Identifying Profiles of School Climate in High Schools

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Abstract

This cross-sectional study analyzed data from 364,143 students in 492 high schools who completed the Georgia School Climate Survey during the 2017-18 school year. Through latent profile analysis, we identified that student perceptions of school climate could be classified into three distinct profiles, including positive, moderate, and negative climate. Using multinomial logistic regression, we then identified school and student characteristics that predicted student classification in the student profiles using the total sample and subsamples by race/ethnicity. Among the key results, we found that most of the school characteristics (e.g., percent of students receiving free or reduced lunch, schools with higher percentages of minoritized students) predicting classification in the negative and positive school climate profiles were different for White students compared to minoritized students. For example, Black students in primarily non-White schools were more likely to view school climate positively, whereas the opposite was the case for White students. We also found that Black and Other (e.g., multiracial) students were more likely to be classified in the negative school climate profile and less likely to be classified in the positive school climate profile compared to White students. In contrast, Latino/a/e students were more likely to be classified in the positive school climate profile and less likely to be classified in the negative school climate profile. Implications for research and practice are discussed.

Keywords: School climate, latent profile analysis, LPA, high schools

Impact Statement: This study demonstrates that high school student perceptions of school climate can be classified into three profiles (positive, moderate, and negative). Both school (e.g., school size) and student characteristics (e.g., race/ethnicity) were associated with classification in these profiles, but classification varied by student race/ethnicity. Study findings emphasize the importance for school leadership teams to collect and disaggregate school climate by student race/ethnicity to improve school climate for minoritized students.

Identifying Profiles of School Climate in High Schools

Selecting and implementing practices to improve school climate is a high priority for leadership teams focused on school improvement efforts. School climate is a multifaceted construct comprised of student and school personnel's perceptions of their school environment, including adult and peer relationships, engagement and connectedness with school environment, cultural acceptance, and school safety (Bradshaw et al., 2021; La Salle et al., 2015). The relation between positive school climate and improved student academic and social-behavior outcomes is well documented. For example, reviews of previous research have shown positive school climate to be associated with higher academic achievement, mental health, graduation rates, and lower exclusionary discipline problems (Aldridge & McChesney, 2018; Thapa et al., 2013; Wang & Degol, 2016).

With the signing of the 2015 *Every Student Succeeds Act* (ESSA, 2015), there is a federal requirement for U.S. states to collect one non-academic indicator to assess school quality or student success, such as school climate and safety. These requirements provide school teams with the opportunity to reflect on their student performance and experiences each year and select and implement universal and targeted supports designed to improvement school climate (Bradshaw et al., 2021). Prior to selecting these supports, it is critical for school teams to understand how student perceptions of school climate can be influenced by different environmental characteristics, personal relationships, and individual characteristics and experiences (Konold et al., 2017; La Salle et al., 2015; Thapa et al., 2013).

Characteristics that Influence Student Perceptions of School Climate

One framework for understanding and classifying how these multilevel characteristics impact student perceptions of school climate is through the Cultural-Ecological Model of School

Climate (La Salle et al., 2015). Influenced from Bronfenbrenner's bioecological theory (Bronfenbrenner & Ceci, 1994; Bronfenbrenner & Morris, 2006), the Cultural-Ecological Model of School Climate framework categorizes these multilevel characteristics across four contexts including community, family, school, and the individual (La Salle et al., 2015). Community characteristics include variables such as neighborhood safety, community resources (e.g., access to libraries), and respect for cultural diversity within the community (Galvez-Nieto et al., 2020; La Salle et al., 2015; Wang & Degol, 2016). School characteristics describe the school or classroom context, such as school locale (e.g., urban vs. rural school), school achievement, school race/ethnicity composition, school and classroom size, and teacher characteristics (e.g., years of experience, education level; Aldridge & McChesney, 2018; Ellis et al., 2022; Koth et al., 2008). Family characteristics include variables like parent education level, family values, number of family members in the household, and socioeconomic status (La Salle et al., 2015; O'Malley et al., 2015). Last, individual characteristics include variables such as student race/ethnicity, student abilities, educational level, and past experiences (La Salle et al., 2015; Thapa et al., 2013). As characteristics across multiple levels impact student perceptions of school climate, school teams seek to identify interventions to improve targeted domains of school climate (e.g., peer relationships, cultural values, and school safety) at multiple levels within a system (e.g., family, school and classroom, individual student experiences). One example is the widespread implementation of Positive Behavioral Interventions and Supports (PBIS; Horner & Kittelman, 2021). PBIS is a multitiered framework that provides varying levels of support to students based on their needs.

Student Patterns of School Climate

In addition to understanding how multilevel characteristics impact student perceptions of school climate, school teams would also benefit from understanding how subpopulations of students may vary in their perceptions of school climate and therefore have poorer school outcomes. For example, Van Eck et al. (2017) conducted a multilevel latent profile analysis using extant data from over 25,000 students across 106 secondary schools to identify whether there were different school climate profiles and whether the profiles were related to chronic absence rates at the school level. The authors identified three distinct student school climate profiles, labeled as positive climate, moderate climate, and negative climate. The authors also found that students in the positive climate profile had significantly lower rates of chronic school absences compared to students in the moderate or negative student climate profiles.

In a related study on school climate, Parris et al. (2018) conducted a cross-sectional study with a sample of over 300,000 middle school students who completed the Georgia School Climate Survey (Georgia Department of Education et al., 2014). Using linear regression analyses, the authors found that overall ratings of school climate were significantly worse for students who identified as Black (i.e., African American) compared to Latino/a/e (i.e., Hispanic), White, Asian, or Other. Similarly, students who identified as Other had significantly lower scores compared to Latino/a/e, White, and Asian students. However, students who identified as Latino/a/e or Asian had significantly higher scores than White students. Parris et al. (2018) also found that schools with higher proportions of non-White students had lower scores of perceived school climate. Although this study provides evidence that student race/ethnicity may predict membership in different climate profiles, additional research is needed to confirm this finding and replicate it across high schools. In addition, it is unclear from previous research whether school characteristics may be differentially predictive of student classification in school climate profiles across student race/ethnicities.

In accordance with the Cultural-Ecological Model of School Climate, some school characteristics may affect perceptions of school climate differently by student race/ethnicity. As an example, La Salle et al. (2020) recently conducted a large cross-sectional study with 360,653 high school students who completed the Georgia School Climate Survey (Georgia Department of Education et al., 2014). Using multilevel regression analyses, the authors examined differences by student race/ethnicity in student perceptions of school climate using two of the school climate survey subscales (Cultural Acceptance and School Connectedness). The authors found that Black, Latino/a/e, and Asian students reported significantly higher ratings of Cultural Acceptance when there were greater percentages of racial/ethnic minoritized students in the school, but there were no significant differences in ratings for White students. In addition, White students reported significantly lower ratings for School Connectedness when there were larger percentages of minoritized students in the schools, but there were no significant differences from Black or Asian students (La Salle et al., 2020).

Study Purpose

To extend the current research on identifying predictors of perceived student climate, we sought to conduct a latent profile analysis using a large sample of high school students who completed the Georgia School Climate Survey (Georgia Department of Education et al., 2014). First, we aimed to identify whether there were distinctive latent student profiles of perceived school climate in high schools. Second, we evaluated whether these student profiles were similar across student race/ethnicity subgroups. Next, we evaluated whether school characteristics (students with free or reduced lunch, percent of minoritized students, school locale, school size, school attendance, 4-year graduation rates, and school achievement) and student characteristics (student race/ethnicity) would predict classification in these profiles. The majority of these school and student demographic characteristics are included within the Cultural-Ecological Model of School Climate (La Salle et al., 2015). Therefore, our research questions for this study were:

1. To what extent are there different student profiles of school climate in high schools, and are these profiles consistent across race/ethnicity subgroups?
2. To what extent do school and student characteristics predict classification in student profiles of school climate, and are predictors consistent across race/ethnicity subgroups?

