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How school climate relates to chronic absence: A multi–level latent profile analysis

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A B S T R A C T

Chronic absence is a significant problem in schools. School climate may play an important role in influencing chronic absence rates among schools, yet little research has evaluated how school climate constructs relate to chronic absence. Using multilevel latent profile analysis, we evaluated how profiles of student perceptions of school climate at both the student and school level differentiated school–level rates of chronic absence. Participants included 25,776 middle and high school students from 106 schools who completed a district administered school climate survey. Students attended schools in a large urban school district where 89% of 6th through 12th grade students were African-American and 61% were eligible for the federally subsidized school meals program. Three student–level profiles of perceptions of school climate emerged that corresponded to "positive," "moderate," and "negative" climate. Two predominant patterns regarding the distribution of these profiles within schools emerged that corresponded to the two school–level profiles of "marginal climate" and "climate challenged" schools. Students reporting "moderate" and "negative" climate in their schools were more likely to attend schools with higher chronic absence rates than students reporting that their school had "positive" climate. Likewise, "climate challenged" schools had significantly higher chronic absence rates than "marginal climate" schools. These results suggest that school climate shares an important relation with chronic absence among adolescent students attending urban schools. Implications for prevention and intervention programs are discussed.

1. Introduction

1.1. How school climate relates to chronic absence: a multilevel latent profile analysis

Chronic absence is a significant risk factor for school dropout and is closely associated with academic underachievement, delinquent behaviors, and limited economic opportunities (Kearney, 2008a). Across seven states surveyed, Balfanz and Byrnes (2012) found that 6% to 23% of youth were chronically absent in the past year; overall, it has been estimated that 5 to 7.5 million students are chronically absent across the country (United States Department of Education [DOE], 2014). A new federal policy, Every Student, Every Day, provides support for initiatives that involve multiple federal agencies to address and reduce chronic

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absenteeism (DOE, U. S. Department of Health and Human Services, U. S. Department of Housing and Urban Development, and U. S. Department of Justice, 2015). Further, chronic absence was added as a school performance metric in the Every Student Succeeds Act (ESSA, 2015), which is a reauthorization of the Elementary and Secondary Education Act or No Child Left Behind Act. Although this represents an increased focus on the problem of chronic absence and an awareness of the complexity of its determinants, more research is need to better understand the correlates of chronic absence (Vaughn, Maynard, Salas-Wright, Perron, & Abdon, 2013) and identify effective ways to reduce chronic absence (Kearney, 2008b).

Given the links school climate has with socio-emotional wellbeing and academic achievement, improving students' perceptions of school climate may be an important intervention strategy for increasing attendance. School climate is a widely recognized predictor of students' social functioning and emotional health and fosters an environment conducive to improved academic functioning (Astor, Benbenishty, Zeira & Vinokur, 2002; Payne, Gottfredson, & Gottfredson, 2003). Literature suggests that key aspects of school climate, including student connectedness with school, engagement in school activities, and perceptions of school safety, may be important determinants of attendance (Chen & Weikart, 2008; deJung & Duckworth, 1986; Hughes, Gaines, & Pryor, 2015). The purpose of the current study was to identify groups of students with similar perceptions of school climate and to determine how their perceptions are related to chronic absence, controlling for school characteristics. This person-centered approach has the potential to identify effective strategies for targeting students at risk for chronic absence.

1.2. The harmful effects of chronic absence

A student is identified as chronically absent when they miss approximately 20 school days or at least 10% of school days during an academic year, whether for excused absences, unexcused absences, or suspensions (Balfanz & Byrnes, 2012). The concerns associated with chronic absence are well-documented and include serious academic, mental, and physical health problems for youth (Maynard, Salas-Wright, Vaughn, & Peters, 2012). Chronic absence is associated with decreased academic achievement, increased rates of special education referral, and grade retention (Kearney, 2008b).

Youth who are chronically absent often experience externalizing and internalizing problems. For example, youth who are chronically absent engage in increased rates of delinquent behaviors, such as violence, risky sexual behaviors, and alcohol, marijuana, tobacco, and other substance use (Chou, Ho, Chen, & Chen, 2006; Henry & Huizinga, 2007; Henry, Knight, & Thornberry, 2012; Hirschfield & Gasper, 2011). Chronic absence is strongly related to other mental health concerns as well, such as increased risk for suicidal behavior, anxiety, and depression (DeWit, Karioja, Rye, & Shain, 2011; Vaughn et al., 2011). The effect of chronic absence is cumulative with research showing that a persistent pattern of chronic absence across multiple years of school is related to poorer outcomes (Connolly & Olson, 2012).

Harmful consequences also extend to other students at the school. Students who are chronically absent require additional attention from teachers when they are present at school to address their learning and social needs (Ginsburg, Jordan, & Chang, 2014). Thus, classrooms may move at a slower pace and become less engaging, detracting from the educational experiences of other students (Gottfried, 2013). Further, students who are chronically absent are more likely to have behavioral issues (Egger, Costello, & Angold, 2003; Farmer et al., 2003), which may contribute to a more negative classroom environment by modeling disengaged behavior and demanding more attention from the teacher. The limited empirical studies of the adverse effects of chronic absence suggest that chronic absence affects both youth who are absent and who attend school.

1.3. Factors related to chronic absence

Numerous factors that contribute to chronic absence have been explored, including student characteristics, environmental characteristics, and the interaction between the two. One potentially overarching correlate of chronic absence may be poverty (Zhang, 2003); students who receive assistance from Free and Reduced Meals (FARMs) programs are three times more likely to be chronically absent from school (Balfanz & Byrnes, 2012). Homelessness, housing instability, family obligations such as caring for younger siblings or elderly family members, and lack of a safe path to school are poverty-related barriers that prevent students from consistently attending schools (DOE, 2004; Henry, 2007; Reid, 2005). Additionally, a subset of children is chronically absent due to persistent or lifelong illness or injury. Students with chronic health conditions living in poverty may be more likely to miss school due to lack of access to physical and behavioral health care as well as poor transportation that may interfere with attention to medical needs (Kearney, 2008a).

Students who are struggling academically, socially, and behaviorally may also increasingly become absent from school if schools are unable to meet their needs. Ineffective school discipline and lack of appropriate or engaging instruction perpetuate chronic absence. Similarly, structural features of the school may also be relevant, such as the type of school and the student-to-teacher ratio (Kearney, 2008a). As students transition to middle school and again to high school, the level of support and higher expectations for autonomy decline as youth move from a single classroom structure to switching classes for each subject area and the number of students each teacher interacts with during the day increases. For youth who are not ready to assume this level of responsibility, this shift may lead to chronic absences for middle school students with social and academic vulnerabilities with escalating increases in chronic absence during high school (DeWit et al., 2011; Eccles et al., 1993). Similarly, students are more likely to drop out of larger schools, again highlighting the importance of connectedness to teachers and peers (Lee & Burkam, 2003).

