .0001$, *p-fdr* < .0001) was associated with lower internalizing symptom levels as well. Similarly, positive school climates ($B = -1.55$, $p < .0001$, *p-fdr* < .0001) and higher family incomes ($B = -2.12$, $p < .0001$, *p-fdr* < .0001) were related to lower levels of externalizing symptoms. These associations were independent, and there were no significant interactions between family income levels and school climate (see Table 2).

With respect to behavioral inhibition and approach, a positive school climate was associated with higher reward responsiveness ($B = 1.23$, $p < .0001$, *p-fdr* < .0001), drive ($B = 0.72$, $p < .0001$, *p-fdr* < .0001), and fun seeking ($B = 0.76$, $p < .0001$, *p-fdr* < .0001) but not with inhibition ($B = 0.001$, $p = .99$, *p-fdr* = .99; see Figure 1, Table 2). Family income was not associated with any measure, and there were no significant interactions between school climate and family income (Table 2).

When utilizing a continuous measure of income to needs, results follow the same pattern for the main effect of income to needs and school climate as well as for interactions (Table A1).

Whole Brain

Results from all whole-brain models are in Table 3. With respect to total subcortical volume, youth from families with higher incomes ($B = 178.47$, $p = .03$) exhibited larger volumes compared to youth from lower income families. This association attenuated and at a trend level, with a continuous measure of income to needs (Table A2). There was no association between school climate and subcortical brain volume, nor any significant interactions between school climate and family income (Table 3).

For cortical surface area, higher family income ($B = 2360.18$, $p < .0001$) was associated with greater total cortical surface area, compared to economic need (Figure 2, Table 3). Although there was no evidence of an independent association of school climate with family income ($B = -115.15$, $p = .83$), there was a significant interaction between school climate and higher family income ($B =$

Table 2. Socioemotional Functioning: School Climate and Family Income-to-Needs Ratio (Categorical), Primary and Moderation Models

	School Climate			*Income-to-Needs Ratio (Categorical, > 2 vs. ≤ 2.0)*			*School Climate × Income-to-Needs Ratio (Categorical)*		
	B	β	*p*	*B*	β	*p*	*B*	β	*p*
Primary model									
Internalizing problems	−2.4	−0.07	<.0001*	−1.35	−0.13	<.0001*			
Externalizing problems	−1.55	−0.05	<.0001*	−2.12	−0.21	<.0001*			
Behavioral inhibition	0.001	0.00	.99	−0.05	−0.01	.64			
Reward responsivity	1.23	0.13	<.0001*	0.01	0.004	.88			
Drive	0.72	0.07	<.0001*	−0.12	−0.04	.16			
Fun	0.76	0.09	<.0001*	0.02	0.01	.83			
Moderation model									
Internalizing problems	−2.63	−0.08	<.0001*	−1.35	−0.13	<.0001*	0.36	0.01	.63
Externalizing problems	−1.47	−0.05	.01*	−2.12	−0.21	<.0001*	−0.12	−0.004	.87
Behavioral inhibition	0.10	0.01	.64	−0.05	−0.01	.63	−0.15	−0.01	.57
Reward responsivity	1.26	0.14	<.0001*	0.01	0.004	.89	−0.04	−0.01	.83
Drive	0.98	0.10	<.0001*	−0.12	−0.04	.15	−0.39	−0.04	.06
Fun	1.04	0.12	<.0001*	0.01	0.01	.85	−0.44	−0.05	.02

All models were adjusted for age, sex, race/ethnicity, and parent education. Income reference group: income to needs ≤ 2.0. *B* = unstandardized beta; β = standardized beta.

* Indicates *p* values < .05 after FDR correction based on adjustment methods of Benjamini & Hochberg. (Benjamini & Hochberg, 1995)

^ Indicates *p* values < .10 after FDR correction.