Method

Participants and Settings

Participants included 364,143 students from 492 high schools in a Southeastern state who completed the Georgia School Climate Survey (Georgia Department of Education et al., 2014) during the 2017-18 school year. The largest group of students were ninth graders (n = 105,600, % = 29%), followed by tenth graders (n = 95,149, % = 26.1%), eleventh graders (n = 86,524, % = 23.8%), and twelfth graders (n = 76,870, % = 21.1%). A slight majority were female (n = 189,019, % = 51.9%) compared to male (n = 175,124, % = 48.1%). In addition, the largest proportion of students were White (n = 151,616, % = 41.6%), followed by Black (n = 124,209, % = 34.1%), Latino/a/e (n = 50,622, % = 13.9%), Asian (n = 19,161, % = 5.3%), and Other (n = 18,535, % = 5.1%). See Table 1 for student and school demographic information and descriptive statistics. Missing data on school and student characteristics used as predictors of student latent climate profiles ranged from 0% (student-level race/ethnicity) to 2.8% (school-level academic achievement).

Measures

School Climate

High school students' perceptions of school climate were assessed through the Georgia School Climate Survey (Georgia Department of Education et al., 2014; https://safesupportivelearning.ed.gov/survey/georgia-department-education-school-climate-surveys), which is part of the Georgia Student Health Survey 2.0 survey (Georgia Department of Education et al., 2014). The Georgia School Climate Survey includes 36 items and is administered annually to all public middle and high school students by the Georgia State Department of Education. Each item is measured using a four-point Likert-type scale (1 = *Strongly Disagree*, 2 = *Disagree*, 3 = *Agree*, 4 = *Strongly Agree*). The measure provides schools with an overall score of school climate (mean of the subscales) and eight subscale scores. The subscales include School Connectedness, Peer Support, Adult Support, Cultural Acceptance, Social/Civic Learning, Physical Environment, Safety, and Order and Discipline. Previous research has shown the measure to have strong psychometric properties (the technical manual is available from the Georgia State Department of Education on request; Georgia Department of Education et al., 2014) through confirmatory factor analyses across large middle (n = 301,520; CFI = .97, RMSEA = .07, SRMR = .03) and high school (n = 327,864; CFI = .98, RMSEA = .06, SRMR = .02) samples (La Salle, 2017), with evidence of measurement invariance across race/ethnicity subgroups (La Salle et al., 2021). A brief description of the eight subscales and coefficient alpha and coefficient omega values for the current sample used for this study (n = 364,143) are provided below.

The School Connectedness subscale includes five items (e.g., I feel connected to others at school; α = .81, McDonald's omega (ω) = .80). The Peer Support subscale includes three items (e.g., I get along with other students at school; $\alpha = .69$, $\omega = .69$). The Adult Support subscale includes four items (e.g., Teachers treat me with respect; $\alpha = .91$, $\omega = .91$). The Cultural Acceptance subscale includes five items (e.g., Students show respect to other students regardless of their academic ability; $\alpha = .91$, $\omega = .91$). The Social/Civic Learning subscale includes six items (e.g., Doing the right thing is important to me; $\alpha = .89$, $\omega = .89$). The Physical Environment subscale includes four items (e.g., My school building is well maintained; $\alpha = .80$, $\omega = .81$). The School Safety subscale includes four items (e.g., I have worried about students hurting me; $\alpha = .77$, $\omega = .78$). School safety items were reverse scored so that higher scores reflect positive perceptions of school safety and lower scores reflect negative perceptions. Last, the Order and Discipline subscale includes five items (e.g., My school has clear rules for behavior; $\alpha = .83$, $\omega = .82$).

Student Race/Ethnicity

Students selected their race/ethnicity[1] from the following five categories: 1 = Black or African American, 2 = Hispanic or Latino, 3 = White or Caucasian, 4 = Asian or Pacific Islander, and 5 = Other (e.g., American Indian/Alaska Native, multiracial). For analyses, White students were used as the reference group (all other race/ethnicities compared) and was not coded because they were the largest group.

School Characteristics

School performance data included student attendance, 4-year graduation rate, and academic achievement. Student attendance was based on the percentage of students missing less than 10% of enrolled days. Four-year graduation rate was defined as the number of students who

[1] The Georgia School Climate Survey (Georgia Department of Education et al., 2014) referred to these categories as ethnicity and we used the term race/ethnicity for this study.

graduated in four years divided by the number of students from the graduating class. Academic achievement was a composite variable consisting of students' content mastery scores in English language arts, mathematics, science, and social studies. An academic achievement composite variable was created from these scores because the four variables were highly correlated (r = .87 - .94).

School demographic data included the percentage of students receiving free or reduced lunch (FRL), percentage of minoritized (non-White) students, school locale (i.e., city, suburb, town, rural) and school size. All non-White students were identified as minoritized due to the power differential among White vs. non-White groups (La Salle et al., 2020). School locale was a categorical variable, and schools implementing in suburbs were used as the reference group (city vs. suburbs, town vs. suburbs, and rural vs. suburbs). School size was based on the number of students enrolled in the school.

Procedure

School and student extant data from the 2017-18 school year was retrieved through several databases. First, we obtained de-identified student data on the Georgia School Climate Survey (Georgia Department of Education et al., 2014) and student demographic characteristics (race/ethnicity, grade level) collected from the Georgia Student Health Survey 2.0 (Georgia Department of Education et al., 2014). School performance data (e.g., attendance, 4-year graduation rates, and academic variables) were obtained from the Georgia Department of Education website (https://www.gadoe.org/CCRPI/Pages/default.aspx). Last, school demographic characteristics were obtained from the National Center for Education Statistics (NCES) database (https://nces.ed.gov/ccd/elsi/tableGenerator.aspx).

Data Analysis

To answer the research questions, we conducted a latent profile analysis (LPA) with continuous latent profile indicators using automatic starting values with random starts to create latent profiles from scores across the eight subscales from the Georgia School Climate Survey. Analyses were conducted in M*plus* 8.7 (Muthén & Muthén, 1998-2017). For research question 1, we fit a series of latent profile models and then determined the optimal number using a series of fit indices, entropy scores, and by evaluating classification of group sizes for distinctiveness in the latent profiles. The TYPE = MIXTURE command in M*plus* was used to conduct the LPA analyses. Subscale variances were estimated, and these variances were held constant across latent classes. Fit indices included the Akaike information criterion (AIC), Bayesian information criterion (BIC), and the sample size-adjusted BIC (SABIC; Ferguson et al., 2020; Masyn, 2013). Smaller AIC, BIC, and SABIC scores indicate improved model fit. Entropy scores closer to 1 (range 0 – 1) indicate greater classification accuracy (Ferguson et al., 2020). Finally, individual latent profile sizes equal to or greater than five percent of the sample are considered more acceptable (Weller et al., 2020).

For research question 1, we first identified both the optimal number of latent profiles for the full sample and across each of the student race/ethnicity subgroups: Black, Latino/a/e, Asian, Other, and White. We further evaluated the similarity of latent profiles across race/ethnicity subgroups by testing the relative fit of progressively more constrained multi-group models (Morin et al., 2016): configural (same number of latent profiles across subgroups), structural (equal within-profile means across subgroups), dispersion (equal within-profile variances across subgroups), and distributional (equal latent class probabilities or profile sizes across subgroups). For research question 2, we first conducted a multinomial logistic regression analysis to evaluate school- and student-level predictors of classification in student profiles using the full sample

(Asparouhov & Muthén, 2014). By evaluating the school- and student-level characteristics as predictors of profiles, our goal was not to evaluate or imply temporal prediction or causality of these student profiles by the characteristics; rather, our goal was to determine which characteristics had the strongest independent associations with the profiles. The AUXILIARY (R3STEP) function in M*plus* was used to include the predictors into the optimal latent profile model (Asparouhov & Muthén, 2014). Next, to determine whether school predictors varied by student race/ethnicity, we evaluated the relative fit of the best-fitting multi-group similarity model (configural, structural, dispersion, or distributional) with the school predictors of latent profile classification freely estimated and then constrained to be equal across student race/ethnicity subgroups.