1.4. Associations of student perceptions of school climate with chronic absence

The large number of relevant risk factors indicates that the pathway to chronic absence is complex, suggesting multiple avenues for intervention. The school environment may play a critical role in chronic absence. School climate is a multi–faceted construct that reflects students' perceptions of their interactions with peers, teachers, and school administrators including shared beliefs, values, and attitudes related to school (Bradshaw, Waasdorp, Debnam & Johnson, 2014b; Kearney, 2008a). The DOE has conceptualized school climate as broadly consisting of the domains of safety, engagement, and environment, which encompass constructs such as perceptions of safety, incidents of delinquent or aggressive behavior, school connectedness, relationships with teachers, parental involvement, school resources, and perceptions of the physical and learning environment (DOE, 2014). A recent meta-analysis by the National School Climate Center identified five broad domains of school climate: safety, relationships, teaching, and learning, and the external environment (Thapa, Cohen, Higgins-D'Alessandro, & Guffey, 2012). These frameworks have informed and improved the measurement of school climate (Bradshaw et al., 2014b).

A focus on the school climate presents an important opportunity to reach students who may be at risk for chronic absence. Thus, identifying typical patterns of school climate perceptions that emerge on the individual and school levels may contribute to advancing our understanding of relations between chronic absence and school climate. Research supports the relationship between several school climate constructs and both attendance and dropout rates (Brookmeyer, Fanti, & Henrich, 2006; Kearney, 2008b). For example, a nationally representative U.S. study (i.e., Youth Risk Behavior Surveillance Study) found that 7.1% of high school students missed school in the past 30 days out of a fear for their safety either at school or traveling to school (Centers for Disease Control, 2014). Additionally, students who feel more connected to teachers and peers show better attendance and lower rates of dropout (Catalano, Haggerty, Oesterle, Fleming, & Hawkins, 2004; Kidger, Araya, Donovan, & Gunnell, 2012). Furthermore, ineffective school discipline and lack of appropriate or engaging instruction perpetuate chronic absence (Kearney, 2008b).

It is important to recognize that multiple stakeholders (i.e., teachers, school staff, students, parents) contribute to school climate and thus have different perspectives of climate. Student perceptions are increasingly of interest as they may be more directly related to student behavior and provide a potential target for interventions (Koth, Bradshaw, & Leaf, 2008; Van Horn, 2003). Although it is clear that various aspects of school climate relate to attendance, little research exists that incorporates a person-centered analytic approach to examining student perceptions of school climate. Students may demonstrate distinct patterns of endorsement across school climate constructs. These heterogeneous subgroups of students with specific profiles of climate perceptions may demonstrate unique associations with chronic absence as well as other school characteristics. Understanding the distinct patterns of student perceptions of school climate may have critical implications for preventing chronic absence, as youth with different perceptions of school climate may require different supports in order to maintain engagement in school and keep their attendance high. Further, student perceptions in aggregate may create a climate or milieu at a school that exacts a unique and independent effect on student attitudes and behavior for individual perceptions. A novel aspect of this study is the multi-level, person-centered approach that identifies profiles of school climate at the student-level and the school-level and their independent association with student behavior.

1.5. Current study

Given the myriad negative outcomes associated with chronic absence, it is crucial to identify targets for intervention to reduce chronic absence rates. School climate presents itself as a multi-faceted component relevant to several risk factors for chronic absence and may have significant implications for developing interventions to address this public health concern and the new federal initiative directed at reducing chronic absence. Therefore, we sought to evaluate how student perceptions of school climate relate to chronic absence. Due to the complex relationship between chronic absence and poverty, which is associated with many of the reviewed risk factors, the current study focused on an at-risk sample of urban schools. We controlled for several relevant school–level organizational characteristics, which have been shown to be potential risk factors for chronic absence.

We proposed the following research questions. First, we sought to identify profiles of school climate at the individual–level and the school–level among adolescents within an urban school district. To evaluate this research question, we used multilevel latent profile analysis to identify meaningful subgroups of student climate perceptions at both the individual and school level for youth in 6th through 12th grades. Second, we sought to identify whether the individual–level and school–level climate perception profiles relate to school-level chronic absence rates. Given the previously reviewed literature, we hypothesized that both individual–level and school–level profiles that represented negative climate perceptions would be associated with higher chronic absence rates among schools than profiles with positive climate perceptions.

2. Method

2.1. Setting and participants

Students from 121 schools serving grades 6–12 within a large urban public school system completed an anonymous self-report survey of school climate during the winter quarter of the 2006–07 school year as part of a district-wide annual initiative to collect information on perceptions of the school climate. Parents were informed of the data collection, and a passive consent process was utilized. The urban school system served a predominantly African American (89%) student population with 61% of students eligible for the federally subsidized school meals program. Approximately 43,094 students were enrolled in grades 6–12 at the start of the 2006–07 school year, and 25,776 of these students (59%) participated in the survey with an average response rate of 41% across schools (SD = 24%; range: 3% to 97%). In schools with higher rates of student mobility and students receiving FARMs, the response rates were lower. Response rate was not related to school climate constructs as described in the measures section below. Model parameter estimates did not change when study analyses included response rate as a predictor of profiles, and response rate was not significantly different across individual- or school-level profiles.

To minimize confounding factors, several inclusion/exclusion criteria were used. Schools were included in analyses only when the response rate on the climate survey reflected >10% of enrolled students. A response rate of 10% corresponded to 1.5 *SD*s below the average response rate, which is the standard cut point for identifying outliers. Visual inspection of the distribution of response rates via box plots and histograms supported the use of 10% as the cut point for outlier response rates (Tabachnick & Fidell, 2013). Schools included in the study had at least 30 or more students complete a survey. Other inclusion criteria included: when schools were a traditional or charter school, when schools were an elementary/middle (K–8th grade), middle (6th–8th grade), or high school (9th–12th grade), and when schools offered enrollment to both girls and boys. The inclusion/exclusion criteria resulted in 15 schools being excluded from analyses, leaving a total school sample size of 106.