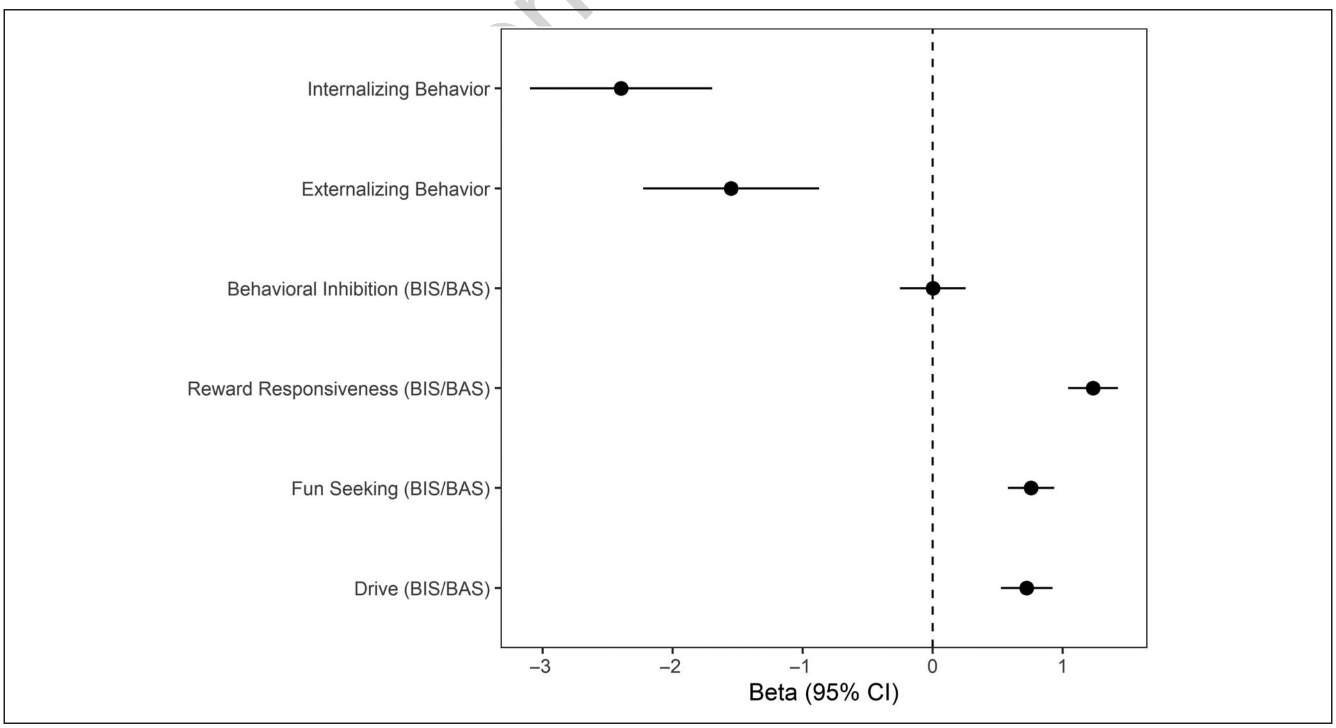

Figure 1. Associations between school climate and socioemotional functioning. Forest plot of unstandardized beta estimates from linear mixed-effects models, adjusted for age, sex, race/ethnicity, parental education, and income level. Bars represent 95% confidence intervals.

Table 3. Whole-Brain Structure: School Climate and Family Income-to-Needs Ratio (categorical), Primary and Moderation Models

	School Climate			*Income-to-Needs Ratio (Categorical, > 2 vs. ≤ 2.0)*			*School Climate × Income-to-Needs Ratio (Categorical)*		
	B	β	*p*	*B*	β	*p*	*B*	β	*p*
Primary model									
Subcortical gray matter volume	3.67	0.00	.97	178.47	0.04	.03			
Total cortical surface area	−115.15	−0.002	.83	2360.18	0.13	<.0001			
Mean cortical thickness	−0.0001	0.00	.97	0.001	0.01	.61			
Moderation model									
Subcortical gray matter volume	8.02	0.00	.96	178.42	0.04	.03	−6.66	0.00	.97
Total cortical surface area	−1738.34	−0.03	.05	2377.3	0.13	<.0001	2483.32	0.04	.03
Mean cortical thickness	0.0027	0.01	.63	0.001	0.01	.61	−0.004	−0.01	.53

All models were adjusted for age, sex, race/ethnicity, parent education, handedness, and MRI manufacturer. Income reference group: Income-to-needs ≤ 2.0. *B* = unstandardized beta; β = standardized beta.

2483.32, p = .03). Results from stratified models utilized to probe this interaction are illustrated in Figure 2 and indicate that more positive school climates were associated with smaller cortical surface area for youth from lower-income families in economic need (B = −1808.19, p = .047), whereas there was no association between school climate and surface area at higher-income levels (B = 824.26, p = .21). There were no significant associations between school climate or family income and mean cortical thickness across the whole brain, nor were there any