To evaluate the significance of predictors on the total and individual race/ethnicity samples, we used the COMPLEX command to adjust standard errors and account for students nested within schools. Prior to including the predictors in the model, we standardized the continuous school variables to aid in the interpretation of the results. Listwise deletion was used to handle missing data in analyses because missing data was minimal across school-level demographic variables (1.7 - 2.8%).

Results

Student Profiles of School Climate in High Schools

Table 2 provides a summary of the fit statistics, entropy values, and profile sizes for a series of 1-4 latent profile models using the eight student climate survey subscale scores for the (a) total sample and (b) each of the student race/ethnicity subgroups. Based on fit statistics and group classifications and sample sizes, the 3-profile model exhibited the best fit for the total sample and for the race/ethnicity subgroups. Specifically, the 3-profile models included smaller

AIC, BIC, and SABIC values compared to the 2-profile models. Entropy values were consistently high across models (0.83 – 0.86) indicating that between 83% and 86% of students were classified in the correct models. Finally, for each of the four-profile models in Table 2, one of the profiles included less than five percent of the total sample, indicating that the three-profile models were more appropriate. As displayed in Supplemental Table S1, model fit deteriorated as constraints were added in the multi-group LPA models for race/ethnicity subgroups, indicating that the configural similarity model, with freely estimated within-profile means and variances (see Supplemental Table S2) and different relative profile sizes, fit best across student race/ethnicity subgroups.

Figure 1 provides a visual depiction of the three-profile model for the full sample, and Figure 2 provides a similar depiction for each of the student race/ethnicity subgroups. For the full sample, the profile with the highest mean subscale scores included 35% of the sample and was referred to as the positive climate profile. The profile with the second highest subscale scores included 56% of the sample and was referred to as the moderate climate profile. Last, the profile with the lowest mean subscale scores included 9% of the sample and was referred to as the negative climate profile. Student membership across three profiles were similar for each of the student race/ethnicity groups (32 - 36% positive climate profile; 54 - 59% moderate climate profile; 7 - 9% negative climate profile) with the exception of the Other student group (52% positive climate profile; 43% moderate student profile; 5% negative student profile; Figure 2; Supplemental Table S3). Moreover, the graphs presented in Figure 2 were qualitatively similar to the graph of the total sample in Figure 1, with the exception of the graph for Other students, which showed lower and less variability in scores for several of the subscales.

School and Student Predictors

School Characteristics for Full Sample

A summary of the results from the multinomial logistic regression predicting student profile classification from the school characteristics is included in Table 3. The moderate climate profile was used as the reference group when reporting parameter estimates for the school characteristics. As shown in Table 3, school predictors statistically associated with student membership in the school climate profiles (negative or positive vs. moderate) for the full sample included schools with greater percentages of minoritized students, larger schools, schools in cities, and schools with higher academic achievement scores. Specifically, students in schools with higher percentages of minoritized students were significantly less likely to be in the positive climate profile ($p = .01$, OR = 0.92, CI [0.86 – 0.98]) compared to the moderate climate profile. Students in schools in cities (compared to schools in suburbs) were less likely to be in the negative climate profile ($p < .01$, OR = 0.86, CI [0.78 – 0.94]) and students in larger schools were less likely to be in the positive climate profile ($p < .01$, OR = 0.86, CI [0.80 – 0.92]). Last, students in schools with higher academic achievement scores were more likely to be in the positive climate profile ($p < .01$, OR = 1.37, CI [1.25 – 1.51]) and less likely to be in the negative climate profile ($p < .01$, OR = 0.81, CI [0.76 – 0.87]).

School Characteristics Across Race/Ethnicity Subgroups

We then evaluated whether school characteristics as predictors of student profile classification varied across student race/ethnicity samples. As displayed in Supplemental Table S1, the multi-group configural similarity model with predictors of profile membership constrained to be equal across race/ethnicity subgroups fit worse than the model with predictors freely estimated across subgroups; thus, there was variability in the patterns across race/ethnicity subgroups.

As displayed in Table 4, most predictive patterns for White students were different compared to minoritized students. First, for Black students, being enrolled in a school with a greater percentage of students receiving FRL predicted classification in the negative vs. moderate climate profile (p = .04, OR = 1.08, CI [1.00 – 1.17]), whereas for White students, being enrolled in a school with more students receiving FRL predicted classification in the positive vs. moderate climate profile (p = .01, OR = 1.17, CI [1.04 – 1.31]). Second, being enrolled in a school with a higher percentage of minoritized students predicted a lower likelihood of being classified in the negative climate profile for Black (p < .01, OR = 0.88, CI [0.83 – 0.95]) and Asian (p = .01, OR = 0.84, CI [0.74 – 0.96]) students, but predicted a lower likelihood of being classified in the positive climate profile for White students (p < .01, OR = 0.86, CI [0.79 – 0.94]). Third, enrollment in schools located in cities and towns (compared to schools located in suburbs) predicted a lower probability of classification in the negative school climate profile for Black (cities; p < .01, OR = 0.79, CI [0.70 – 0.89]; towns; p = .04, OR = 0.83, CI [0.70 – 0.99]) and Latino/a/e (cities; p = .03, OR = 0.84, CI [0.72 – 0.98]; towns; p = .01, OR = 0.70, CI [0.52 – 0.93]) students, but did not predict climate profile classification for White students. Fourth, school size was a significant predictor of climate profile classification for all groups other than White students; Black (p < .01, OR = 0.81, CI [0.75 – 0.88]), Latino/a/e (p < .01, OR = 0.85, CI [0.78 – 0.93]), Asian (p = .03, OR = 0.86, CI [0.75 – 0.99]), and Other (p = .02, OR = 0.91, CI [0.83 – 0.98]) students in larger schools were less likely to be classified in the positive school climate profile, and Latino/a/e students (p = .01, OR = 0.89, CI [0.82 – 0.97]) in larger schools were also less likely to be classified in the negative school climate profile. Last, for White students only, being enrolled in a school with a higher four-year graduation rate predicted classification in the positive school climate profile (p = .03, OR = 1.13, CI [1.01 – 1.27]).

In contrast with the above patterns, prediction of classification in climate profiles by school academic achievement was more consistent across White and minoritized groups. Being enrolled in a higher achieving school was predictive of a lower likelihood of classification in the negative climate profiles for Black ($p < .01$, OR = 0.83, CI [0.76 – 0.91]), Asian ($p < .01$, OR = 0.70, CI [0.58 – 0.84]), and White ($p < .01$, OR = 0.75, CI [0.79 – 0.81]) students. Similarly, being enrolled in a higher achieving school predicted classification in the positive school climate profile for all race/ethnicity groups (Black [$p < .01$, OR = 1.31, CI [1.17 – 1.46]]); Latino/a/e [$p < .01$, OR = 1.35, CI [1.15 – 1.59]]; Asian [$p < .01$, OR = 1.56, CI [1.23 – 1.96]]; Other [$p < .01$, OR = 1.39, CI [1.22 – 1.58]]; White [$p < .01$, OR = 1.49, CI [1.30 – 1.71]]).