The demographics of the 106 schools in the study are reported in Table 1. Thirty-nine of the schools (32%) were high schools compared to 22 middle schools (21%); most of the schools were elementary/middle schools ($n = 48$; 47%). Average enrollment for high schools was 596 students (range: $n = 65$ to 1548). Middle and elementary/middle schools had lower enrollments (middle: $M = 472$, range: $n = 77$ to 930; elementary/middle: $M = 452$, range: $n = 121$ to 1199). Average student-to-teacher ratio across schools was 17.92 (SD = 3.98). The schools in the study were on average 50% male with an average of 68% of students receiving FARMs and average student mobility was 41% across of schools.

2.2. Procedures

School climate surveys were administered to students in paper and pencil form during homeroom or their first class period on a date designated by the school during a six-week survey window. Surveys were proctored by classroom teachers or other designated school staff as appropriate. To maintain consistent administration of surveys, staff read a scripted description of the survey and survey instructions, which was included in the school survey toolkit provided to school administrators. All completed surveys were submitted to the school district headquarters for processing. All data used in the present study were obtained from the school district headquarters through a formal data request process. Administrative data files obtained included school demographics, student attendance, chronic absence, and student responses on the school climate survey.

2.3. Measures

2.3.1. School climate

The School Climate Survey was designed based on existing measures of school climate (e.g., Cantillon, Davidson, & Schweitzer, 2003; Haynes, Emmons, & Ben-Avie, 2001; Sampson & Raudenbush, 1999; Sampson, Raudenbush, & Earls, 1997). The measure was pilot tested with several adolescent students in the school district and in consultation with several community organizations serving Baltimore City youth to incorporate specific concerns of area youth into the survey. Forty items formed the 10 school climate subscales. Students responded by indicating whether they agreed or disagreed with a series of statements about their school climate on a 4-point scale where 1 = *Strongly Disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly Agree*. Items were averaged to create subscales.

Table 1
School–level descriptive statistics for continuous variables.

	Correlations				
	1	2	3	4	5
1. Student-to-teacher ratio	1.00				
2. % mobility	−0.29**	1.00			
3. % FARM	0.08	−0.02	1.00		
4. % male	−0.38*	0.20*	0.08	1.00	
5. % chronic absence	−0.12	0.63**	−0.25*	0.12	1.00
Mean	17.92	40.61	67.81	50.03	32.29
SD	3.68	21.28	16.26	8.63	20.58
Skew	−0.68	0.44	−0.66	−1.00	0.65
Minimum	5.47	5.0	16.0	0.80	0
Maximum	26.67	95.0	92.5	89.60	87.9

Notes. FARM = percent of the students who qualified for federally subsidized meal program at school; mobility = percentage of students enrolling in and withdrawing from the school during the school year divided by the average daily school enrollment. School–level: $N = 106$.

* $p < 0.05$.

** $p < 0.005$.

Subscales included Perceptions of Safety, which had 3 items (e.g., "Students feel safe at this school"; $\alpha = 0.88$) and referred to the sense of safety that the students experienced traveling to and from school and at school. Delinquent Behavior at School had 4 items (e.g., "Vandalism of school property is a problem at this school"; $\alpha = 0.81$) with 2 items reverse scored; this construct referred to awareness that activities such as vandalism, fire-setting, substance use, and weapon carrying occurred at school. Aggressive Behavior at School had 4 items (e.g., "Students fighting is a problem at my school"; $\alpha = 0.62$) with 1 item reverse scored; this construct referred to awareness that physical and verbal altercations occurred among students or toward teachers. Value Placed on Academics had 4 items (e.g., "It is important for student to try hard in school"; $\alpha = 0.87$) and referred to the value the student placed on attending school, finishing high school, and putting forth effort on academics. School connectedness had 4 items (e.g., "I would choose to stay at this school even if given the option of transferring"; $\alpha = 0.77$) and referred to experience of belonging to the school, enjoying being at school, and thinking highly of the school overall. Learning environment had 4 items (e.g., "Teachers make expectations for meeting instructional goals clear to students"; $\alpha = 0.67$) and referred to the orderliness of the school environment including consistent expectations of students and application of rules and consequences. Teacher relationships had 5 items (e.g., "Teachers encourage me to work hard in my classes"; $\alpha = 0.76$) and referred to students feeling like their teachers encouraged them, believed in them, and were willing to help them when needed. School resources had 3 items (e.g., "There is someone at school who I can talk to about personal matters"; $\alpha = 0.61$) and referred to the presence of programs for academic support, emotional and behavioral concerns, and personal concerns. Parental involvement had 4 items (e.g., "When a student does something good at school, parents are informed"; $\alpha = 0.70$) and referred to students perceiving that their parents were welcome at school, invited to be involved, and heard about their positive achievements as well as negative things that happen. Physical environment had 3 items (e.g., "The temperature in this school is comfortable all year round"; $\alpha = 0.75$) and referred to the building being clean and the temperature being comfortable. Higher values on constructs represented a more positive experience with these features in the school environment, except for Aggression and Delinquent Behavior at School. For these two constructs, higher scores indicated a greater presence of these negative behaviors at school.

These 10 subscales provided general representation of the five domains of school climate (i.e., safety, learning, relationships, teaching, and the external environment) identified in a recent meta-analysis (Thapa et al., 2012). For example, perceptions of safety, aggressive behavior, and delinquent behavior provide some indication of safety. School connectedness, teacher relationships, and parental involvement indicated the relationships that students had at school. The teacher relationships and school resources represented teaching. The external environment was identified through the physical environment subscale, and the learning environment and value placed on academics indicated the domain of learning.

Confirmatory factor analysis (CFA) was used to establish construct validity for these constructs using estimation with robust standard errors to account for the clustering of individuals within schools (White, 1980). The full model achieved satisfactory model fit ($\chi^2 = 16{,}376.71$, $p < 0.001$; CFI = 0.95, RMSEA = 0.041, SRMR = 0.041). As expected, the chi-square value remained significant indicating the fit of the data to the proposed model was not exact; however, the values for the other fit indices fell within acceptable limits (Brown, 2015; Hu & Bentler, 1999). Correlations among the constructs were in the expected direction and fell within the moderate range. These results suggest that the constructs that formed the school climate survey demonstrated sufficient construct validity and concurrent and discriminant validity among constructs.