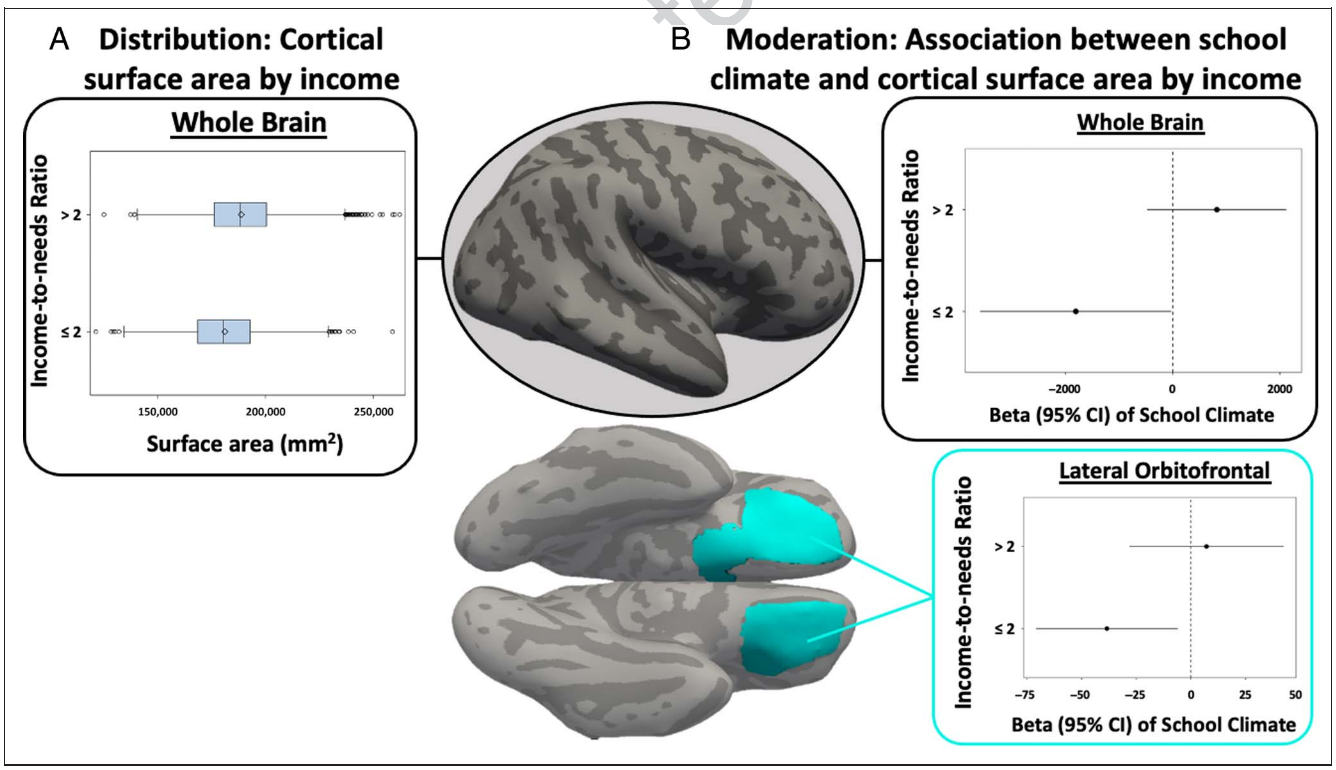

Figure 2. Cortical surface area: (A) Distribution of total cortical surface area by family income level and (B) income level moderates the association of school climate and total cortical surface area (top), and within a lateral orbitofrontal ROI (bottom). (A) Boxplot representing the raw distribution of total cortical surface area across levels of income to needs; (B) forest plots of unstandardized beta estimates from linear mixed-effects models, adjusted for age, sex, race/ethnicity, parental education, handedness, and scanner type, within each income level. Bars represent 95% confidence intervals. Brain images illustrate the whole-brain cortical surface and lateral orbitofrontal ROI (bottom, blue), based on the Desikan-Killiany Atlas (Desikan et al., 2006).

significant interactions. Although continuous measure of income to needs was still positively associated with whole-brain cortical surface area, this interaction was attenuated, and at a trend level, with such a measure (Table A2).

ROIs

Higher family income was related to increased volume in the hippocampus ($B = 25.55$, $p = .007$, $p\text{-}fdr = .042$). In addition, there were no associations between school climate and differences in volume within specific ROIs, nor was there any evidence of moderation, as there were no interactions between school climate and family income that survived correction for multiple comparisons (see Table 4). A similar pattern of results was found using a continuous measure of income to needs (Table A3).

In terms of cortical surface area, higher family income was associated with greater surface area in all ROIs examined (see Table 5). There were no independent associations between school climate and surface area in any ROI (Table 5). However, there was evidence of moderation, with a significant interaction between school climate and higher family income in the lateral orbitofrontal cortex ($B = 72.10$, $p = .0004$, $p\text{-}fdr = .004$). As with total cortical surface area, more positive school climates were associated with smaller cortical surface area within the lateral orbitofrontal cortex for youth families in economic need ($B = -45.84$, $p = .006$), whereas the association between school climate and surface area was positive at higher-income levels ($B = 24.2$, $p = .043$; see Figure 2). This interaction was attenuated and no longer significant after false discovery rate (FDR) correction when using a continuous income-to-needs measure (Table A4).

In addition, there were no significant main effects of school climate on cortical thickness in specific ROIs, whereas higher income was associated with thinner cortex in the rostral anterior cingulate (Table 6). There was a significant interaction between school climate and higher family income in the lateral orbitofrontal cortex ($B = -0.03$, $p = .003$, $p\text{-}fdr = .036$). More positive school climates were associated with greater mean cortical thickness within the lateral orbitofrontal cortex for youth from lower-income families ($B = 0.022$, $p = .008$), whereas there was no association at higher-income levels. No associations or interactions were observed for cortical thickness when using a continuous measure of income to needs (Table A5).

Table 4. Subcortical Volume: School Climate and Family Income-to-Needs Ratio (Categorical), Primary and Moderation Models

	School Climate			*Income-to-Needs Ratio (Categorical, > 2 vs. ≤ 2.0)*			*School Climate × Income-to-Needs Ratio (Categorical)*		
	B	β	*p*	*B*	β	*p*	*B*	β	*p*
Primary model									
Amygdala	2.69	0.004	.63	5.36	0.02	.26			
Caudate	2.89	0.002	.85	−4.17	−0.01	.75			
Hippocampus	4.48	0.003	.69	25.55	0.06	.007*			
Nucleus accumbens	2.96	0.01	.28	−0.2	−0.002	.93			
Pallidum	3.67	0.004	.52	5.27	0.02	.28			
Putamen	−9.77	−0.01	.60	31.12	0.05	.05			
Moderation model									
Amygdala	9.98	0.01	.29	5.27	0.02	.26	−11.16	−0.02	.33
Caudate	−42.72	−0.03	.10	−3.64	−0.01	.78	69.74	0.04	.03
Hippocampus	−5.66	−0.004	.76	25.67	0.06	.007*	15.51	0.01	.50
Nucleus accumbens	5.17	0.02	.26	−0.22	−0.002	.92	−3.38	−0.01	.55
Pallidum	0.94	0.001	.92	5.3	0.02	.28	4.18	0.01	.72
Putamen	17.76	0.01	.57	30.81	0.05	.05	−42.10	−0.02	.28

All models were adjusted for age, sex, race/ethnicity, parent education, handedness, MRI manufacturer, and intracranial volume. Income reference group: Income-to-needs ≤ 2.0. *B* = unstandardized beta; β = standardized beta.