Student Characteristics for Full Sample

Prediction of climate profile classifications by student characteristics (student race/ethnicity) was only evaluated using the full sample (see Table 3). White students were used as the reference group for student race/ethnicity and the moderate climate profile was used as the reference group when comparing positive and negative school climate profile classification. Student characteristics statistically associated with student membership in the school climate profiles included students who identified as Latino/a/e, Black, and Other. Specifically, Black students were significantly less likely to be in the positive climate profile ($p < .01$, OR = 0.94, CI [0.90 – 0.98]) and more likely to be in the negative climate profile ($p = .01$, OR = 1.08, CI [1.02 – 1.15]) compared to White students. In contrast, Latino/a/e students were more likely to be in the positive climate profile ($p < .01$, OR = 1.14, CI [1.07 – 1.21]) and less likely to be in the negative climate profile ($p < .01$, OR = 0.90, CI [0.84 – 0.96]) compared to White students. Finally, similar to Black students, Other students were less likely to be in the positive climate profile ($p < .01$, OR = 0.76, CI [0.72 – 0.82]) and more likely to be in the negative climate profile ($p < .01$, OR = 1.65, CI [1.55 – 1.76]) compared to White students.

Discussion

There were two purposes of this study. First, using a large extant sample of high school students, we sought to explore whether there were distinct latent student profiles of perceived school climate in high schools (total sample) and if profiles were consistent across race/ethnicity subgroups (research question 1). Second, we aimed to identify whether student and school characteristics predicted student classification in these profiles (research question 2).

Extends Research on School Climate Profiles

Through latent profile analyses, we identified three distinct student profiles using the total sample and then replicated and confirmed the presence of three profiles across each of the student race/ethnicity subgroups. Specifically, students could be classified into positive climate, moderate climate, or negative climate profiles in all subgroups. Although statistical tests indicated that the within-profile means and variances and the relative proportions of students in the three profiles varied across subgroups, these features appeared to be qualitatively similar for all but the Other subgroup (see Figure 2).

The findings from research question 1 provide some conceptual replication and extend previous research on patterns and predictors of student classification (Parris et al., 2018; Van Eck et al., 2017). For example, similar to Van Eck et al. (2017), we found three distinct latent school climate profiles using a different measure assessing student perceptions of school climate. In addition, for this study and Van Eck et al. (2017), the student latent profiles were found to capture differences in overall level of perceived school climate instead of having qualitatively different patterns across the subscales for the two measures. Extending this work with a larger sample comprised of only high school students and by examining student race/ethnicity subgroup differences, we evaluated novel school and student predictors of profile classification.

Classification in School Climate Profiles

For research question 2, we first examined school and student characteristics as predictors of student classification using the full sample. For the full sample, students enrolled in schools with a lower percentage of minoritized students, in smaller schools, and in schools with higher academic achievement were more likely to be classified in the positive vs. moderate climate profile. Also, students who identified as Black or Other were less likely to be classified in the positive profile, whereas students who identified as Latino/a/e were more likely to be classified in the positive profile. For classification in the negative vs. moderate profile, students enrolled in schools in cities vs. suburbs and in higher achieving schools were less likely to be classified in the negative climate, as were students who identified as Latino/a/e. By contrast, students who identified as Black or Other were more likely to be classified in the negative profile.

Classification in School Climate Profiles by Race/Ethnicity

We then examined school-level predictors of student classification for each of the student race/ethnicity subgroups. In sum, we found that many of the school characteristics associated with White students being classified in school climate profiles were different compared to minoritized students. For example, being enrolled in schools with a greater percentage of minoritized students, Black students were significantly less likely to be classified in the negative school climate (compared to moderate) profile and White students were significantly less likely be classified in the positive climate profile (compared to moderate). These results confirm and extend findings by La Salle et al. (2020) who examined whether student perceptions on school climate significantly differed by the percentage of minoritized students within schools. For example, La Salle et al. (2020) found that higher percentages of minoritized students within schools was predictive of (a) higher scores on the Cultural Acceptance school climate subscale for Black, Latino/a/e, and Asian students (not for White students) and (b) lower scores for White students on the School Connectedness subscale (not for Black and Asian students).

Our finding that school-level percentages of students receiving FRL differentially predicted climate profiles for Black and White students also extends the findings of La Salle et al. (2020). Although La Salle et al. (2020) did not evaluate if the association between school-level FRL and Cultural Acceptance differed by student race/ethnicity, the authors found that students tended to have lower scores on Cultural Acceptance when they were enrolled in schools with a greater percentage of students receiving FRL. By contrast we found that being enrolled in schools with a greater percentage of students receiving FRL predicted a higher probability of being classified in the positive climate profile for White students, but a higher probability of being in the negative climate profile for Black students.

Interestingly, schools in different locales (cities, towns, and rural areas) and school size were not significantly associated with student classification in the school climate profiles for White students, but these characteristics were significant, to some degree, for all other minoritized student groups. In addition, 4-year graduation rate was significantly associated only with classifying White students in the positive school climate profile but was not significant in classifying other minoritized students. Last, school academic achievement was significantly associated with classifying all student subgroups in the positive school climate profile.

The results from research question 2 also confirm and extend findings from Parris et al. (2018), who found that middle school students who identified as Black or Other had lower scores of perceived school climate and students who identified as Latino/a/e had higher scores than their White peers on the Georgia School Climate Survey. Also similar, Parris et al. (2018) found that students in schools with higher percentages of minoritized students had more negative perceptions of school climate for the total sample; however in contrast with this study, when examining perceptions of school climate by race/ethnicity subgroups, we found the same finding to be true only for White students and the opposite to be true for Black and Asian students. By using the multinomial logistic regression approach to examine school and student-level predictors of student profile classification, we were able to show how certain school and student-level characteristics were uniquely predictive of specific student profile classifications but not others.

Last, findings of this study also provide theoretical implications for the Cultural-Ecological Model of School Climate (La Salle et al., 2015) influenced from Bronfenbrenner's bioecological theory (Bronfenbrenner & Ceci, 1994; Bronfenbrenner & Morris, 2006). For example, we addressed calls from La Salle et al. (2015) to "integrate [and validate] variables into school climate research in order to identify effective ways that schools can develop and modify school reform efforts to meet student needs" (p. 164). This research provided additional validation to individual (i.e., race/ethnicity) and school characteristics (i.e., school size, school achievement, school race/ethnicity composition, and social-economic status) associated with school climate and described in the Cultural-Ecological Model of School Climate model. Our findings demonstrating school locale to be associated with student perceptions of school climate may warrant additional examination and consideration inclusion in the Cultural-Ecological Model of School Climate model. Last, we did not find school attendance to be associated with student perceptions of school climate, which provides some justification for not including this variable in the Cultural-Ecological Model of School Climate.

Limitations and Future Research

Despite the strengths and findings of this study, there are several limitations worth discussing. First, student and school data were collected and analyzed from only one U.S. state. This limits the generalizability of the findings, and these profiles may not be generalizable to other states. For example, it is possible that the number of optimal student profiles varies for students in other states and the degree to which student (e.g., race/ethnicity) and school characteristics (e.g., school size) used in this study are predictive of profile classification. To address this limitation, future research could replicate and extend these findings by conducting additional analyses for students in additional states. Another limitation associated with generalizability is that we analyzed student and school data from high schools only. Therefore, we cannot make conclusions or comparisons for student climate profiles for in elementary or middle schools. Future researchers could also extend the findings of this study by answering similar research questions using data collected from students in elementary and middle schools. Third, we used cross-sectional data from the 2017-18 school year to answer the research questions, thus we were not able to determine whether certain school characteristics (e.g., academic achievement) were temporally predictive or caused changes in school climate or whether school climate was predictive of these school characteristics. Future longitudinal research could be used to investigate these types of research questions. Fourth, we conducted an LPA to answer the research questions, which a form of latent mixture modeling used to identify qualitatively distinct patterns of change or groups. Ultimately, findings showed that perceptions of student school climate varied more in degree versus being qualitatively distinct, suggesting that the climate groups identified in the LPA may be categorical approximations of continuous climate score distributions more so than true, distinct groupings (Bauer, 2007). Future research may find similar results using more simplified multilevel regression approaches. Finally, at the time data were collected for the current study, the Georgia School Climate Survey (Georgia Department of Education et al., 2014) included only five race/ethnicity categories (i.e., Black or African American, Hispanic or Latino, White or Caucasian, Asian or Pacific Islander, or Other). The Other race/ethnicity category could have included students identifying as American Indian/Alaska Native, multiracial, or those who did not identify as any of the other options. Future research is needed to determine if the findings of this study replicate across the expanded race/ethnicity categories of the revised Georgia School Climate Survey.