2.3.2. School–level chronic absence

Student attendance and absences were tracked daily for all schools. School–level attendance and chronic absence rates are calculated annually at the end of a school year. In order for a student to be identified as chronically absent, the student had to have been enrolled in the district for at least 90 days and missed >20 days of school. An absence referred to a day when the student attended school for two hours or less during the school day (Maryland State Department of Education [MSDE], 2006). School–level chronic absence rates were calculated by dividing the total number of students absent >20 days by the total number of students enrolled for >90 days at each school during the school year. The cut point of 20 missed days applies for students if they were enrolled in their school for 90 to 180 days. Twenty missed days out of 180 days in a school year corresponds to missing 10% of the school year. This does not include prorating the 10% missing school days to the number of days students were enrolled. This definition of chronic absence is consistent with definitions used in research on chronic absence (Balfanz & Byrnes, 2012) as well as definitions used in federal policies (DOE, 2014; DOE et al., 2015; ESSA, 2015).

2.3.3. Student-to-teacher ratio

The ratio of students to teachers was calculated by dividing the enrollment of a school by the number of teachers employed by that school.

2.3.4. Student poverty

Student poverty was represented as the percentage of students in a school eligible for the federally subsidized school meals program (i.e., FARM).

2.3.5. Student mobility

Mobility referred to the total of the percentage of students enrolling in and withdrawing from the school after the first day of school during the 2006–07 school year divided by the average daily school enrollment (MSDE, 2016).

2.3.6. Percent of male students at each school

This value represented the percentage of enrolled students in a school that identified as male as provided by the school district.

2.3.7. Individual-level male students

This value reflects the report of gender that students answered about themselves on their school climate surveys.

2.3.8. Grade range of schools

The grade range of school was represented with a discrete effect coded variable, indicating whether the school was a traditional high school rather than an elementary/middle or middle school.

2.4. Analytic procedures

Multilevel latent profile analysis (MLPA) was conducted in MPlus 7.4 (Muthén & Muthén, 1998–2015) to identify the number of meaningful perceptions of school climate subgroups that existed on the individual level (level–1) and the school level (level–2) among students in grades 6 through 12. Using the multilevel modeling framework outlined in Asparouhov and Muthén (2008) and Henry and Muthén (2010), the hierarchical structure of data was represented with student perceptions at the individual level, which was aggregated within schools. LPA has the assumption that cases provide independent observations. When students provide perceptions of school climate, responses are dependent on the school that they attend; thus, a multilevel analytic approach was necessary to account for clustering of students within schools. Using a multilevel approach also afforded the unique opportunity to identify the extent to which individual–level patterns of school climate vary at the school level (Asparouhov & Muthén, 2008; Henry & Muthén, 2010). The multilevel latent profile framework provides findings that integrate both the individual–level perception of school climate, as well as the overarching effect of student climate perceptions at the school level.

At the individual level, associations with school–level characteristics then indicate the degree to which individual students are more likely to attend schools with specific characteristics if they belong to climate profiles with specific patterns of climate perceptions. The multilevel approach accounts for the deviation of individual climate intercepts from the mean from all cases as well as the mean within schools. This variability is then partitioned into profiles that estimate the student–level profiles to identify the optimal profile structure.

This study used non-parametric MPLA, where the indicators for the school–level profiles are not the individual–level indicators, but the individual–level profiles themselves. If school membership affects individual–level profile membership, the distribution of individual–level profiles among schools may significantly vary. Thus, the MLPA may produce a higher order set of profiles that represent the distinct distributions of individual–level profiles within schools (Asparouhov & Muthén, 2008; Henry & Muthén, 2010). At the school level, associations with school characteristics indicate the degree to which schools with distinct distributions of school climate profiles of student perceptions are more likely to display specific characteristics, such as chronic absence.

To identify the best fitting model, we first conducted a series of LPAs to determine the optimal number of profiles at the individual, student level. These individual–level models did not include covariates. Once the best individual–level profile solution was selected, models that included school–level profiles were estimated. Once the best fitting multilevel latent profile solution was selected, covariates were added at both levels to examine their associations with profile membership.

Model fit and profile interpretability were identified using comparison of goodness-of-fit indices and the distinctiveness of profiles. Goodness-of-fit indices included the Bayesian Information Criterion (BIC; Schwarz, 1978) and the Akaike Information Criteria (AIC; Akaike, 1987). The BIC, in particular, may continue decreasing as the number of profiles extracted increases even though these profiles are not meaningfully different and may not represent distinct groups. Thus, we chose the k–class model with BIC and AIC values showing the largest decrease compared to a $k + 1$ profile model (Nylund, Asparouhov & Muthén, 2007). The Vuong Lo Mendell Rubin log likelihood ratio test (LRT; Lo, Mendell, & Rubin, 2001) and the bootstrap likelihood ratio test (BLRT; McLachlan & Peel, 2000) were also used to select the individual–level model. These fit statistics provide an estimate and a *p*-value for the difference in log likelihood values between a k–class model and a k–1 class model. The LRT and the BLRT were not available when school–level profiles were included. Further, school-level profile sample sizes were also considered in the MLPAs, given that small Level–2 sample size can influence the BIC (Lukociene & Vermunt, 2010).

Within the MLPA, the primary covariate of interest was school–level chronic absence. Several additional covariates were entered into the model to control for their effect on profile membership when considering the link between school–level chronic absence and profile membership. The individual–level covariate of profile membership was gender. School–level covariates of profile membership included school demographics (i.e., student-teacher ratio and being a high school) and school–level student characteristics (i.e., percent of students within each school that were male, participated in the federally subsidized school meals program, and moved to more than one school during the school year [mobility]). We conducted multiple group analyses comparing the profile structure between middle school and high school students and found that there were no significant differences. Thus, we analyzed data from high school and middle school students in the same model.

School–level covariates indicated the degree to which individual students who belonged to specific school climate profiles attended schools with different rates of school–level characteristics.

2.4.1. Treatment of missing data

Approximately 87% of the data were available for analyses with covariance coverage ranging from 69% to 100%. Missingness was only related to attending a school with a higher rate of student mobility. Missing data were managed with full information maximum likelihood (FIML) estimation. FIML produces parameter estimates that are less biased than other missing data strategies when the data are missing completely at random or missing at random (Enders, 2010). There may also be data that is missing not at random, given that students who were chronically absence may have been absent from school when the school climate survey was administered. This type of missing data cannot be identified or managed and is discussed in the limitation section.

3. Results

3.1. Descriptive statistics

Continuous school–level predictors (see Table 1) and school climate domains (see Table 2) generally displayed skew within acceptable bounds (Cohen, Cohen, West, & Aiken, 2003). Nearly 48% of student respondents were male ($n = 11{,}003$). The level of chronic absence in schools in the current study ranged from 0 to 88% ($M = 32.29$; SD = 20.58). Among the continuous school–level predictors, both mobility and percentage of students eligible for FARMs were correlated with level of chronic absence (see Table 1). Schools with higher mobility had greater chronic absence ($r = 0.63$). Whereas schools with a higher percentage of students eligible for FARMs had lower chronic absence ($r = -0.25$).