* Indicates p values < .05 after FDR correction (Benjamini & Hochberg, 1995).

^ Indicates p values < .10 after FDR correction.

Table 5. Cortical Surface Area: School Climate and Family Income-to-Needs Ratio (Categorical), Primary and Moderation Models

	School Climate			*Income-to-Needs Ratio (Categorical, > 2 vs. ≤ 2.0)*			*School Climate × Income-to-Needs Ratio (Categorical)*		
	B	β	*p*	*B*	β	*p*	*B*	β	*p*
Primary model									
Caudal anterior cingulate	3.14	0.01	.50	10.02	0.06	.01*			
Rostral anterior cingulate	3.06	0.01	.49	10.81	0.06	.004*			
Lateral orbitofrontal	−0.21	0.00	.98	33.40	0.11	<.0001*			
Medial orbitofrontal	0.22	0.00	.98	20.26	0.09	.0007*			
Pars opercularis	−8.67	−0.01	.30	28.74	0.09	<.0001*			
Rostral middle frontal	−25.42	−0.01	.33	71.49	0.08	.002*			
Superior frontal	−5.05	−0.002	.86	101.49	0.10	<.0001*			
Superior temporal	10.19	0.01	.48	46.19	0.09	.0002*			
Middle temporal	0.15	0.00	.99	43.73	0.09	.0003*			
Entorhinal	−4.30	−0.02	.09	7.51	0.08	.0005*			
Insula	−0.11	0.00	.99	21.77	0.08	.001*			
Moderation model									
Caudal anterior cingulate	0.56	0.001	.94	10.05	0.06	.01*	3.95	0.01	.68
Rostral anterior cingulate	−2.4	−0.004	.75	10.86	0.06	.004*	8.35	0.02	.37
Lateral orbitofrontal	−47.33	−0.05	.004*	33.89	0.11	<.0001*	72.10	0.07	.0004*
Medial orbitofrontal	−11.24	−0.02	.34	20.38	0.09	.0006*	17.53	0.02	.23
Pars opercularis	−17.84	−0.02	.21	28.84	0.09	<.0001*	14.03	0.01	.42
Rostral middle frontal	−77.54	−0.03	.08	72.04	0.08	.001*	79.73	0.03	.15
Superior frontal	−104.5	−0.03	.03	102.53	0.10	<.0001*	152.15	0.05	.01^
Superior temporal	−35.09	−0.02	.15	46.67	0.09	.0002*	69.26	0.04	.02^
Middle temporal	−46.49	−0.03	.05	44.22	0.09	.0002*	71.31	0.04	.02^
Entorhinal	−6.25	−0.02	.14	7.53	0.08	.0005*	2.99	0.01	.57
Insula	−21.45	−0.03	.11	21.99	0.09	.001*	32.65	0.04	.05

All models were adjusted for age, sex, race/ethnicity, parent education, handedness, and MRI manufacturer. Income reference group: Income-to-needs ≤ 2.0. *B* = unstandardized beta; β = standardized beta.

* Indicates *p* values < .05 after FDR correction (Benjamini & Hochberg, 1995).

^ Indicates *p* values < .10 after FDR correction.

DISCUSSION

A positive school climate, capturing opportunities for engagement, communication with parents/students, and the use of positive reinforcement, was associated with better mental health and socioemotional functioning across family income levels. Moreover, with respect to cortical surface area, there was a moderating relationship—school climate was associated with cortical surface area only for youth from lower-income families experiencing economic need. This suggests that school climate may potentially have an independent, promotive role for affective development while functioning as a possible protective factor for structural brain development, and thus an important focus of future, longitudinal research.

With respect to socioemotional function, school climate was associated with lower internalizing and externalizing problems, and thus lower symptoms of psychopathology, consistent with prior literature (Astor & Benbenishty, 2019; Aldridge & McChesney, 2018; Wang & Degol, 2016; Thapa et al., 2013; Wang & Peck, 2013; Durlak et al., 2011; Li & Lerner, 2011; Wang, 2009; Witvliet

Table 6. Cortical Thickness: School Climate and Family Income-to-Needs Ratio (Categorical), Primary and Moderation Models