Implications for Practice

Findings from this study demonstrate that student perceptions of school climate vary substantially in high schools and by different student race/ethnicities. As shown in Figure 1, some of these differences were more pronounced across student profiles for subscales measuring School Connectedness, Peer Support, Adult Support, and Cultural Acceptance. As student race/ethnicity was found to be predictive of student classification, these findings present opportunities for school leaders and personnel to select and implement practices designed to improve these specific domains of school climate (i.e., School Connectedness, Peer Support, Adult Support, and Cultural Acceptance) and to ensure that these practices are implemented equitability and effectively for every student group.

For schools implementing preventive and multi-tiered frameworks, such as Positive Behavioral Interventions and Supports (PBIS), representative school leadership teams are established and responsible for identifying, implementing, and monitoring implementation of these evidence-based practices (VanLone et al., 2019). Prior to selecting practices to prove a specific school climate domain, school teams may want to conduct a universal climate survey to all students at the beginning of the school year (e.g., Georgia School Climate Survey). These data can then be used to examine whether specific school climate domains are scored lower than others (e.g., peer support) using the total sample and disaggregate the data to examine differences by student race/ethnicity. For example, if the peer support school climate domain was scored lower for certain student race/ethnicities (multiracial students; Figure 2), school teams could then adjust or implement new practices with the goal of improving this domain for these students. For example, this may include school leadership teams establishing positive peer mentorship and peer advising programs that identify and promote multiracial students who are successfully navigating high school (e.g., in good academic standing; Flannery et al., 2020).

Conclusion

Previous research has documented the relation between students' perceptions of positive school climate and improved student outcomes (Jones et al., 2020; Kwong & Davis, 2015). This study extends previous research by documenting how student profiles of school climate vary within schools and by different student race/ethnicities. In addition, we identified school and student characteristics that predicted student classification in these profiles and described how specific school characteristics were uniquely associated with climate profiles for specific student race/ethnicity subgroups. These findings highlight the importance and need for school leadership teams to regularly assess students' perceptions of school climate, disaggregate data by student racial/ethnic groups, and to select and implement practices that are evidence-based and culturally responsive to improve school climate for specific student groups.

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Table 1

School Characteristics of the High Schools

School characteristics	Total sample	Percent missing
Schools	492	0
Districts	182	0
% FRL, *M* (*SD*)	62.0 (28.7)	8.7
% Minoritized, *M* (*SD*)	59.4 (28.7)	8.1
School locale		
City, *N* (%)	80 (17.7)	8.1
Suburb, *N* (%)	149 (33.0)	
Town, *N* (%)	77 (17.0)	
Rural, *N* (%)	146 (32.3)	
School size, *M* (*SD*)	1,135 (769)	8.1
Attendance, *M* (*SD*)	80.38 (13.66)	8.1
4-year graduation, *M* (*SD*)	81.98 (17.99)	13.0
Academic achievement, *M* (*SD*)	60.18 (21.08)	16.3
Student characteristics		
Student participants	364,143	
Race/ethnicity		
Black, *N* (%)	124,209 (34.1)	0
Latino/a/e, *N* (%)	50,622 (13.9)	0
Asian, *N* (%)	19,161 (5.3)	0
Other, *N* (%)	18,535 (5.1)	0
White, *N* (%)	151,616 (41.6)	0
Climate subscales		
School connectedness, *M* (*SD*)	2.87 (0.67)	0
Peer support, *M* (*SD*)	3.18 (0.66)	0
Adult support, *M* (*SD*)	2.84 (0.83)	0
Culture Acceptance, *M* (*SD*)	2.64 (0.80)	0
Social/civic learning, *M* (*SD*)	3.50 (0.57)	0
Physical environment, *M* (*SD*)	2.81 (0.74)	0
Safety, *M* (*SD*)	2.99 (0.79)	0
Order and discipline, *M* (*SD*)	3.04 (0.74)	0

Note. FRL = Students with free or reduced-price lunch.

Table 2

Model Fit for Latent Student Profiles of School Climate for Full Sample

Number of profiles	*n* per profile			AIC	BIC	SABIC	Entropy
		n	%				
Full sample							
1		361,028	100%	6276334.69	6276507.44	6276456.59	--
2	P1	256,155	71%	5642286.90	5642556.45	5642477.45	0.84
	P2	104,873	29%				
3	P1	201,591	56%	5366865.75	5367232.83	5367124.78	0.83
	P2	127,229	35%				
	P3	32,208	9%				
4	P1	198,924	55%	5214062.84	5214527.10	5214390.44	0.84
	P2	91,949	26%				
	P3	61,643	17%				
	P4	8,512	2%				

Note. n = Sample in each profile; AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = Sample-size-adjusted BIC; P = profile

Table 3

Multinomial Logistic Regression Predicting Latent Student Profiles of School Climate for Full Sample

Full sample	Negative vs. Moderate						Positive vs. Moderate					
Predictor	*b*	SE	*p*	OR	95% CI		*b*	SE	*p*	OR	95% CI	
					LL	UL					LL	UL
% FRL	0.05	0.03	.09	1.05	0.99	1.12	0.04	0.04	.24	1.04	0.97	1.12
% Minoritized	-0.03	0.02	.24	0.97	0.93	1.02	**-0.09**	**0.04**	**.01**	**0.92**	**0.86**	**0.98**
School locale												
City	**-0.15**	**0.05**	**<.01**	**0.86**	**0.78**	**0.94**	0.03	0.07	.67	1.03	0.89	1.19
Town	-0.10	0.06	.13	0.91	0.81	1.03	0.01	0.09	.87	1.01	0.86	1.20
Rural	<0.00	0.05	.98	1.00	0.90	1.11	-0.08	0.08	.34	0.93	0.79	1.08
School size	<0.00	0.03	.89	1.00	0.96	1.05	**-0.15**	**0.03**	**<.01**	**0.86**	**0.80**	**0.92**
Attendance	-0.03	0.02	.17	0.98	0.92	1.01	-0.04	0.04	.23	0.96	0.89	1.04
4-year graduation	0.03	0.02	.06	1.03	1.00	1.06	<0.00	0.03	.95	1.00	0.94	1.07
Academic achievement	**-0.21**	**0.03**	**<.01**	**0.81**	**0.76**	**0.87**	**0.32**	**0.05**	**<.01**	**1.37**	**1.25**	**1.51**
Race/ethnicity												
Black	**0.08**	**0.03**	**.01**	**1.08**	**1.02**	**1.15**	**-0.07**	**0.02**	**<.01**	**0.94**	**0.90**	**0.98**
Latino/a/e	**-0.11**	**0.03**	**<.01**	**0.90**	**0.84**	**0.96**	**0.13**	**0.03**	**<.01**	**1.14**	**1.07**	**1.21**
Asian	0.07	0.05	.16	1.07	0.97	1.17	0.09	0.05	.06	1.09	1.00	1.19
Other	**0.50**	**0.03**	**<.01**	**1.65**	**1.55**	**1.76**	**-0.28**	**0.03**	**<.01**	**0.76**	**0.72**	**0.80**

Note. FRL = Students with free or reduced lunch; *b* = beta coefficient; *p* = p-value; SE = standard error; OR = odds ratio; high schools located in suburbs and White students were used as the reference groups for school locale and student race/ethnicity; CI = Confidence Interval; LL = lower limit; UL = upper limit.