3.2. Multilevel latent profile model

A series of LPAs were estimated to identify individual–level subgroups of school climate perceptions for students in 6th through 12th grades. The first set of models identified the individual–level profile structure, which resulted in a three profile solution providing the best fit for the data (see Table 3). The BLRT continued to display significant differences as additional profiles were extracted, whereas the LRT was not significant for any model comparisons. The BIC and AIC continued to decrease as complexity increased, but examination of a scree plot revealed that improvements in relative fit reached an elbow at three profiles. The posterior probabilities of profile membership demonstrated strong separation among the profiles (0.00–0.10) and homogeneity of each profile (0.90–0.91). The interclass correlation (ICCs) of most likely class membership across schools was 0.13 (SE = 0.02) and the ICCs of probability of membership in each class across schools ranged from 0.07 (SE = 0.01) to 0.22 (SE = 0.03). These findings suggested that schools varied in the distribution of students who were most likely to belong to the three school climate profiles and that schools themselves may demonstrate different profiles of student membership in school climate profiles.

A MLPA was then estimated to identify the degree to which distinct distributions of individual–level climate profiles existed among schools. The model with two school–level profiles and three individual–level profiles (2×3 model) provided the best fit for several reasons. Although the BIC and AIC were lower in a model with three school–level profiles and three individual–level profiles (3×3 model), models with three school–level profiles displayed estimation problems that limited their utility. Although the level-two sample sizes generated in both the two ($n = 47$, 44%) and three ($n = 31$, 29%) school-level profiles were sufficient, one of the individual-level profiles within the three school-level profiles was quite small ($n = 109$, 0.5%). This characteristic suggested insufficient sample size within multilevel profile combinations when three school–level profiles were extracted. Inspection of the three school–level profiles indicated that the third school–level profile closely replicated another profile demonstrating an insufficient meaningful distinction between this third profile and the other two profiles. The lack of differentiation was supported by posterior probabilities of profile membership which were weaker for the 3×3 model (separation probabilities: 0.00–0.10; homogeneity probabilities: 0.87–0.91) compared to the 2×3 model (separation probabilities: 0.00–0.10; homogeneity probabilities: 0.89–0.96).

The three individual–level profiles were distinct and interpretable (see Fig. 1). The "moderate school climate" profile contained the most cases ($n = 12{,}269$, 59%) and demonstrated moderate levels of all school climate domains. The "positive school climate" profile ($n = 5198$, 25%) had the highest means of the positive school climate domains and the lowest means for negative domains

Table 2
Individual–level school climate descriptive statistics.

	Mean	SD	Skew
Delinquent behavior	2.22	0.94	0.51
Aggressive behavior	2.52	0.69	0.06
Perceptions of safety	2.62	0.81	−0.34
Value placed on academics	3.55	0.56	−1.59
School connectedness	2.57	0.77	−0.21
Teacher relationships	2.78	0.63	−0.54
Learning environment	2.67	0.61	−0.23
Physical environment	1.83	0.71	0.65
School resources	2.46	0.64	−0.17
Parental involvement	2.55	0.68	−0.16

Notes. Delinquent behavior and Aggressive behavior refer to the degree to which adolescent respondents knew of these behaviors occurring at school; minimum and maximum values for the school climate domains were 1 and 4; Individual–level: $N = 25{,}776$.

Table 3
Model fit statistics for multilevel latent profile model of school climate.

Number of level–1 profiles	df	LL	BIC	AIC	Model comparisons	LRT		BLRT		Entropy	Smallest profile *n* (%)
						Δ2 × LL	*p*	Δ2 × LL	*p*		
Model with only level–1 profiles											
1	34	−234,631.88	469,605.92	469,331.76	–	–	–	–	–	–	–
2	38	−183,594.46	367,567.03	367,264.92	2 vs. 1	33,597.30	0.13	33,784.89	<0.001	0.766	8954 (42.7%)
3	56	−177,094.54	354,746.29	354,301.08	3 vs. 2	12,927.66	0.28	12,999.84	<0.001	0.802	3468 (16.5%)
4	74	−173,419.36	347,575.04	346,986.71	4 vs. 3	7309.55	0.27	7350.36	<0.001	0.764	3825 (18.3%)
Model with level–1 and level–2 profiles											
Level–2: 2 profiles					–	–	–	–	–		Level-1/level-2
2	46	−183,279.90	367,017.51	366,651.79	–	–	–	–	–	0.868	2454 (11.7%)/47 (44.3%)
3	65	−176,629.92	353,906.62	353,389.85	–	–	–	–	–	0.876	900 (4.3%)/47 (44.3%)
4	84	−172,893.76	346,623.35	345,955.52	–	–	–	–	–	0.843	1075 (5.1%)/47 (44.3%)
Level–2: 3 profiles					–	–	–	–	–		
2	54	−183,175.98	366,889.27	366,459.95	–	–	–	–	–	0.885	265 (1.3%)/31 (29.2%)
3*	74	−176,498.12	353,732.56	353,144.24	–	–	–	–	–	0.887	518 (2.5%)/31 (29.2%)
4*	99	−172,746.00	346,427.61	345,680.01	–	–	–	–	–	0.863	109 (0.5%)/31 (29.2%)

Notes. BIC = Bayesian information criterion; BLRT = bootstrapped log likelihood ratio test; df = degrees of freedom; LL = log likelihood; LRT = Lo-Mendel-Rubin; models included contextual predictors (i.e., gender, intervention status, race, and lunch status).
* These models encountered estimation problems that resulted in fixed parameters.

(i.e., delinquent and aggressive behavior at school). The "negative school climate" profile ($n = 3492$, 17%) had the lowest perceptions of the positive school climate domains and the highest means for the negative domains. All school climate indicators were significantly different among all profiles at $p < 0.01$.

Two subtypes of schools represented the predominant distributions of these profiles at the school level. "Climate challenged" schools represented 66% of students and 56% of schools compared to the "marginal climate" schools which accounted for 34% of students and 45% of schools. We identified schools as "climate challenged" given that they had a larger proportion of students reporting "moderate" and "negative" climate in their schools compared to "marginal climate" schools. We selected the label "marginal climate" rather than "positive" or "satisfactory" climate given that these schools still had >60% of students reporting school climate as "moderate" or "negative." "Climate challenged" schools had 63% of student in the "moderate climate" profile, 19% in the "negative climate" profile, and 19% in the "positive climate" profile. Schools in the "marginal climate" profile had 51% of students in the "moderate climate" profile, 37% in the "positive climate" profile, and 12% in the "negative climate" profile (see Fig. 2).