	School Climate			*Income-to-Needs Ratio (Categorical, > 2 vs. ≤ 2.0)*			*School Climate × Income-to-Needs Ratio (Categorical)*		
	B	β	*p*	*B*	β	*p*	*B*	β	*p*
Primary model									
Caudal anterior cingulate	−0.003	−0.004	.65	−0.01	−0.05	.05			
Rostral anterior cingulate	−0.002	−0.003	.73	−0.01	−0.07	.007*			
Lateral orbitofrontal	0.002	0.004	.69	−0.002	−0.01	.61			
Medial orbitofrontal	−0.01	−0.01	.24	−0.01	−0.07	.004*			
Pars opercularis	−0.002	−0.01	.62	0.003	0.02	.42			
Rostral middle frontal	0.001	0.003	.74	−0.002	−0.01	.68			
Superior frontal	0.001	0.001	.89	−0.001	−0.003	.90			
Superior temporal	0.001	0.002	.84	0.01	0.04	.15			
Middle temporal	0.004	0.01	.48	−0.002	−0.01	.67			
Entorhinal	0.01	0.01	.20	−0.01	−0.03	.33			
Insula	0.003	0.01	.55	0.002	0.02	.57			
Moderation model									
Caudal anterior cingulate	0.01	0.01	.66	−0.01	−0.05	.05	−0.01	−0.02	.38
Rostral anterior cingulate	0.01	0.01	.58	−0.01	−0.07	.007*	−0.01	−0.02	.34
Lateral orbitofrontal	0.02	0.04	.01*	−0.002	−0.01	.57	−0.03	−0.06	.003*
Medial orbitofrontal	0.01	0.01	.55	−0.01	−0.07	.004*	−0.02	−0.03	.11
Pars opercularis	−0.001	−0.002	.91	0.003	0.02	.42	−0.002	−0.004	.82
Rostral middle frontal	0.01	0.02	.18	−0.002	−0.01	.67	−0.01	−0.03	.16
Superior frontal	0.003	0.01	.74	−0.001	−0.003	.90	−0.003	−0.01	.76
Superior temporal	0.01	0.02	.30	0.01	0.04	.15	−0.01	−0.02	.25
Middle temporal	0.01	0.01	.44	−0.002	−0.01	.66	−0.01	−0.01	.67
Entorhinal	0.01	0.01	.68	−0.01	−0.03	.33	0.01	0.01	.67
Insula	0.004	0.01	.63	0.002	0.02	.57	−0.002	−0.003	.86

All models were adjusted for age, sex, race/ethnicity, parent education, handedness, and MRI manufacturer. Income reference group: Income-to-needs ≤ 2.0. *B* = unstandardized beta; β = standardized beta.

* Indicates *p* values < .05 after FDR correction (Benjamini & Hochberg, 1995).

^ Indicates *p* values < .10 after FDR correction.

et al., 2009; Costello et al., 2008; Bond et al., 2007; Loukas & Murphy, 2007; Way et al., 2007; Loukas et al., 2006; Roeser & Eccles, 1998), as well as greater positive emotion and motivation (Oberle et al., 2018). Similarly, consistent with prior work, higher family income was associated with lower internalizing and externalizing symptoms as well (Duncan et al., 2017; Reiss, 2013; Akee et al., 2010; Wadsworth & Achenbach, 2005; Costello et al., 2003; Aneshensel & Sucoff, 1996). Notably, these differences correspond to symptom differences within the typical range of symptomatology and thus may be interpreted in terms of socioemotional or affective functioning, rather than psychopathology symptoms that are at the clinical or at-risk level. Nevertheless, despite some prior literature suggesting that school climate may serve as a moderator or buffer against low SES or poverty in more localized samples (Arora & Wheeler, 2018; Hopson & Lee, 2011), there was no evidence of moderation, suggesting that the role of school environments were equivalent for all. Consequently, this relationship is more consistent with a model of school environments as an independent promotive factor, rather than a protective factor.

Overall, there was no evidence of a direct association between school climate and cortical surface area, cortical thickness, or subcortical volume on the whole-brain level or in any regions implicated in emotion or mental health (see Methods section for a complete list of ROIs). Moreover, the absence of a direct association in such a large and diverse sample suggests that it is not because of low power, or to the specificity of a particular regional sample. There was a clear association, however, between lower family income and smaller cortical surface area across all regions, as well as in subcortical volume and specifically in the hippocampus. These results are largely consistent with prior research on SES and brain structure (Hackman et al., 2021; Noble & Giebler, 2020; McDermott et al., 2019; Merz, Tottenham, et al., 2018; Noble et al., 2015; Brito & Noble, 2014). In addition, the association between school climate and brain structure depended on family income, primarily for cortical surface area. For whole-brain cortical surface area, there was a significant interaction, such that the association with school climate was limited to youth in lower-income families. Although this specific pattern was only significant in one ROI—the lateral orbitofrontal cortex—the whole-brain pattern suggests that this is a widespread pattern, although small in magnitude. It is important to note this pattern was only a trend when utilizing a more continuous measure of income to needs, although this may be because of the imprecision in this measure introduce by assuming specific income levels when they were originally assessed as ordinal categories. Although associations found in this study between school climate and brain structure were not observed in a smaller sample (Piccolo et al., 2019), perhaps because of low power for such interactions, this pattern of results is consistent with the pattern of findings for resting-state functional connectivity in the ABCD cohort as well (Rakesh et al., 2021). Therefore, the present findings suggest that the school climate is worthy of future study as potential policy-relevant protective factor for brain development and that its role as a possible supportive factor for low-income youth is of particular interest.

The direction of the association between school climate and cortical surface area was, however, unexpected. Lower family income and a positive school climate, specifically for lower-income youth, were associated with less surface area in the whole brain and in lateral orbitofrontal cortex, suggesting that putative risk and protective factors are associated with similar differences in brain structure. This interpretation, however, must be cautioned against. First, cortical surface area exhibits a nonlinear developmental trajectory that tends to peak approximately during the developmental window covered by this study (Tamnes et al., 2017; Mills & Tamnes, 2014; Wierenga, Langen, Oranje, & Durston, 2014). Second, although surface area in the orbitofrontal cortex has been previously associated with moderate depressive symptomology in childhood (Schmaal et al., 2017), in this study, symptom severity was associated with lower surface area in youth and, in general, there have been mixed findings with many studies finding no association between surface area and symptoms (Bos, Peters, van de Kamp, Crone, & Tamnes, 2018; Merz, He, & Noble, 2018; Brumback et al., 2016; Luby et al., 2016). Moreover, neurodevelopmental models have highlighted that both environmental stressors and supports may influence the rate of growth in development, potentially related to changes in neuronal pruning, and have proposed that although stressors may accelerate development, particularly in limbic and prefrontal regions, greater environmental supports may be associated with extended developmental trajectories (Tooley, Bassett, & Mackey, 2021; Callaghan & Tottenham, 2016). Combined, the evidence suggests that interpretation of the meaning of smaller or larger surface area may be contingent on the overall pattern of developmental change over time, which is most critical. Consequently, future longitudinal research is needed to further probe how the intersection of supportive school environments and lower family SES is associated with patterns of change over time.