Table 4

Multinomial Logistic Regression Predicting Latent Student Profiles of School Climate by Race/Ethnicity Subgroups

Black	Negative vs. Moderate						Positive vs. Moderate					
Predictor	*b*	SE	*p*	OR	95% CI		*b*	SE	*p*	OR	95% CI	
					LL	UL					LL	UL
% FRL	**0.08**	**0.04**	**.04**	**1.08**	**1.00**	**1.17**	0.04	0.04	.36	1.04	0.96	1.14
% Minoritized	**-0.12**	**0.04**	**<.01**	**0.88**	**0.83**	**0.95**	-0.06	0.04	.15	0.94	0.86	1.02
School locale												
City	**-0.24**	**0.06**	**<.01**	**0.79**	**0.70**	**0.89**	0.10	0.09	.27	1.11	0.92	1.33
Town	**-0.09**	**0.09**	**.04**	**0.83**	**0.70**	**0.99**	0.01	0.10	.96	1.01	0.82	1.23
Rural	-0.09	0.08	.28	0.92	0.79	1.07	-0.01	0.09	.92	0.99	0.83	1.18
School size	<0.01	0.03	.76	1.00	0.94	1.07	**-0.21**	**0.04**	**<.01**	**0.81**	**0.75**	**0.88**
Attendance	-0.04	0.03	.16	0.96	0.92	1.01	-0.04	0.05	.41	0.96	0.87	1.06
4-year graduation	0.02	0.02	.48	1.02	0.97	1.06	-0.03	0.03	.35	0.97	0.92	1.03
Academic achievement	**-0.19**	**0.05**	**<.01**	**0.83**	**0.76**	**0.91**	**0.27**	**0.06**	**<.01**	**1.31**	**1.17**	**1.46**
Latino/a/e	Negative vs. Moderate						Positive vs. Moderate					
Predictor	*b*	SE	*p*	OR	95% CI		*b*	SE	*p*	OR	95% CI	
					LL	UL					LL	UL
% FRL	0.04	0.07	.57	1.04	0.91	1.19	0.02	0.06	.80	1.02	0.90	1.14
% Minoritized	0.04	0.05	.47	1.04	0.94	1.16	-0.07	0.07	.30	0.93	0.81	1.07
School locale												
City	**-0.18**	**0.08**	**.03**	**0.84**	**0.72**	**0.98**	0.16	0.12	.16	1.18	0.94	1.48
Town	**-0.36**	**0.15**	**.01**	**0.70**	**0.52**	**0.93**	0.16	0.15	.27	1.18	0.88	1.57

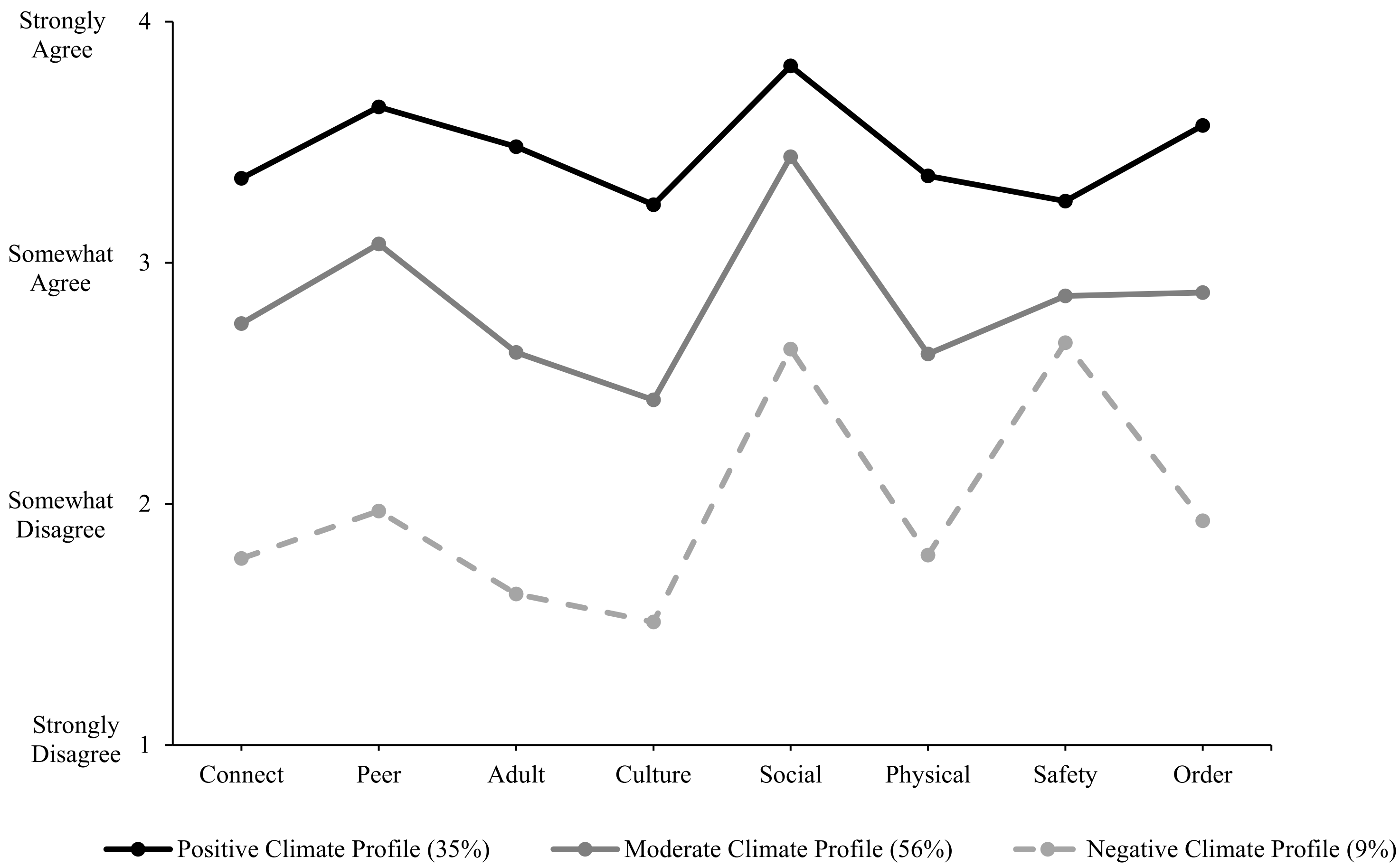
Rural	-0.08	0.11	.48	0.93	0.75	1.15	0.06	0.13	.62	1.06	0.83	1.36
School size	**-0.12**	**0.04**	**.01**	**0.89**	**0.82**	**0.97**	**-0.16**	**0.05**	**<.01**	**0.85**	**0.78**	**0.93**
Attendance	-0.04	0.04	.35	0.96	0.88	1.05	-0.08	0.07	.21	0.92	0.81	1.05
4-year graduation	0.06	0.03	.08	1.06	0.99	1.13	-0.02	0.05	.70	0.98	0.87	1.08
Academic achievement	-0.09	0.08	.25	0.91	0.78	1.07	**0.30**	**0.08**	**<.01**	**1.35**	**1.15**	**1.59**
Asian	Negative vs. Moderate						Positive vs. Moderate					
Predictor	*b*	SE	*p*	OR	95% CI		*b*	SE	*p*	OR	95% CI	
					LL	UL					LL	UL
% FRL	0.03	0.10	.75	1.03	0.85	1.26	0.08	0.13	.65	1.08	0.90	1.31
% Minoritized	**-0.17**	**0.07**	**.01**	**0.84**	**0.74**	**0.96**	-0.06	0.09	.53	0.95	0.80	1.13
School locale												
City	0.09	0.16	.56	1.09	0.81	1.48	0.18	0.12	.13	1.20	0.95	1.52
Town	-0.04	0.17	.80	0.96	0.68	1.35	0.11	0.16	.49	1.12	0.82	1.52
Rural	0.05	0.14	.75	1.05	0.79	1.39	0.06	0.13	.65	1.06	0.83	1.36
School size	-0.09	0.05	.11	0.92	0.82	1.02	**-0.15**	**0.07**	**.03**	**0.86**	**0.75**	**0.99**
Attendance	0.03	0.08	.66	1.04	0.89	1.20	0.01	0.09	.90	1.01	0.85	1.20
4-year graduation	0.04	0.10	.69	1.04	0.86	1.25	-0.09	0.09	.31	0.91	0.77	1.09
Academic achievement	**-0.36**	**0.10**	**<.01**	**0.70**	**0.58**	**0.84**	**0.44**	**0.12**	**<.01**	**1.56**	**1.23**	**1.96**
Other	Negative vs. Moderate						Positive vs. Moderate					
Predictor	*b*	SE	*p*	OR	95% CI		*b*	SE	*p*	OR	95% CI	
					LL	UL					LL	UL
% FRL	-0.05	0.08	.54	0.96	0.83	1.11	-0.07	0.06	.19	0.93	0.84	1.04
% Minoritized	-0.06	0.07	.33	0.94	0.83	1.07	-0.06	0.06	.27	0.94	0.85	1.05