When considering the association between the individual-level and school-level profiles, the difference in school-level profiles was driven by differences in the proportion of students in the "moderate" and "negative" school climate profiles. Youth in the "positive" climate profile were significantly more likely to attend schools that belonged to "marginal climate" schools ($B = 0.39$, $SE = 0.09$, $t = 4.59$, $p < 0.001$). On the other hand, youth in the "moderate" and "negative" climate profiles were more likely

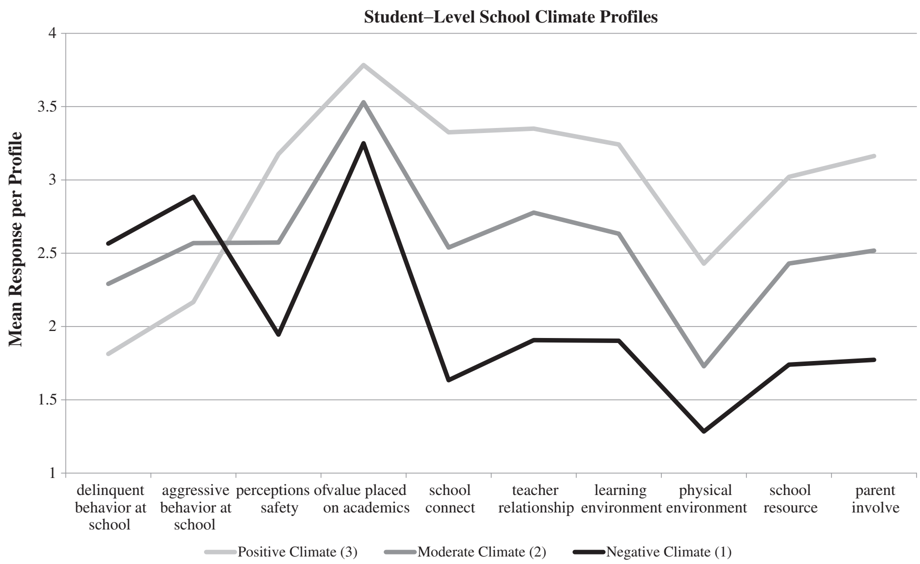

Fig. 1. Mean levels of each school climate domain among the three profiles of students' school climate perceptions; higher scores reflect better school climate except for delinquent and aggressive behavior at school where lower values indicate better school climate.

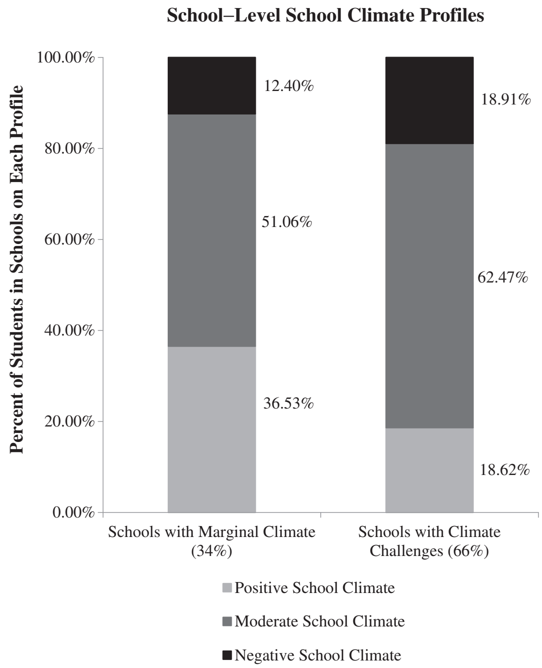

Fig. 2. Distribution of student–level school climate profiles across school–level climate profiles.

to attend schools that belonged to the "climate challenged" profile ("moderate climate" profile: B = 1.64, SE = 0.16, $t = 10.31$, $p < 0.001$; "negative climate" profile: B = 1.26, SE = 0.12, $t = 10.82$, $p < 0.001$).

3.3. Associations with chronic absence

At the individual level, results indicated that students in the "positive climate" profile attended schools with significantly lower chronic absence rates compared to those in the "moderate" and "negative" climate profiles after controlling for school–level

Table 4
Level–1 profiles: fixed effects of differentiating variables with individual–level school climate profile membership.

	Schools with marginal climate (individuals: $n = 7336$, 35%; schools: $n = 47$)		
	Positive school climate $n = 2724$; 13% M (SD)/%	Moderate school climate $n = 3731$; 17.8% M (SD)/%	Negative school climate $n = 901$; 4.3% M (SD)/%
Chronic absences	24.00	32.14	35.79
Male (school–level)	47.96	49.47	50.67
High school	45.0	44.2	40.0
Student-to-teacher ratio	19.18 (2.89)	19.56 (3.38)	19.45 (3.44)
Mobility	23.71	30.76	35.55
FARM	58.62	62.67	63.78
Male (individual–level)	39.74	43.50	43.37
	Schools with climate challenges (individuals: $n = 13{,}614$, 66%; schools: $n = 59$)		
	Positive school climate $n = 2473$; 11.8%	Moderate school climate $n = 8530$; 40.7%	Negative school climate $n = 2599$; 12.4%
	M (SD)/%	M (SD)/%	M (SD)/%
Chronic absences	27.13	40.94	44.71
Male (school–level)	49.82	51.60	52.02
High school	37.30	52.40	56.40
Student-to-teacher ratio	18.03 (3.44)	18.24 (2.74)	17.95 (2.82)
Mobility	35.53	48.72	53.34
FARM	65.56	65.23	63.69
Male (individual–level)	41.61	42.72	43.63

Note. FARM = percent of the students who qualified for federally subsidized meal program at school; mobility = percentage of students enrolling in and withdrawing from the school during the school year divided by the average daily school enrollment; the following school–level variables refer to percent of characteristics present in each school: male, mobility, FARM, and chronic absence; these values reflect modal assignment.

Table 5
Level–1 profiles: fixed effects of differentiating variables with individual–level school climate profile membership.