It is also important to highlight the dissociation between the apparent role of school climate in socioemotional functioning, in which family income and school climate were independently associated with internalizing and externalizing, and brain structure, for which there is an interaction between school climate and family income. This suggests that, in terms of the role of school climate, a simple mediation model is unlikely. Instead, it is possible that the role of brain structure in socioemotional disparities is more nuanced. One possibility is moderation, such that brain structure may play a different role in the relationship between school climate and socioemotional function at different income levels (Hackman & Kraemer, 2020). Alternatively, should such differences have relevance for functional outcomes related to school climate, or buffering the effect of adversity, they may emerge over time. Nevertheless, findings for family income suggest that it is possible that structural differences may, along with other social factors, account for part of the relationship between income and internalizing and externalizing symptoms. Given the potential bias in cross-sectional mediation analysis (Maxwell & Cole, 2007), such possibilities should be examined in future longitudinal studies.

The reliance on self-report in the baseline data raises a number of limitations and implications. On the one hand, school climate captures several constructs that are salient in terms of subjective perceptions (Astor & Benbenishty, 2019; Wang & Degol, 2016; Thapa et al., 2013). Relatedly, self-report allows to capture the degree to which the experienced climate may vary either for individuals or systematically for groups, in a manner that is difficult to capture from objective measures. At the same time, it is possible that subjective perceptions of school climate are confounded with self-reports of socioemotional functioning. Moreover, such measures are limited in keeping the focus on the level of individual experience of context, rather than collective or structural constructs and measures that capture the function of the broader environment. Consequently, future work in this area would benefit both from including reports from multiple perspectives, such as including teachers or parents, and including school-level measures in addition to student perceptions (Berkowitz et al., 2017; Thapa et al., 2013).

In addition, the observational, cross-sectional nature of the data precludes causal inference about the role of school climates as well as family income. In particular, the present neural results are potentially interesting markers for later developmental outcomes, but given the unexpected direction of the interactions between school climate, SES, and cortical surface area, longitudinal data are required to understand the potential implications, if any, for future mental health, emotional development, or neural development. Future work would benefit not only from longitudinal analyses within studies such as ABCD but also from the integration of neuroscience measures within experimental and quasi-experimental studies of school climate, particularly in programs and interventions that are targeted to support low-income youth. Moreover, such longitudinal work would benefit from characterizing the school environment over time, to more accurately capture the more cumulative, longer-term experience for youth that may be most likely to play a role in brain and socioemotional development. Although there is a need for stronger evidence of the causal role of school climate in general, prior work on school-wide, multicomponent interventions suggests that such causal processes may be possible (Durlak et al., 2011). Similarly, although there is no experimental evidence to date concerning the causal impact of SES on brain structure, there is a significant literature suggesting that family income changes can have a causal effect on mental health and child development (Leventhal & Dupéré, 2019; Duncan et al., 2017; Dahl & Lochner, 2012; Akee et al., 2010; Costello et al., 2003). Similarly, there is no reason to infer that such correlations will not change over time, potentially because of plasticity as social environments change or in terms of interventions that provide families with income supplements or other supports or that improve school environments. Finally, it is important to note that although the sample is diverse and includes a large subsample of families experiencing significant economic need, the sample is not representative of the U.S. population (Compton et al., 2019) and has higher income than the United States as a whole.

In summary, in the first-of-its-kind analysis of a large, multisite, diverse community sample, there is evidence that school climate has distinct correlations with socioemotional functioning and brain structure. In particular, positive school climates and family income have independent associations with more positive emotion and fewer mental health symptoms, suggestive of a role for schools in promoting affective development for all youth. At the same time, the association between positive school climates and cortical surface area depend on family income, such that the association is present only for low-income youth and thus it is a candidate-protective factor for future longitudinal research. Combined, these findings suggest that simultaneous consideration of school and family environments is important for future prospective research concerning brain development as well as research on potential policies or program to support health and equitable development.