School locale												
City	-0.09	0.13	.48	0.91	0.70	1.18	0.04	0.09	.66	1.04	0.87	1.25
Town	0.09	0.16	.55	1.10	0.81	1.49	0.12	0.13	.34	1.13	0.88	1.44
Rural	-0.12	1.22	.34	0.89	0.70	1.13	-0.06	0.10	.55	0.94	0.78	1.14
School size	<0.01	0.06	.94	1.00	0.90	1.12	**-0.10**	**0.04**	**.02**	**0.91**	**0.83**	**0.98**
Attendance	-0.05	0.06	.42	0.95	0.84	1.08	<0.01	0.05	.94	1.00	0.91	1.10
4-year graduation	<0.01	0.06	.97	1.00	0.90	1.12	-0.03	0.04	.36	0.97	0.90	1.04
Academic achievement	-0.08	0.09	.32	0.92	0.78	1.09	**0.33**	**0.07**	**<.01**	**1.39**	**1.22**	**1.58**
White	Negative vs. Moderate						Positive vs. Moderate					
Predictor	*b*	SE	*p*	OR	95% CI		*b*	SE	*p*	OR	95% CI	
					LL	UL					LL	UL
% FRL	0.02	0.03	.59	1.02	0.95	1.09	**0.15**	**0.06**	**.01**	**1.17**	**1.04**	**1.31**
% Minoritized	0.06	0.03	.07	1.07	1.00	1.13	**-0.15**	**0.04**	**<.01**	**0.86**	**0.79**	**0.94**
School locale												
City	-0.11	0.07	.12	0.89	0.78	1.03	-0.17	0.10	.08	0.84	0.69	1.02
Town	-0.03	0.07	.71	0.98	0.86	1.11	0.05	0.11	.66	1.05	0.85	1.29
Rural	0.07	0.06	.20	1.07	0.96	1.19	-0.11	0.11	.32	0.90	0.73	1.11
School size	0.04	0.03	.21	1.04	0.98	1.10	-0.09	0.05	.08	0.92	0.83	1.01
Attendance	-0.01	0.03	.81	0.99	0.94	1.05	0.01	0.05	.82	1.01	0.92	1.10
4-year graduation	0.04	0.03	.13	1.04	0.99	1.09	**0.13**	**0.06**	**.03**	**1.13**	**1.01**	**1.27**
Academic achievement	**-0.30**	**0.04**	**<.01**	**0.75**	**0.79**	**0.81**	**0.40**	**0.07**	**<.01**	**1.49**	**1.30**	**1.71**

Note. FRL = Students with free or reduced lunch; *b* = beta coefficient; *p* = p-value; SE = standard error; OR = odds ratio; high schools located in suburbs was used as the reference groups for school locale; CI = Confidence Interval; LL = lower limit; UL = upper limit.

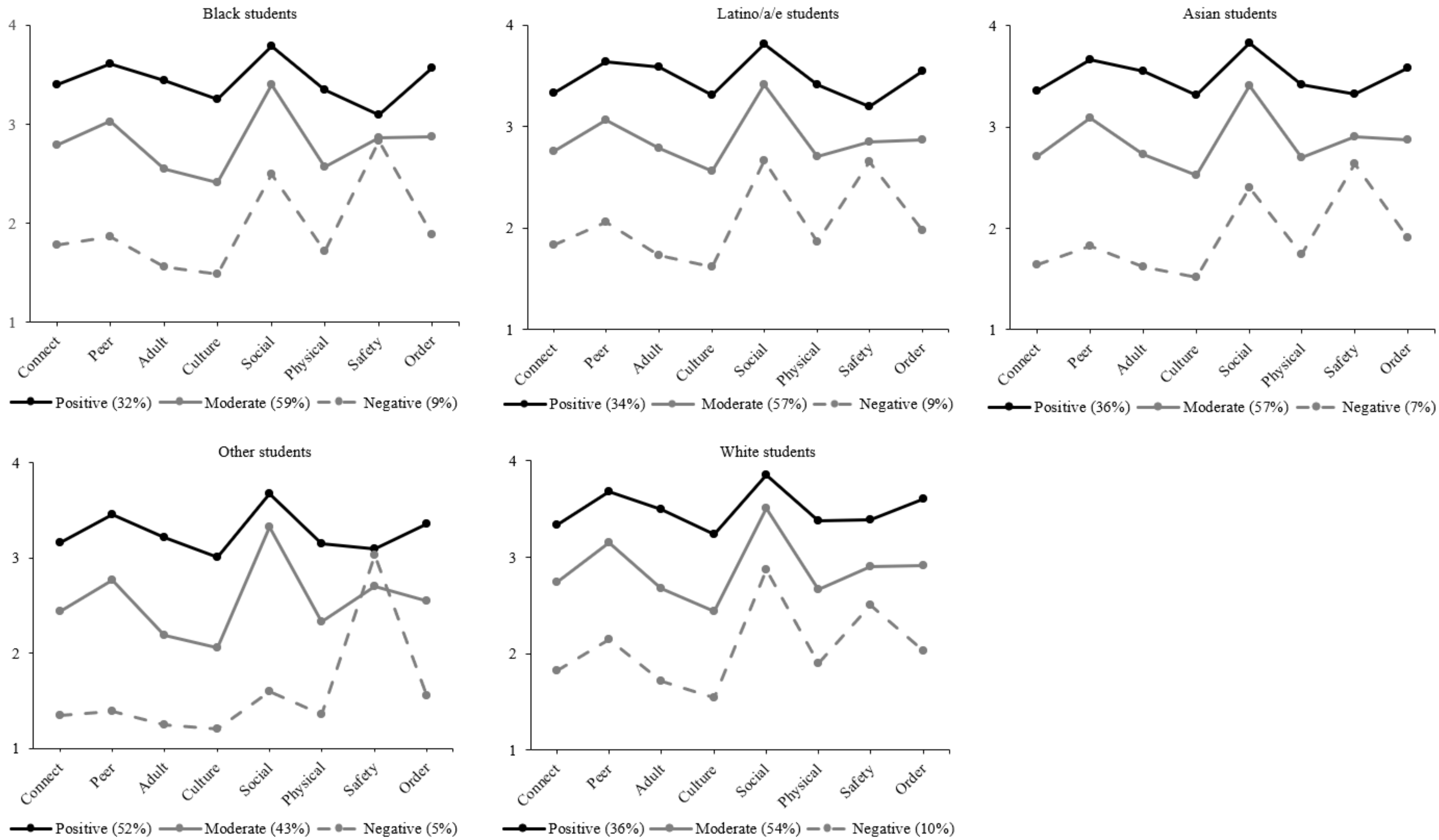
Figure 1

Latent Student Profiles of School Climate for the Full Sample



Note. Percentages in parentheses include the percentage of the student sample in each latent profile. The y-axis includes mean scores on the school climate subscales. The x-axis includes the eight school climate survey subscales.