	Schools with marginal climate vs. school with climate challenges			
	B	SE	*t*	*p*
Chronic absences	**0.033**	**0.015**	**2.234**	**0.025**
Male (school–level)	−0.039	0.025	−1.567	0.117
High school	0.908	0.769	1.182	0.237
Student-to-teacher ratio	−0.041	0.064	−0.640	0.522
Mobility	**0.039**	**0.014**	**2.742**	**0.006**
FARM	0.013	0.021	0.584	0.559

	Individual–level profile comparisons											
	Positive vs. moderate climate				Positive vs. negative climate				Moderate vs. negative climate			
	B	SE	*t*	*p*	B	SE	*t*	*p*	B	SE	*t*	*p*
Chronic Absences	**0.011**	**0.004**	**2.776**	**0.005**	**0.016**	**0.005**	**2.997**	**0.003**	0.004	0.003	1.445	0.148
Male (school–level)	0.011	0.015	0.762	0.446	0.020	0.015	1.337	0.181	0.011	0.007	1.635	0.102
High school	**0.465**	**0.162**	**2.876**	**0.004**	0.224	0.190	1.180	0.238	**−0.245**	**0.121**	**−2.021**	**0.043**
Student-to-teacher ratio	**0.075**	**0.022**	**3.337**	**0.001**	**0.103**	**0.026**	**4.005**	**<0.001**	**0.031**	**0.014**	**2.242**	**0.025**
Mobility	**0.021**	**0.006**	**3.692**	**<0.001**	**0.032**	**0.007**	**4.853**	**<0.001**	**0.011**	**0.003**	**3.673**	**<0.001**
FARM	0.009	0.005	1.774	0.076	0.001	0.006	0.177	0.859	**−0.008**	**0.004**	**−2.020**	**0.043**
Male (individual–level)	**0.221**	**0.050**	**4.418**	**<0.001**	**0.242**	**0.070**	**3.477**	**<0.001**	0.021	0.054	0.383	0.701

Notes. B = log odds estimates; FARM = percent of the students who qualified for federally subsidized meal program at school; mobility = percentage of students enrolling in and withdrawing from the school during the school year divided by the average daily school enrollment; significant parameter estimates are notated in bold text; the following school–level variables refer to percent of characteristics present in each school: male, mobility, FARM, and chronic absence.

characteristics ("moderate climate" profile: B = 0.011, SE = 0.004, $t = 2.776$, $p = 0.005$; "negative climate" profile: B = 0.016, SE = 0.005, $t = 2.997$, $p = 0.003$). The rate of chronic absence between schools with students in the "moderate" and "negative" climate profiles was not significantly different (B = 0.004, SE = 0.003, $t = 1.445$, $p = 0.148$). At the school level, "climate challenged" schools had significantly higher chronic absence rates than "marginal climate" schools (B = 0.033, SE = 0.015, $t = 2.234$, $p = 0.025$). Differentiation among profiles by school–level covariates can be found in Tables 4 and 5.

4. Discussion

Chronic absence is an important problem that has received relatively limited attention in the literature, yet forms the focus of a new federal initiative (DOE et al., 2015). It is a significant risk factor for school dropout (Allensworth & Easton, 2007; Neild & Balfanz, 2006; Neild, Balfanz, & Herzog, 2007), which is closely associated with academic underachievement, delinquent behaviors, and limited economic opportunities (Kearney, 2008a). School climate may play a critical role in chronic absenteeism, yet little research on the association between these constructs exists. We sought to fill this gap in the literature by considering a multilevel latent profile analysis to identify meaningful subgroups of school climate at the individual and school level, and examine how these profiles were related to chronic absence, controlling for a range of important school–level organizational characteristics. Three student–level climate profiles emerged corresponding to "positive," "moderate", and "negative" perceptions of school climate. These profiles displayed two distinct distributions at the school level, a subgroup of schools with "marginal climate" and a subgroup of schools with "challenged climate." Chronic absence was significantly lower in the "positive climate" profile than the "moderate" or "negative" climate profiles, a difference that emerged at the school level as well with "climate challenged" schools having significantly higher chronic absence than "marginal climate" schools.

These findings provide support for a link between school climate and chronic absence. Students who perceive their schools climate to be more negative are more likely to attend schools with higher rates of chronic absence. Results extended to the school–level profiles, indicating that as the proportion of students who perceive the school's climate to be "moderate" or "negative" increases, chronic absence rates likewise increase. These findings suggest that simply targeting youth who are chronically absent, as has been the focus with intervention for chronic absences, is not enough. Instead, school-wide climate improvement strategies appear critical for improving the overarching experience of attending school and increasing school attendance. Such an approach requires a multi-tiered intervention framework, such a Positive Behavioral Interventions and Supports (PBIS; Sugai & Horner, 2006). PBIS has been found to improve school climate in elementary schools (Bradshaw, Koth, Thornton, & Leaf, 2009) and emerging research demonstrates that this approach extends to middle and high schools as well (Bradshaw et al., 2014a).

The school climate constructs that demonstrated the greatest difference across the profiles included school connectedness, parent involvement, relationship with teachers, and the learning environment. Interestingly, these areas of school climate that appear to differentiate the school climate profiles the most relate to the interpersonal links youth and families have to school staff. Identifying ways to foster and strengthen these relationships across the school seems to be critical for improving school climate and chronic absence rates. For example, effective interventions may include encouraging teachers and staff to build supportive relationships with students, monitoring and supporting positive peer relations, offering tailored resources for academic and socio-emotional student difficulties, finding creative and engaging ways to involve parents in school activities during and after the school day, and offering engrossing learning environments with increased exchange between teachers and students.

Current efforts to reduce chronic absence often include interventions such as mentoring and strengthening school staff to student connections for youth with many school absences (Balfanz & Byrnes, 2013). These strategies have been related to improvements in attendance and this study provides support for this approach. School administrators also report using strategies that focus on building school-to-family partnerships through a range of activities such as providing school-based workshops on parenting practices to improve attendance, reaching out to provide parents with their child's attendance rates, inviting community members to speak to parents on topics impacting school attendance, and inviting parents to attend ceremonies related to their child's class achievements. Schools attempting to implement school-family partnership activities display modest improvements in attendance as well (Sheldon & Epstein, 2004). These findings suggest that there are a variety of activities school staff are already using with some success to improve attendance. Future research should include more rigorous, empirical evaluation of these approaches. Further, our research suggests that an increased focus on the quality of school climate may also be critical for reducing the chronic absence rate in middle and high schools.

Notably, youth in the "negative climate" profile observed the highest rate of delinquent and aggressive behavior at school. These results may reflect a responder's greater engagement in these behaviors or greater affiliation with youth demonstrating these behaviors (Farmer et al., 2003; Lounsbury, Steel, Loveland, & Gibson, 2004). On the other hand, these youth may also experience higher rates of victimization and bullying than other youth (Waasdorp, Pas, O'Brennan, & Bradshaw, 2011). These results highlight the fact that those youth who reported a "negative climate" at their school may represent diverse socio-and emotional concerns that require different school-based supports to reduce risk of chronic absence and school drop-out. Future research should explore the range of concerns associated with "negative" school climate among youth who demonstrate poor attendance at school to better characterize this group of youth.