APPENDIX

Table A1. Socioemotional Functioning: School Climate and Family Income-to-Needs Ratio (Continuous), Primary and Moderation Models

	School Climate			*Income-to-Needs Ratio (Continuous)*			*School Climate × Income-to-Needs Ratio (Continuous)*		
	B	β	*p*	*B*	β	*p*	*B*	β	*p*
Primary model									
Internalizing problems	−2.38	−0.07	<.0001*	−0.30	−0.08	<.0001*			
Externalizing problems	−1.53	−0.05	<.0001*	−0.33	−0.09	<.0001*			
Behavioral inhibition	0.002	0.00	.99	−0.01	−0.01	.71			
Reward responsivity	1.23	0.13	<.0001*	−0.01	−0.01	.47			
Drive	0.72	0.07	<.0001*	0.00	0.00	.98			
Fun	0.76	0.09	<.0001*	0.01	0.02	.28			
Moderation model									
Internalizing problems	−2.63	−0.07	<.0001*	−0.29	−0.08	<.0001*	0.07	0.01	.59
Externalizing problems	−1.77	−0.05	.002*	−0.33	−0.09	<.0001*	0.07	0.01	.58
Behavioral inhibition	0.13	0.00	.55	−0.01	−0.01	.69	−0.03	−0.01	.45
Reward responsivity	1.22	0.13	<.0001*	−0.01	−0.01	.47	0.002	0.001	.94
Drive	0.73	0.04	<.0001*	0.00	0.00	.98	−0.002	−0.001	.95
Fun	0.89	0.09	<.0001*	0.01	0.01	.23	−0.04	−0.01	.26

* Indicates p values < .05 after FDR correction based on adjustment methods of Benjamini & Hochberg. (Benjamini & Hochberg, 1995).

^ Indicates p values < .10 after FDR correction. All models were adjusted for age, sex, race/ethnicity, and parent education. B = unstandardized beta; β = standardized beta.

Table A2. Whole-Brain Structure: School Climate and Family Income-to-Needs Ratio (Continuous), Primary and Moderation Models

	School Climate			*Income-to-Needs Ratio (Continuous)*			*School Climate × Income-to-Needs Ratio (Continuous)*		
	B	β	*p*	*B*	β	*p*	*B*	β	*p*
Primary model									
Subcortical gray matter volume	0.98	0.00	.99	23.71	0.01	.08			
Total cortical surface area	−151.42	−0.003	.78	383.97	0.06	<.0001			
Mean cortical thickness	0.00	0.00	.96	0.001	0.02	.20			
Moderation model									
Subcortical gray matter volume	37.27	0.002	.99	23.57	0.01	.08	−9.74	−0.002	.77
Total cortical surface area	−1326.67	−0.001	.89	388.43	0.06	<.0001	315.49	0.02	.09
Mean cortical thickness	0.003	−0.001	.91	0.001	0.02	.21	−0.001	−0.01	.41

All models were adjusted for age, sex, race/ethnicity, parent education, handedness, and MRI manufacturer. Models for subcortical brain volume were also adjusted for intracranial volume. B = unstandardized beta; β = standardized beta.

Table A3. Subcortical Volume: School Climate and Family Income-to-Needs Ratio (Continuous), Primary and Moderation Models

	School Climate			*Income-to-Needs Ratio (Continuous)*			*School Climate × Income-to-Needs Ratio (Continuous)*		
	B	β	*p*	*B*	β	*p*	*B*	β	*p*
Primary model									
Amygdala	2.60	0.004	.64	1.76	0.02	.02			
Caudate	2.96	0.002	.85	−1.92	−0.01	.37			
Hippocampus	4.08	0.003	.71	4.12	0.03	.008*			
Nucleus accumbens	2.96	0.01	.28	−0.17	−0.004	.66			
Pallidum	3.59	0.004	.53	1.17	0.01	.14			
Putamen	−10.24	−0.01	.58	3.78	0.02	.14			
Moderation model									
Amygdala	14.37	0.002	.11	1.71	0.02	.03	−3.16	−0.01	.10
Caudate	−45.87	0.004	.07	−1.73	−0.01	.42	13.10	0.02	.01
Hippocampus	13.89	0.002	.44	4.08	0.03	.008*	−2.63	−0.005	.49
Nucleus accumbens	5.84	0.01	.19	−0.18	−0.01	.64	−0.77	−0.01	.41
Pallidum	0.22	0.005	.98	1.19	0.01	.14	0.91	0.003	.64
Putamen	14.86	−0.005	.62	3.68	0.02	.15	−6.73	−0.01	.29

All models were adjusted for age, sex, race/ethnicity, parent education, handedness, MRI manufacturer, and intracranial volume. *B* = unstandardized beta; β = standardized beta.

* Indicates p values < .05 after FDR correction (Benjamini & Hochberg, 1995).

^ Indicates p values < .10 after FDR correction.

Table A4. Cortical Surface Area: School Climate and Family Income-to-Needs Ratio (Continuous), Primary and Moderation Models

	School Climate			*Income-to-Needs Ratio (Continuous)*			*School Climate × Income-to-Needs Ratio (Continuous)*		
	B	β	*p*	*B*	β	*p*	*B*	β	*p*
Primary model									
Caudal anterior cingulate	2.97	0.01	.52	1.80	0.03	.005*			
Rostral anterior cingulate	2.88	0.01	.51	2.15	0.04	.0005*			
Lateral orbitofrontal	−0.71	−0.001	.94	4.99	0.05	.0003*			
Medial orbitofrontal	−0.12	0.00	.99	3.85	0.05	<.0001*			
Pars opercularis	−9.14	−0.01	.27	3.43	0.03	.003*			
Rostral middle frontal	−26.49	−0.01	.31	12.70	0.04	.001*			
Superior frontal	−6.59	−0.002	.82	18.44	0.06	<.0001*			
Superior temporal	9.48	0.01	.51	7.27	0.04	.0003*			
Middle temporal	−0.52	0.00	.97	6.78	0.04	.0005*			
Entorhinal	−4.41	−0.02	.08	1.17	0.04	.001*			
Insula	−0.46	−0.001	.95	3.52	0.04	.001*			
Moderation model									
Caudal anterior cingulate	5.67	0.01	.45	1.79	0.03	.005*	−0.72	−0.004	.65
Rostral anterior cingulate	3.37	0.01	.64	2.15	0.04	.0005*	−0.13	−0.001	.93
Lateral orbitofrontal	−29.95	0.001	.06	5.10	0.05	.0002*	7.85	0.02	.02
Medial orbitofrontal	−6.68	0.00	.56	3.87	0.05	<.0001*	1.76	0.01	.47
Pars opercularis	−23.73	−0.01	.08	3.48	0.03	.003*	3.92	0.01	.18
Rostral middle frontal	−50.84	−0.01	.4	12.79	0.04	.0005*	6.54	0.01	.47
Superior frontal	−83.62	−0.001	.08	18.74	0.06	<.0001*	20.68	0.02	.04
Superior temporal	−17.11	0.01	.47	7.38	0.04	.0003*	7.14	0.01	.15
Middle temporal	−30.11	0.001	.19	6.89	0.04	.0004*	7.94	0.01	.10
Entorhinal	−7.25	−0.01	.08	1.18	0.04	.001*	0.76	0.01	.38
Insula	−20.18	0.001	.12	3.60	0.04	.001*	5.30	0.02	.05