Figure 2



Note. Percentages in parentheses include the percentage of the student sample in each latent profile. The y-axis includes mean scores on the school climate subscales. The x-axis includes the eight school climate survey subscales. 4 = Strongly Agree; 3 = Somewhat Agree; 2 = Somewhat Disagree; 1 = Strongly Disagree.

Table S1

Model Fit for Race/Ethnicity Multi-group Latent Profile and Predictive Similarity Models

Model	LL	*df*	AIC	BIC	SABIC
Configural	-3140603.42	174	6281554.83	6283433.46	6282880.48
Structural	-3151059.24	78	6302274.47	6303116.61	6302868.73
Dispersion	-3155969.74	46	6312031.48	6312528.13	6312381.94
Distributional	-3157487.84	38	6315051.68	6315461.95	6315341.19
Predictors:Configural	-3046605.65	264	6093739.30	6096582.04	6095743.03
Predictors:Constrained	-3047273.55	192	6094931.10	6096998.54	6096388.35

Note. Predictors:Configural = the configural similarity model with predictors of profile membership freely estimated; Predictors:Constrained = the configural similarity model with predictors of profile membership constrained to be equal across race/ethnicity subgroups; LL = Loglikelihood; AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = Sample-size-adjusted BIC.

Table S2

Subscale Means and Standard Deviations by Profile and Group from the Configural Similarity Model

Subscale	Student Group	Positive Climate Profile		Moderate Climate Profile		Negative Climate Profile	
		M	*SD*	*M*	*SD*	*M*	*SD*
School Connectedness	Black	3.41	0.50	2.80	0.50	1.78	0.50
	Latino/a/e	3.34	0.47	2.76	0.47	1.83	0.47
	Asian	3.36	0.49	2.71	0.49	1.64	0.49
	Other	3.15	0.54	2.44	0.54	1.35	0.54
	White	3.34	0.48	2.74	0.48	1.82	0.48
Peer Support	Black	3.62	0.49	3.03	0.49	1.87	0.49
	Latino/a/e	3.64	0.46	3.07	0.46	2.06	0.46
	Asian	3.67	0.44	3.09	0.44	1.83	0.44
	Other	3.46	0.52	2.77	0.52	1.39	0.52
	White	3.67	0.44	3.16	0.44	2.15	0.44
Adult Support	Black	3.44	0.64	2.55	0.64	1.57	0.64
	Latino/a/e	3.58	0.58	2.78	0.58	1.74	0.58
	Asian	3.55	0.57	2.73	0.57	1.62	0.57
	Other	3.21	0.65	2.19	0.65	1.26	0.65
	White	3.50	0.61	2.68	0.61	1.72	0.61
Cultural Acceptance	Black	3.26	0.62	2.41	0.62	1.49	0.62
	Latino/a/e	3.31	0.46	2.56	0.46	1.61	0.46
	Asian	3.31	0.57	2.53	0.57	1.52	0.57
	Other	3.01	0.63	2.06	0.63	1.21	0.63
	White	3.23	0.59	2.44	0.59	1.54	0.59
Social/Civic Learning	Black	3.79	0.50	3.40	0.50	2.51	0.50
	Latino/a/e	3.81	0.56	3.41	0.56	2.67	0.56
	Asian	3.83	0.46	3.41	0.46	2.41	0.46
	Other	3.67	0.48	3.33	0.48	1.62	0.48
	White	3.85	0.45	3.50	0.45	2.88	0.45
Physical Environment	Black	3.35	0.59	2.57	0.59	1.72	0.59

	Latino/a/e	3.41	0.46	2.70	0.46	1.86	0.46
	Asian	3.42	0.55	2.70	0.55	1.75	0.55
	Other	3.14	0.59	2.33	0.59	1.37	0.59
	White	3.37	0.55	2.66	0.55	1.90	0.55
School Safety	Black	3.10	0.79	2.86	0.79	2.83	0.79
	Latino/a/e	3.20	0.73	2.85	0.73	2.65	0.73
	Asian	3.32	0.74	2.90	0.74	2.64	0.74
	Other	3.09	0.78	2.70	0.78	3.01	0.78
	White	3.38	0.73	2.90	0.73	2.51	0.73
Order and Discipline	Black	3.57	0.59	2.88	0.59	1.89	0.59
	Latino/a/e	3.54	0.54	2.87	0.54	1.98	0.54
	Asian	3.58	0.52	2.88	0.52	1.91	0.52
	Other	3.35	0.60	2.55	0.60	1.55	0.60
	White	3.60	0.52	2.92	0.52	2.03	0.52

Table S3

Model Fit for Latent Student Profiles of School Climate By Student Race/Ethnicity

Number of profiles	*n* per profile		AIC	BIC	SABIC	Entropy
	n	%				
Black students						
1	124,209	100%	2222048.57	2222204.24	2222153.39	--
2	P1 88,861	72%	2014734.75	2014977.99	2014898.54	0.83
	P2 35,348	28%				
3	P1 73,259	59%	1922680.29	1923011.10	1922903.04	0.83
	P2 39,550	32%				
	P3 11,400	9%				
4	P1 70,855	57%	1870212.29	1870630.67	1870494.01	0.84
	P2 26,279	21%				
	P3 23,479	19%				
	P4 3,596	3%				
Latino/a/e students						
1	50,622	100%	848917.16	849058.47	849007.62	--
2	P1 36,606	72%	761950.42	762171.23	762091.78	0.84
	P2 14,016	28%				
3	P1 28,728	57%	723050.01	723350.30	723242.25	0.84
	P2 17,411	34%				
	P3 4,483	9%				
4	P1 27,999	55%	702720.51	703100.29	702963.63	0.85
	P2 13,033	26%				
	P3 8,441	17%				
	P4 1,149	2%				
Asian students						
1	19,161	100%	325423.62	325549.39	325498.54	--
2	P1 14,316	75%	290480.79	290677.31	290597.86	0.85
	P2 4,845	25%				
3	P1 10,879	57%	271586.50	271853.76	271745.71	0.86

	P2 6,960	36%				
	P3 1,322	7%				
4	P1 10,608	55%	261990.10	262328.11	262191.46	0.86
	P2 5,221	27%				
	P3 2,873	15%				
	P4 459	2%				
Other students						
1	18,535	100%	344128.99	344254.23	344203.386	--
2	P1 12,904	70%	307994.33	308190.02	308110.57	0.85
	P2 5,631	30%				
3	P1 9,696	52%	291799.67	292065.80	291957.75	0.86
	P2 7,901	43%				
	P3 938	5%				
4	P1 9,866	53%	283369.71	283706.29	283569.64	0.84
	P2 4,005	22%				
	P3 3,921	21%				
	P4 743	4%				
White students						
1	151,616	100%	2563567.94	2563726.81	2563675.96	--
2	P1 104,475	69%	2288083.24	2288331.47	2288252.02	0.83
	P2 47,141	31%				
3	P1 81,788	54%	2173556.35	2173893.94	2173785.87	0.83
	P2 55,149	36%				
	P3 14,679	10%				
4	P1 81,204	54%	2113227.02	2113653.97	2113517.31	0.85
	P2 43,877	29%				
	P3 23,841	16%				
	P4 2,694	2%				

Note. n = Sample in each profile; AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = Sample-size-adjusted BIC; P = profile