Decreasing chronic absence is critical as it sets students on a negative trajectory toward high school dropout (Mac Iver & Mac Iver, 2010). Chronic absence is a strong predictor of school drop-out (Allensworth & Easton, 2007; Neild & Balfanz, 2006; Neild et al., 2007), with some research indicating that youth who were chronically absent in the previous year were 7.4 times more likely to drop out (Utah Data Alliance, 2012). Once youth dropout of school, they often lose connection to much-needed support from school-based programs. Further, school administration and staff often have limited capacity to remain in contact with these youth, making efforts to re-engage them in academics extremely difficult. Although many factors have been posited to account for the link between chronic absence and school dropout, academic difficulty and failure appears to play an important role (Kearney, 2008a). Academic achievement clearly suffers when a student's attendance drops, but perceptions of school climate may also link chronic absence to drop-out in addition to impacting academic achievement. Future research should explore the effect of school climate perceptions on academic achievement and on the progression from chronic absence to school dropout. Understanding the temporal links among academic achievement, chronic absence, and school climate are critical for informing the development of effective intervention.

Importantly, the cross-sectional design of this study does not allow the causal direction of the association between chronic absence and school climate to be examined. It may be that school climate leads to chronic absence, but chronic absence may also negatively impact school climate, and additional analyses are necessary to clarify the directionality of this association. Youth who are chronically absent may require significant amounts of teacher attention when they attend school to catch up and stay engaged in difficult academic material, detracting from educational instruction of consistently attending youth (Ginsburg et al., 2014). Given associations that externalizing symptoms and academic difficulties share with chronic absence (Henry et al., 2012; Kearney 2008a), these youth may also engage in disruptive, aggressive, and off-task behavior in class as a result of unmet mental health needs and frustration with academic difficulties (Madill, Gest, & Rodkin, 2014). Given that insufficient or punitive classroom management practices and low quality of instruction are linked to poor student perceptions of school climate (Mitchell & Bradshaw, 2013), classroom management and instruction quality may have already contributed to attendance problems for youth with academic struggles and disruptive behavior. Chronic absence is likely to tax this dynamic further, eroding the capacity for teachers to meet the academic and behavioral needs of the classroom. Future research should identify the directional associations between chronic absence and school climate, as well as identify how classroom characteristics influence chronic absence. Such findings will be critical for designing effective prevention and intervention approaches.

This study was unique in that it used MLPA to identify subtypes of school climate and explored how these subtypes of school climate varied at the school level. Little to no research to date has used latent person-centered modeling strategies to identify profiles of school climate. Understanding common profiles of youth school climate perceptions may be informative for tailoring intervention to specific school climate concerns. But also, individual climate perceptions contribute to a cumulative, overarching climate at the school level that may have an important and unique impact on student experiences at school and contribute to negative outcomes for youth such as chronic absence. Future research should explore consistent and differential ways that individual-level and school–level climate impact student outcomes.

4.1. Limitations

This study included ratings from only one school district, which included an urban, predominantly African-American sample of youth. The unique demographic characteristics of this sample may reduce generalizability to the broader population of middle and high school students. However, many studies include samples with low representation of African-American youth. Thus, this study also contributes to this gap in the literature. Nonetheless, future research should clarify subtypes of school climate in samples with different demographic characteristics. These analyses were also cross-sectional, which, as mentioned previously, prevents identification of directional associations between chronic absence and school climate.

The measure of chronic absence was limited to the school level. Therefore, it was not possible to identify if students who responded were chronically absent at any point during the school year. Thus, it is not possible to identify how chronically absent youth perceive their school's climate. However, research suggests that student report can collectively provide an accurate representation of typical experiences of a school's climate (Van Horn, 2003). Future research should specifically explore how chronically absent youth perceive school climate. However, this study's results suggest that even youth who attend school have negative perceptions of climate which are related to poor attendance at that school.

Other limitations include the fact that some of the reliability for the constructs in this study were below the standard cut point for 0.80. Future research should use measurement strategies with strong reliability and validity. Although estimation procedures (i.e., FIML) were sufficient for managing the impact of data missing at random or completely at random, data missing not missing at random may have impacted findings. Data collection by completing surveys as a part of normal classroom activities may have led to students who were chronically absent not completing the survey. Further, there is no way to evaluated the proportion of students where were chronically absent who did not complete the survey. Thus, the impact of missing these responses cannot be identified. Future research should use different methodological designs that incorporate other sampling and measurement approaches to identify how school climate and chronic absence relate. Finally, this study included only student perceptions. Teachers and parents may have different perceptions of school climate, and measurement strategies involving objective observers cannot provide validity for the student perceptions reported herein. On the other hand, students may hold unique perceptions of school climate that meaningfully link to important outcomes. For example, youth self-report of delinquent and aggressive behavior shows only small to moderate correlations with the reports of their parents or teachers (Youngstrom, Loeber, & Stouthamer-Loeber, 2000). These experiences may occur outside the purview of parents and teachers, making youth more accurate reporters of these experiences. Difference in student perceptions as compared to teacher and outside observer report may be critical in understanding youth's experience of attending a specific school, their behavior at school, and their academic performance. Thus, consideration of student perceptions of school climate may be an important window into a risk process for chronic absence and school dropout. Future research should explore how sensitive these perceptions are to interventions targeting school climate.

Finally, the response rate and missing data from students who did complete a survey was also a limitation. Both types of missing data were related to study variables indicating that data are missing not at random. The response rate of this study is similar to response rates of many school districts implementing district-wide survey collection. Further, effective missing data strategies were used to minimize the influence of missing data on analyses. However, these findings should be replicated with data collected through multi-method survey administration where many strategies and attempts are made to ensure that response rate and survey completion remains high.

4.2. Summary and conclusion

Using a MLPA approach, we identified three individual–level school climate profiles that displayed two predominant distributions across schools. Chronic absence differentiated individual–level profiles in a pattern suggesting that as perceptions of the school climate became more negative chronic absence in their school was higher. Schools with the higher proportion of students in the "moderate" and "negative" climate profiles also demonstrated higher chronic absence rates. These results suggest a meaningful association between school climate and chronic absence at the individual and school levels. Future research should explore the directionality of this association and effective prevention and intervention approaches to improve school climate and reduce chronic absence.

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