All models were adjusted for age, sex, race/ethnicity, parent education, handedness, and MRI manufacturer. *B* = unstandardized beta; β = standardized beta.

* Indicates *p* values < .05 after FDR correction (Benjamini & Hochberg, 1995).

^ Indicates *p* values < .10 after FDR correction.

Table A5. Cortical Thickness: School Climate and Family Income-to-Needs Ratio (Continuous), Primary and Moderation Models

	School Climate			*Income-to-Needs Ratio (Continuous)*			*School Climate × Income-to-Needs Ratio (Continuous)*		
	B	β	*p*	*B*	β	*p*	*B*	β	*p*
Primary model									
Caudal anterior cingulate	−0.003	−0.004	.66	−0.001	−0.02	.16			
Rostral anterior cingulate	−0.002	−0.003	.75	−0.002	−0.03	.005			
Lateral orbitofrontal	0.002	0.004	.69	0.001	0.01	.30			
Medial orbitofrontal	−0.01	−0.01	.26	−0.001	−0.02	.23			
Pars opercularis	−0.002	−0.01	.61	0.001	0.01	.30			
Rostral middle frontal	0.002	0.003	.74	0.00	−0.003	.78			
Superior frontal	0.001	0.001	.89	0/00	−0.01	.71			
Superior temporal	0.001	0.002	.85	0.002	0.03	.01			
Middle temporal	0.004	0.01	.47	0.00	0.01	.64			
Entorhinal	0.01	0.01	.20	0.00	−0.002	.87			
Insula	0.003	0.01	.56	0.00	0.004	.74			
Moderation model									
Caudal anterior cingulate	−0.001	−0.004	.92	−0.001	−0.02	.16	0	−0.002	.83
Rostral anterior cingulate	−0.01	−0.002	.50	−0.002	−0.03	.01	0.001	0.01	.54
Lateral orbitofrontal	0.01	0.003	.23	0.001	0.01	.32	−0.002	−0.01	.22
Medial orbitofrontal	−0.002	−0.01	.84	−0.001	−0.02	.22	−0.001	−0.01	.53
Pars opercularis	0.003	−0.01	.67	0.001	0.01	.31	−0.001	−0.01	.35
Rostral middle frontal	0.01	0.001	.06	0.00	−0.004	.73	−0.003	−0.02	.04
Superior frontal	0.01	0.001	.47	0.00	−0.01	.69	−0.001	−0.01	.42
Superior temporal	0.01	0.001	.27	0.002	0.03	.01	−0.002	−0.01	.22
Middle temporal	0.002	0.01	.77	0.00	0.01	.63	0	0.002	.85
Entorhinal	0.02	0.01	.19	0.00	−0.002	.85	−0.002	−0.01	.50
Insula	0.01	0.01	.49	0.00	0.004	.75	−0.001	−0.004	.68

All models were adjusted for age, sex, race/ethnicity, parent education, handedness, and MRI manufacturer. *B* = unstandardized beta; β = standardized beta.

* Indicates *p* values < .05 after FDR correction (Benjamini & Hochberg, 1995).

^ Indicates *p* values < .10 after FDR correction.

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Diversity in Citation Practices

Retrospective analysis of the citations in every article published in this journal from 2010 to 2021 reveals a persistent pattern of gender imbalance: Although the proportions of authorship teams (categorized by estimated gender identification of first author/last author) publishing in the *Journal of Cognitive Neuroscience* (*JoCN*) during this period were M(an)/M = .407, W(oman)/M = .32, M/W = .115, and W/W = .159, the comparable proportions for the articles that these authorship teams cited were M/M = .549, W/M = .257, M/W = .109, and W/W = .085 (Postle and Fulvio, *JoCN*, 34:1, pp. 1–3). Consequently, *JoCN* encourages all authors to consider gender balance explicitly when selecting which articles to cite and gives them the opportunity to report their article's gender citation balance.

Note

1. We considered that missing data might be not at random or at random, with the majority of missing data (97.7%) coming from income-to-needs, one of the independent variables in the model. List-wise deletion was selected, as power is not a concern because of sample size, and this approach is likely to lead to unbiased estimates in both cases (might be not at random and at random), given that most missing data are on the independent variable (Allison, 2001).

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